Balance Sheet Forecast

Model ID# 2502

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Validation Report:	Andrea Ghiringhelli, Model Risk Management March 11, 2016

Purpose and Use

A. <u>Purpose of Model:</u>

BNY Mellon's Asset and Liability Management team (ALM team) has developed balance and rate forecasting models. The models are intended to be used to generate balance sheet projections for the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act supervisory stress testing (DFAST) programs. Eventually, the models may be used in the monthly forecasting and planning process executed by BNY Mellon's ALM team

The project scope was to develop comprehensive forecasts for the entire balance sheet as well as certain off-balance sheet segments. It also covered all customer interest rate forecasting approaches, such as rates paid on deposits and rates received on loans. However, it did not cover the rates on securities held in BNY Mellon's Investment Portfolio.

B. <u>Areas of Use:</u>

Bank of New York Mellon (BNY Mellon) has developed its next generation forecasting approach to predict balances and rates under the CCAR and DFAST programs. In the future, the Firm may also choose to use this framework as a benchmark for the lines of businesses' monthly forecasts used for planning purposes, though such an application is outside of the scope of this document and subject to future discussions.

C. <u>Work Stream Category</u>: PPNR – Balance Sheet – RWA

D. <u>Limitations:</u>

The key limitations of the model-based approach are as follows:

- The chosen approach is dependent on the existence of a sufficient number of observations in the balances and rates data as well as the quality of the data. Short time series data or data with measurement errors may reduce the robustness of conclusions drawn from a statistical model.
    - While measurement error has not emerged as a concern for any segments, the development data period is short, starting in January 2008 due to the merger between Bank of New York and Mellon Financial in 2007. This period covers a recession period

(per NBER, the latest recession started in December 2007 and ended in June 2009 – the development data covers all months but one in this period) and post-recession environment. However, some macroeconomic factors are subject to cycles that behave somewhat differently from business cycles that are based on economic growth. Therefore, the development data does not cover a full cycle for some macroeconomic factors. This is particularly the case for interest rates given the initially decreasing and subsequently low rate environment since 2008. As a result, models might not fully capture balance and rate responses to interest rate movements.

  - The modeling team recommends that interest rate effects be given special consideration during the management review and challenge process that is part of BNY Mellon's CCAR process.

- It might not be always possible to find an intuitive and statistically significant relationship between the balances or rates and the macroeconomic variables. In some segments macroeconomic factors are not drivers of balances and rates, in particular if they have been driven by management decisions or idiosyncratic events over extended periods in the past.
  - The developed models are subject to the same rigorous statistical process but differ in their statistical significance and/or the intuitiveness of their forecasted behavior.
  - The weaker models should be treated with higher scrutiny during the management review and challenge process.
  - For segments where no model could be developed with intuitive relationships, a structural approach was developed.
- Both balances and customer rates are driven by macroeconomic drivers which are explicitly captured in the developed models for balances and customer rates.
  - It is possible that BNY Mellon might have chosen (or will choose in the future) to incentivize or disincentivize certain customer behavior by increasing or decreasing customer rates.
  - This strategic interaction between balances and rates is not captured in the models. However, when there were such customer rate actions in the past. The Working Group[1] considered the implications in the model selection process.
- A small number of macroeconomic variables, e.g., GDP, do not exist as a monthly frequency. For these variables a cubic-spline interpolation method was used to derive the monthly data from the historically available quarterly data. This is based on the assumption that a cubic-spline function approximates the actual historical part of these variables reasonably well.

The key limitations of the structural approach are as follows:

- Structural approaches, just like statistical models, rely on historical relationships and patterns, and they can fall short of predicting balances and rates in changing environments.

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[1] The project was driven by two governing bodies that met regularly to review the methodology, progress, results. Decisions on final models and approaches were made by the Steering Committee based on the recommendations of the Working Group. The responsibilities of the Working Group were to discuss methodological approaches, review of interim results and analyses, recommendations to Steering Committee on all modeling decisions necessary to determine final model, transfer of knowledge to modeling team, resource and data sourcing. The meeting schedule was at least weekly, often bi-weekly.

Background

Appendix A attached to this document contains the documentation for the balance and customer rates model development. Section 1 contains more information on the background and the business need of the balance and rate forecasting approach.

Model Specification

A. Methodology

Overview:

Section 3 of Appendix A describes the methodology used for the development of the balance sheet and rates forecasting models and approaches.

Assumptions:

Section 3.7 of Appendix A describes the assumptions necessary for the statistical models and the structural approaches.

Formulation:

Section 3 of Appendix A describes the approach for both the statistical models as well as the structural approaches.

Section 4 of Appendix A describes the development data for the statistical models.

B. Input Data and Data Assumptions

Input Data:

The input data is based on the supervisory scenarios – baseline, adverse, and severely adverse – that the Board of Governors of the Federal Reserve System (Federal Reserve) will use in its supervisory stress test and that banks must use in conducting its annual company-run stress test. BNY Mellon's CCAR process determines how the data released by the Federal Reserve is used to derive the actual inputs for the models. The process currently relies on using internal processes as well as the third-party vendor Moody's to provide the input data for the forecasting approaches.

Assumptions Used as Inputs:

All input data will be available for all structural and statistical approaches. The balance sheet forecasting process has been developed to create all required input data. Input data for the structural and statistical approaches will be available from BNY Mellon and the Federal Reserve resources.

C. Calculations

An overview of the results is presented in Section 1.3 of Appendix A.

The results for all segments are presented in Sections 5 to 12 of Appendix A:

- Section 5 contains the results of the deposit balance segments
- Section 6 contains the results of the deposit rates segments

- Section 7 contains the results of the total facility amounts, drawn amounts, letters of credit amounts, and closed-end loan balance segments
- Section 8 contains the results of the loan rates segments
- Section 9 contains the results of the Investment Portfolio forecasting approach development
- Section 10 contains the results of the other balance sheet balance segments
- Section 11 contains the results of the other balance sheet rate segments
- Section 12 contains the results of the segments for which net interest incomes are directly modeled.

Testing the Model

A. Analysis of the Model

Assumption Validity:

For all models a set of diagnostic tests were executed. Table 1 lists the diagnostic tests used.

Table 1: List of diagnostic tests

Test	Definition	Application in modeling approach
VIF	The Variance Inflation Factor is a measure of the correlation among the independent variables.	A VIF in excess of 5 indicates that a model's selection of independent variables should be reviewed and the model dropped unless there is strong intuition for the selection of independent variables.
Breusch-Pagan test	The Breusch-Pagan test is a test used to assess heteroskedasticity in a linear regression model, that is, it tests whether the variance of the residuals are dependent from the values of the independent variables.	A detection of heteroskedasticity indicates that a heteroskedasticity robust estimation should be used to obtain significance tests with the correct size.
Breusch-Godfrey test	The Breusch-Godfrey test is a test used to assess serial correlation in the residuals of a model, i.e., it tests whether residuals dependent on past residual values.	A detection of serial correlation indicates that a heteroskedasticity and autocorrelation consistent estimation should be used to obtain significance tests with the correct size.
RESET test	The RESET test is designed to detect misspecifications in the estimated model.	A detection of a misspecification will result in a review for omitted variables and functional form of the model. As such misspecifications are often not easily corrected because, a failure of this test is most likely to result in an exclusion of the model.

The results of these diagnostic tests are listed in the sections containing the results for each segment where statistical approach is used. The results for the segments are presented in Sections 5 to 12 of Appendix A. In every segment result section, a subsection titled "Significance tests" and a subsection titled “Diagnostic tests” contains the results. A subsection titled “Model limitations” contains the limitations based on the modeling results.

Parameter sensitivity:

For all statistical models, sensitivity tests were executed. The results of these sensitivity tests are presented in the segment result sections. The results for the segments are presented in Sections 5 to 12 of Appendix A. In every segment result section (where statistical approach is used), a subsection titled “Sensitivity to changes in independent variables” contains the results of the sensitivity tests. Note that the independent variables are the input data, i.e., this specific sensitivity test describes the standard deviation change in the predicted dependent variable due to a one standard deviation increase in a specific input variable (i.e., the macroeconomic variables derived from the supervisory stress scenarios). A subsection titled “Model limitations” contains the limitations based on the modeling results.

Result accuracy:

For all statistical models, back-tests as well as sensitivity tests to the modeling period are executed. The results of these back-tests and sensitivity tests are presented in the segment result sections. The results for the segments are presented in Sections 5 to 12 of Appendix A. In every segment result section (where statistical approach is used), a subsection titled “Diagnostic tests” contains the back-tests and a subsection titled “Sensitivity to estimation period” contains the sensitivity tests to the modeling period.

Model fidelity (stability and behavior):

The models are tested for their behavior under stressed input data, i.e., different macroeconomic stress scenarios. The macroeconomic stress scenarios used are based on the CCAR 2015 supervisory stress scenarios. The methodology to create these input data is described in Section 4.7 of Appendix A. The results of these sensitivity tests to stressed input data are presented in the segment result sections. The results for the segments are presented in Sections 5 to 12 of Appendix A. In every segment result section (where statistical approach is used), a subsection titled “Sensitivity to stressed independent variable scenarios” contains the sensitivity tests to stressed input data.

For every group of models, the sensitivity to stressed input data is described in Section 1.3.

B. Analysis of Implementation

This section is not applicable to the balance and rates forecasting models.

C. Ongoing Performance Monitoring Plan

The ongoing monitoring plan includes four modules:

I. Quarterly model auditing
II. Forecast performance review
III. Model re-estimation
IV. Annual model re-assessment

These modules will be implemented in the consecutive four quarters through a full year:

	Q1	Q2	Q3	Q4
Quarterly Auditing	X	X	X	X
Forecast performance review	X		X	
Annual model re-assessment		X		
re-estimation or calibration if applicable				X

In Q4, quarterly model auditing and model re-estimation & calibration (if applicable) will be performed.

In Q1 and Q3, model outputs for CCAR and DFAST stress testing will be prepared. Model forecasting performance will be reviewed to see whether model calibrations or adjustments are needed. Quarterly model auditing result is performed as well.

In Q2, annual model re-assessment will be processed. The purpose of this re-assessment is to comprehensively evaluate whether a model re-development is needed for current year. Besides assessment, every three years from last model development date, re-development rule directly applies. If applicable, re-development will be produced in a staggered schedule, e.g. model re-developed in the second and third quarter, and model being validated by model validation group in the fourth quarter; and new sets of models will be implemented before next year CCAR submission.

I. Quarterly Model Auditing

Auditing template will be set up to compare most recent quarterly performance with Benchmark model. This developed Balance Sheet Forecasting model will be used as a Benchmark.

The following aspects will be in focus when proceeding quarterly auditing:

- Segmentation stability assessment using measurements such as volume difference and distribution stability index (percentage change compared to benchmark)
- Out-of-sample prediction accuracy (one-step prediction based on last month actual in most recent 12 month time window) could be measured through the difference of MAPE(mean absolute percentage error) from benchmark
- Back-testing accuracy (rolling-over prediction starting from a single actual month through most recent 12 month time window) could be measured through the difference of MAPE(mean absolute percentage error) from benchmark
- New quarter’s prediction accuracy can be measured through the slope of absolute average prediction to average actual ratio compared with model building period overall absolute ratio

In this template, criteria will be directly set up to generate by-segment auditing flags. Green flag gives an overall satisfaction of recent model performance; Yellow flag will drive the investigation of corresponding factors and documentation of abnormal observations. Model continues to be monitored; while red flag notifies consideration of re-development for such segment in the following annual model re-assessment.

Criteria for quarterly auditing flags:

- Green: good performances in the following criteria's - segmentation stability index, Out-of-sample MAPE, Back-testing MAPE, new quarter's prediction slope; For example, segmentation stability index is less than 30%.
- Yellow: at least one adverse performance in the following criteria's - segmentation stability index, Out-of-sample MAPE, Back-testing MAPE, new quarter's prediction slope; For example, segmentation stability index is between 30% to 50%.
- Red: at least one severe adverse performance in the following criteria's - segmentation stability index, Out-of-sample MAPE, Back-testing MAPE, new quarter's prediction slope; For example, segmentation stability index is larger than 50%.

II. Forecast Performance Review

- Document stress testing procedures and forecast outputs
- If there is significant variation(for example, over 50% peak-to-peak growth) in the forecast outputs compared to previous historical data or previous stress testing results: investigate drivers of such change in the new forecasting scenarios, whether the key macroeconomic assumptions changed, or whether forecasting methodology and process are incurring special situations; evaluate whether the model using current drivers produce a robust forecasting result or not
- Whether the new forecast numbers align with LOB updated expectation: Different Line of Business provides varied strategy assumptions, and produces their expected forecasting numbers on different segments. The variation between statistical forecasting numbers and LOB's expectations will be viewed. Overlay documentation will be updated if any new overlay is applied.

III. Re-Estimation & Calibration

Re-estimate and calibrate the model using recent performance and updated business expectations. Calibration is Calibration is applied when there is model adjustment need. Document re-estimated segments and adjusted parameters. If calibration is applied, describe the benchmark to which calibration is made and through which calibration algorithm.

IV. Annual Model Re-Assessment

After each year's CCAR submission, annual model re-assessment will be implemented. Incorporating previous three quarters' auditing flags and observations, together with CCAR submission feedback, the existing models will be evaluated. If other methodologies for similar business use have been initiated in other banks or industry, it would be better to test the new methodologies on our portfolio data, and compare the outputs of new model with that of old model. If our portfolio structure has significant change which impacting the product distribution pattern, then some of the segmentations need to be re-considered; or if some segments of our products have new business assumptions, we may also need to consider rebuilding models for those segments. Detailed re-development plan can refer to formal model documentation.

During year-end assessment, the following items should be evaluated and documented.

1. Business Context and Model Use

Review model information such as model name, tier level, owner and user of this model, products/business covered by this model, date model placed in use, how long the model has been in use, the date of last documentation submitted, outstanding dollar amount and other impacts, and secondary use of this model if any. In the next year, whether the model's objective is remaining the same, including the primary uses of the model and what business purposes and exposures need is addressed by the model.

2. Segmentation

Describe current business products distribution pattern. Assess whether the up-to-date business mixtures align with existing segmentation or not. List the waterfall of the existing segmentation with all inclusion/exclusion criteria. Along with segmentation reevaluation, apply qualitative review of statistical models and structural approaches, to see whether some segments which were having structural approaches could be changed to statistical model, and vice versa.

3. Methodological Approach and Comparison to Alternatives

Review existing model methodology. Describe methodology's assumptions and model assessment metrics. Highlight key equations and model flow charts. Examples of model assessment include tests of assumptions, predictive power interpretation, and other goals such as level of granularity, robustness, stability and consistency and etc. If this model is an upgrade to an existing model, explain limitations of the old model that are being addressed.

4. Input Source and Data Quality

The input processing method should be specified, whether manual or automated, whether through some software or platforms. Describe the data source. Details should include platform or data warehouse where the data is available. If there are multiple warehouses can provide data with same business definition, explain why choose one versus the other. Data access and version control is needed.

Quality check can be done on sample data. This includes distribution of data defaults such as ranges, quantiles and characteristics. Example input should be provided. After raw data is pulled, whether other treatments are needed like data cleansing, transformations, proxies/interpolation techniques for fixing missing data and etc.

5. Model Estimation and Outputs

Details model estimation process, including code processing order, driver selection criteria, output transfer and documentation. Document model estimation results. Provide relevant testing and model diagnostics. Examples include statistical significance, residual behavior, stationary, multi-collinearity and convergence tests and etc.

List sample model outputs and reports. Check outcomes and compare with benchmark model performance. Examples include review of model estimation, prediction on sample segment and back-testing and etc.

6. Recent model performance auditing

As described in previous section 'Quarterly Model Auditing'.

7. Platforms and Operating Environment

List the platform and databases in which the model is implemented. Monitor on whether such operating environment has access control, version control, and operational risk.

8. Model Limitations

Describe the details of circumstances where model should not be used without other adjustments. Explain the sources of such model limitations, e.g. whether associated with data inputs or assumptions or implementation process and etc.

References for Model Documentation: Include references to supporting papers and literature.

Change Log

Track updates made to the documentation. The change log should capture what changes have been made, when, and by whom.

Revision History of Model

Date	Section	Description of Change	Validation of Change	Validation Date
9/18/15	All	Start development document draft		
11/9/15	Asset Servicing IB Balance	After model development was completed, the ALM team developed an infrastructure that automates the monthly extracts of balances and rates from the management accounting system. During the set-up of these templates and programs, the ALM team discovered that the balance of a sub-segment of Asset Servicing Interest Bearing Deposits mistakenly contained accounts that were also included in the segment AIS/GCS IB. These balances were therefore double counted between the AS IB and the AIS/GCS IB model. To obtain the correct AS IB balances, the double-counted account balances have to be subtracted from the AS IB balances as created previously. A spreadsheet showing the	Validation in progress	

		correction is attached. The modeling team re-developed the AS IB model based on the corrected balances. The changes resulted in a different selection of candidate models. The candidate models were discussed with the model owner as well as other stakeholders and a final model was selected. It contains the same variables as the pre-correction final model, a world-wide equity index as well as a short-term interest rate. The coefficient estimates are slightly different from the pre-correction final model. The model development documentation has been updated to reflect these changes.		
12/7/15	Foreign Deposits in Currencies Other than USD, Euro and GBP Balance	After model development was completed, the ALM team developed an infrastructure that automates the monthly extracts of balances and rates from the management accounting system. During the set-up of these templates and programs, the ALM team discovered that the balances of the segment Foreign Other were not correctly aggregated. The MAQ data extract listed foreign currency balances in native currencies while the modeling team had erroneously treated them as USD. The modeling team attempted to redevelop the Foreign Other deposit model, but no viable statistical models could be found. The modeling team therefore developed a structural approach for the Foreign Other deposit segment in collaboration with the Model Owner and the lines of business. The structural approach is described in the revised model development documentation as submitted to the model validation team on November 20, 2015.	Validation in progress	
12/7/15	Asset Servicing DDA Balance	After completion of the model development, the modeling team discovered that the SAS program log of one of the segments, the AS DDA deposit segment, contained error messages that had previously been missed. The error messages reported that the SAS optimization procedure for the selected estimator (GMM) of the Newey-West p-values had not converged for certain models. As a result, the modeling team had used Newey-West p-values in the AS DDA segment that were based on a different estimator (2SLS) that SAS Software defaulted to whenever the GMM estimator failed to converge. The modeling team determined that the failures to converge were due to the very large numbers in the dependent variable of the AS DDA segment (up to around 16,000,000,000) in combination with certain independent variables. The dependent	Validation in progress	

		variable was rescaled from USD to USD Million and the SAS code was rerun to re-estimate all Newey-West p-values of the models extracted through the SAS procedure. The modeling team confirmed in the SAS program log that no errors occurred after the re-scaling of the dependent variable. It reselected the candidate models based on the corrected SAS output and presented them to the Working Group. The Working Group selected a new final model. The documentation was updated for the new model. The modeling team has checked the candidate and final models of all segments for this issue by reviewing the SAS program logs and the team confirmed that no other segment has been affected by this issue. The documentation now also contains instructions to rescale all dependent variables from USD to USD MM to avoid similar issues during future re-estimation and redevelopment of the models.		
02/03/2016	Corporate Trust Euro Balance	The previous model was rejected by MRMG, and doubted on the validity of forecasting pattern. So the model is changed to a new candidate model, which shows more promising forecasting trends, and is also in line with the expectation of Line of Business of the selected drivers and forecasting shapes.	Validation in progress	
03/08/2016	Corporate Trust GBP Balance	The previous model was rejected by MRMG, and doubted on the intuitiveness of model forecasting and use of drivers including Dow Jones index as a US driver to predict UK balance sheet item. Through communication with line of business, it is suggested that there is strong correlation between Corporate Trust Euro balance and Corporate GBP balance. Thus, a new approach using Corporate Trust Euro balance as the base, and a most recent 3 month average balance ratio between Euro and GBP balance as the scaling factor is applied.	Validation in progress	

03/08/2016	Two segments: Pershing Repo Rate and Pershing Reverse Repo Rate	Due to our most recent communication with Pershing line of business, the Pershing Repo Rate and Pershing Reverse Repo Rate, these two segments' historical data need to be refreshed. Previous historical Pershing Repo rate and Pershing Reverse Repo rate data were including a portfolio part called "Specials", while now the data is refreshed to exclude this part. So the model development data is refreshed and the models for Pershing Repo rate and Pershing Reverse Repo rate are refitted as the new model. The reason to exclude the "Specials" from the rates data is because of the following: Securities are either "general collateral" (GC) or "hard-to-borrow" (HTB) securities. Specials are hard-to-borrow securities. Generally, when Pershing borrows GC securities in exchange for cash, Pershing would earn a market rate on the cash it gives up. If securities were HTB, Pershing would earn a below market rate. When securities are in such demand that the lender of the security is asking Pershing to pay a premium for borrowing them, such securities are deemed "specials". Pershing would then mark up the rate (cost) and pass it on to the short seller. Conversely, if Pershing has access to such HTB /Specials securities in its portfolio (hypothecated by customers), Pershing would lend them out to the street to earn a rate (premium) on them. Market conditions determine the rate earned or paid on HTB/Specials. This could change daily, depending on the demand and supply for such securities. The income / expense from specials can vary a lot and if blended into the GC stock borrow / loan rates (tied to overnight rates) could cause the overall stock borrow / lending rate to swing a lot (fluctuations cannot be explained by changes in the overnight market rates).	Full scope validation (except documentation updates)	3/11/2016

3/31/2016	Editorial Changes	The model development documentation has been updated to reflect all the changes since Feb. 2016 on balance sheet forecasting (the changes are already approved, either by MRMG (on statistical approaches and single models) or QFP (on qualitative approaches) :
		
		▪ Model redevelopment
		    ○ CT EUR balance (with new variables)
		    ○ Pershing Repo Rate
		    ○ Pershing Reverse Repo Rate
		▪ Segment switch from statistical approach to qualitative framework
			Full Scope validation – Model Documentation Review	3/31/2016

		o Corporate Treasury Interest Bearing Deposits (Balances) (first used overlay and rejected by MRMG and then switched to QFP) o Short-term borrowings: Fed funds Purchased, Repos (Treasury) (Balances) o Securities Financing (rate) ▪ Segments identified as simple model and transferred by QFP to MRMG review: o Nostro balance o Pershing Placements balance o CT GBP balance (first switched from statistical model to QFP and then identified as Simple Model) o Foreign Deposits in Currencies Other than USD/Euro/GBP Balance o Trading Liability (Capital Markets) balance o Trading Liability (Global Markets) balance ▪ Additional segment added for qualitative approach: o Loan Fees Net Interest Income NII o Interest Income from Specials Net Interest Income NII o Short Term Borrowings: Capital Markets Balance and Rate: Liabilities (Other) (Balance and Rate) ▪ Incorporate editorial changes for qualitative approach segment ▪ Additional editorial wording change		

Access Controls (List of those authorized to change the model)

Randhir Ahluwalia
Huijuan (Gracie) Li

Appendix B: All Segments for Balance Sheet Forecasting

					Reasons for qualitative framework			
#	Segment	Model Category	Model Type	Model Approach	Lack of economic relationship	Materiality	Feasibility (data availability)	Other
1	Commercial Loans (balance segment)	Assets (Loans)	Closed End Loan Balance	Statistical				
2	Commercial Loans (balance segment)	Assets (Loans)	Draw %	Statistical				
3	Commercial Loans (balance segment)	Assets (Loans)	LC Usage %	Statistical				
4	Commercial Loans (balance segment)	Assets (Loans)	Total Commitment	Statistical				
5	CRE Loans	Assets (Loans)	Closed End Loan Balance	Statistical				
6	CRE Loans	Assets (Loans)	Draw %	Statistical				
7	CRE Loans	Assets (Loans)	LC Usage %	Qualitative	X			
8	CRE Loans	Assets (Loans)	Total Commitment	Statistical				
9	Financial Institution Loans	Assets (Loans)	Closed End Loan Balance	Statistical				
10	Financial Institution Loans	Assets (Loans)	Draw %	Statistical				
11	Financial Institution Loans	Assets (Loans)	LC Usage %	Statistical				
12	Financial Institution Loans	Assets (Loans)	Total Commitment	Statistical				
13	Margin Loans	Assets (Loans)	Closed End Loan Balance	Statistical				
14	Margin Loans	Assets (Loans)	Total Commitment	Qualitative	X	X	X	
15	Other mortgage loans	Assets (Loans)	Balance	Qualitative	X	X		
16	Overdrafts	Assets (Loans)	Balance	Statistical				
17	Reverse mortgages	Assets (Loans)	Balance	Qualitative	X	X	X	
18	Wealth Management Loans	Assets (Loans)	Balance	Statistical				
19	Wealth Management Loans	Assets (Loans)	Draw %	Statistical				
20	Wealth Management Loans	Assets (Loans)	LC Usage %	Qualitative	X	X		
21	Wealth Management Loans	Assets (Loans)	Total Commitment	Statistical				
22	Wealth Management Mortgage	Assets (Loans)	Balance	Statistical				
23	HELOCs	Assets (Loans)	Balance	Qualitative	X	X		

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
24	Iron Hound Loans	Assets (Loans)	Balance	Qualitative	X	X	X	
25	Lease Financing	Assets (Loans)	Balance	Qualitative	X			
26	Central bank deposits: Fed deposits	Assets (Other BS)	Balance	Qualitative	X			
27	Central bank deposits: Foreign Central Bank deposits	Assets (Other BS)	Balance	Qualitative	X			
28	Fed Fund Sold and Rev Repos: Non-Pershing	Assets (Other BS)	Balance	Qualitative		X		
29	Investment Portfolio	Assets (Other BS)	Balance	Qualitative	X			
30	Non-interest earning assets (excl Goodwill, Intangibles)	Assets (Other BS)	Balance	Qualitative	X			
31	Non-interest earning assets: Goodwill	Assets (Other BS)	Balance	Qualitative	X			
32	Non-interest earning assets: Intangibles	Assets (Other BS)	Balance	Qualitative	X			
33	Placements: Nostro	Assets (Other BS)	Balance	Simple Model	X		X	
34	Placements: Pershing	Assets (Other BS)	Balance	Simple Model	X	X		
35	Placements: Treasury	Assets (Other BS)	Balance	Qualitative	X			
36	Reverse Repos: Pershing	Assets (Other BS)	Balance	Statistical				
37	Securities Financing	Assets (Other BS)	Balance	Statistical				
38	Trading Assets: Capital Markets	Assets (Other BS)	Balance	Statistical				
39	Trading Assets: Global Markets	Assets (Other BS)	Balance	Statistical				
40	Alternative Investment Services and Global Collateral Services Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
41	Alternative Investment Services and Global Collateral Services Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
42	Asset Servicing Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
43	Asset Servicing Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
44	Asset Servicing/ Treasury Services EU	Liabilities (Deposits)	Balance	Statistical				
45	Asset Servicing/ Treasury Services GB	Liabilities (Deposits)	Balance	Statistical				

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
46	Broker Dealer Services Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
47	Corporate Treasury Interest Bearing Deposits	Liabilities (Deposits)	Balance	Qualitative	X			
48	Corporate Trust Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
49	Corporate Trust Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
50	Corporate Trust Interest Bearing Deposits EU	Liabilities (Deposits)	Balance	Statistical				
51	Corporate Trust Interest Bearing Deposits GB	Liabilities (Deposits)	Balance	Simple Model			X	
52	Foreign deposits in currencies other than USD, Euro and GBP	Liabilities (Deposits)	Balance	Simple Model			X	
53	Treasury Services Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
54	Treasury Services Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
55	Wealth Management Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
56	Wealth Management Personal Deposits	Liabilities (Deposits)	Balance	Statistical				
57	Wealth Management Sweep Deposits	Liabilities (Deposits)	Balance	Statistical				
58	Broker Dealer Payables	Liabilities (Other BS)	Balance	Statistical				
59	Long term debt	Liabilities (Other BS)	Balance	Qualitative	X			
60	Non-interest bearing liabilities	Liabilities (Other BS)	Balance	Qualitative	X			
61	Repos: Pershing	Liabilities (Other BS)	Balance	Statistical				
62	Short-term borrowings: Commercial Paper	Liabilities (Other BS)	Balance	Qualitative	X	X		
63	Short-term borrowings: Fed funds, Repos (Treasury)	Liabilities (Other BS)	Balance	Qualitative	X			
64	Short-term borrowings: Other borrowed funds	Liabilities (Other BS)	Balance	Qualitative	X	X		
65	Trading Liabilities: Capital Markets	Liabilities (Other BS)	Balance	Simple Model				Modeled off of Trading Assets
66	Trading Liabilities: Global Markets	Liabilities (Other BS)	Balance	Simple Model				Modeled off of Trading Assets

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
67	Broker Dealer Loans	Rate: Assets (Loans)	Rate	Statistical				
68	C&I Loans	Rate: Assets (Loans)	Rate	Statistical				
69	Commercial Loans (rates segment)	Rate: Assets (Loans)	Rate	Statistical				
70	CRE Loans	Rate: Assets (Loans)	Rate	Statistical				
71	HELOCs	Rate: Assets (Loans)	Rate	Qualitative	X	X		
72	Iron Hound Loans	Rate: Assets (Loans)	Rate	Qualitative	X	X	X	
73	Lease Financing	Rate: Assets (Loans)	Rate	Qualitative	X			
74	Margin Loans	Rate: Assets (Loans)	Rate	Statistical				
75	Mortgage Loans (Wealth Management)	Rate: Assets (Loans)	Rate	Statistical				
76	Other mortgage loans	Rate: Assets (Loans)	Rate	Qualitative	X	X		
77	Overdrafts	Rate: Assets (Loans)	Rate	Statistical				
78	Reverse mortgages	Rate: Assets (Loans)	Rate	Qualitative	X	X	X	
79	Central bank deposits: Fed deposits	Rate: Assets (Other BS)	Rate	Qualitative				Use Moody's forecast
80	Central bank deposits: Foreign Central Bank deposits	Rate: Assets (Other BS)	Rate	Qualitative				Use Moody's forecast
81	Fed Fund Sold and Rev Repos: Non-Pershing	Rate: Assets (Other BS)	Rate	Qualitative			X	
82	Placements: Nostro	Rate: Assets (Other BS)	Rate	Qualitative			X	
83	Placements: Pershing	Rate: Assets (Other BS)	Rate	Qualitative			X	
84	Placements: Treasury	Rate: Assets (Other BS)	Rate	Qualitative			X	
85	Reverse Repos: Pershing	Rate: Assets (Other BS)	Rate	Statistical				
86	Securities Financing	Rate: Assets (Other BS)	Rate	Qualitative	X			
87	Trading Assets: Capital Markets	Rate: Assets (Other BS)	Rate	Statistical				
88	Trading Assets: Global Markets	Rate: Assets (Other BS)	Rate	Qualitative	X			
89	Alternative Investment Services and Global Collateral Services Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Qualitative			X	

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
90	Asset Servicing Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
91	Asset Servicing/ Treasury Services Deposits EU	Rate: Liabilities (Deposits)	Rate	Statistical				
92	Asset Servicing/ Treasury Services Deposits GB	Rate: Liabilities (Deposits)	Rate	Statistical				
93	Corporate Treasury Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Qualitative	X		X	
94	Corporate Trust Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
95	Corporate Trust Interest Bearing Deposits EU	Rate: Liabilities (Deposits)	Rate	Statistical				
96	Corporate Trust Interest Bearing Deposits GB	Rate: Liabilities (Deposits)	Rate	Statistical				
97	Foreign deposits in currencies other than USD, Euro and GBP	Rate: Liabilities (Deposits)	Rate	Qualitative			X	
98	Treasury Services Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
99	Wealth Management Personal Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
100	Wealth Management Sweep Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
101	Broker Dealer Payables	Rate: Liabilities (Other BS)	Rate	Statistical				
102	Long term debt	Rate: Liabilities (Other BS)	Rate	Qualitative	X			
103	Repos: Pershing	Rate: Liabilities (Other BS)	Rate	Statistical				
104	Short-term borrowings: Commercial Paper	Rate: Liabilities (Other BS)	Rate	Qualitative	X	X		
105	Short-term borrowings: Fed funds, Repos (Treasury)	Rate: Liabilities (Other BS)	Rate	Qualitative			X	
106	Short-term borrowings: Other borrowed funds	Rate: Liabilities (Other BS)	Rate	Qualitative	X	X		

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
107	Trading Liabilities: Capital Markets	Rate: Liabilities (Other BS)	Rate	Statistical				
108	Trading Liabilities: Global Markets	Rate: Liabilities (Other BS)	Rate	Statistical				
109	Other Loans	Assets (Loans)	Balance	Qualitative	X	X		
110	Loan Fees	Net Interest Income	NII	Qualitative	X	X		
111	Interest Income from Specials	Net Interest Income	NII	Qualitative	X	X		
112	Short Term Borrowings: Capital Markets	Balance: Liabilities (Other BS)	Balance	Qualitative			X	
		Rate: Liabilities (Other BS)	Rate	Qualitative			X	

BALANCE SHEET FORECASTING METHODOLOGY DEVELOPMENT

BANK OF NEW YORK MELLON

MARCH 31, 2016

Contents

1. Summary

This document describes the balance and rate forecasting model development undertaken by BNY Mellon's Asset and Liability Management team (ALM team) from June to September 2015 (balance and rate modeling project, or, simply, project). The models are intended to be used to generate balance sheet projections for the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act supervisory stress testing (DFAST) programs. Eventually, the models may be used in the forecasting and planning process executed by BNY Mellon's ALM team monthly.

The development approach taken in the balance and rate modeling project is designed to improve rigor, repeatability, and transparency of the forecasting process.

The project scope was to develop comprehensive forecasts for the entire balance sheet as well as certain off-balance sheet segments. It also covered all customer interest rate forecasting approaches, such as rates paid on deposits and rates received on loans, however, did not cover the rates on securities held in BNY Mellon's Investment Portfolio.

1.1. Purpose and requirements

Bank of New York Mellon (BNY Mellon) has developed its next generation balance sheet forecasting approach to predi ct balances and rates under the CCAR and DFAST programs. The models will be implemented in BNY Mellon's monthly business forecasting process executed by BNY Mellon's Treasury group and will serve as a benchmark for the Bank's balance sheet forecasting process as part of its CCAR and DFAST programs. In the future, the Bank may also choose to use this framework as a benchmark for the lines of businesses' monthly forecasts used for planning purposes, though such an application is outside of the scope of this document and subject to future discussions. As part of this exercise, the Bank engaged Oliver Wyman to support development of the framework as well as the approaches, which may be statistical or qualitative in nature.

The requirements for the balance and rate modeling project are:

- The forecasting framework must be based on a robust set of quantitatively supported approaches for balances and rates. The framework must satisfy supervisory expectations as well as firm-specific requirements and standards
- The model development process must be rigorous, repeatable and transparent
- Where applicable, the models must use macroeconomic factors or other factors influenced by macroeconomic factors as inputs.
- The models must be calibrated on monthly historical data as integration into the monthly business forecasting process is a requirement

During the model development process the Oliver Wyman team and the ALM team (jointly, the modeling team) collaborated closely, with frequent input from a large number of other BNY Mellon areas, including Credit and Market Risk groups, representatives of both deposits and loan businesses as well as their Financial Management and Analysis (FM&A) departments, the Model Risk Management group and Treasury Management.

1.2. Development process

The development process proceeded in three steps, each of which was widely discussed prior to execution and is discussed in greater detail in this document:

1. **Balance sheet segmentation:** The modeling team defined a set of criteria to segment BNY Mellon's balance sheet. The segmentation has the goal to create segments that are homogeneous, meaning that the account balances contained in a segment are expected to respond to similar macroeconomic factors with a comparable sensitivity. (Section 3.1)
2. **Determination of methodological approach for each segment:** The pre-determined set of criteria is applied to assign each segment with either a statistical approach or a qualitative framework to create forecasts under different economic scenarios. The statistical approach uses historical balance and rate data for the calibration of multivariate regression models. The selection of macroeconomic variables for each segment is based on driver hypotheses that are developed in collaboration with the lines of business. The selected models are developed to incorporate statistical rigor and alignment with business intuition. The qualitative framework intends to develop a set of rules based on the bank management and business fundamentals to inform a forecast. It uses available data to the greatest extent possible, as well as otherwise codified information such as BNY Mellon policies, accounting rules or logic and information collected from experts in the businesses related to the segments. (Section 3.2)
3. **Selection of specific forecasting approach, either a statistical model or qualitative framework:** Both the statistical and the qualitative framework followed a transparent set of rules and guidelines to arrive at the final statistical or qualitative framework. During this step, both the initial segmentation and the initially attributed methodological approach were revised if newly obtained knowledge suggested that a revision of the initial segmentation and the initially attributed approach would improve forecasting quality. (Sections 3.3 to 3.8)

Throughout the development process, the modeling team collaborated closely with BNY Mellon's Treasury team, the Market and Credit Risk groups as well as the lines of business responsible for the respective segments.

The project had two governing bodies: The Working Group and the Steering Committee. The Working Group supported the project team day-to-day with knowledge and data transfer as well as input on approaches and review of interim results. The Steering Committee was responsible for key decisions and overall guidance of the project. In addition to the meetings with these two governing bodies, the modeling team engaged a number of other stakeholders. Most importantly, the lines of business and other subject matter experts played an important role in the development process. The modeling team relied on their input for the review of data and historical trends, understanding of lines of business and products, the development of driver hypotheses, and the assessment of the intuitiveness of the forecasting approach.

The methodological approaches and results were reviewed by both the Working Group and the Steering Committee. The development process involved iterations of review sessions of methodological approaches and results with both the Working Group and the Steering Committee, revisions of approaches based on feedback, and repeated review by the governing bodies and lines of business.

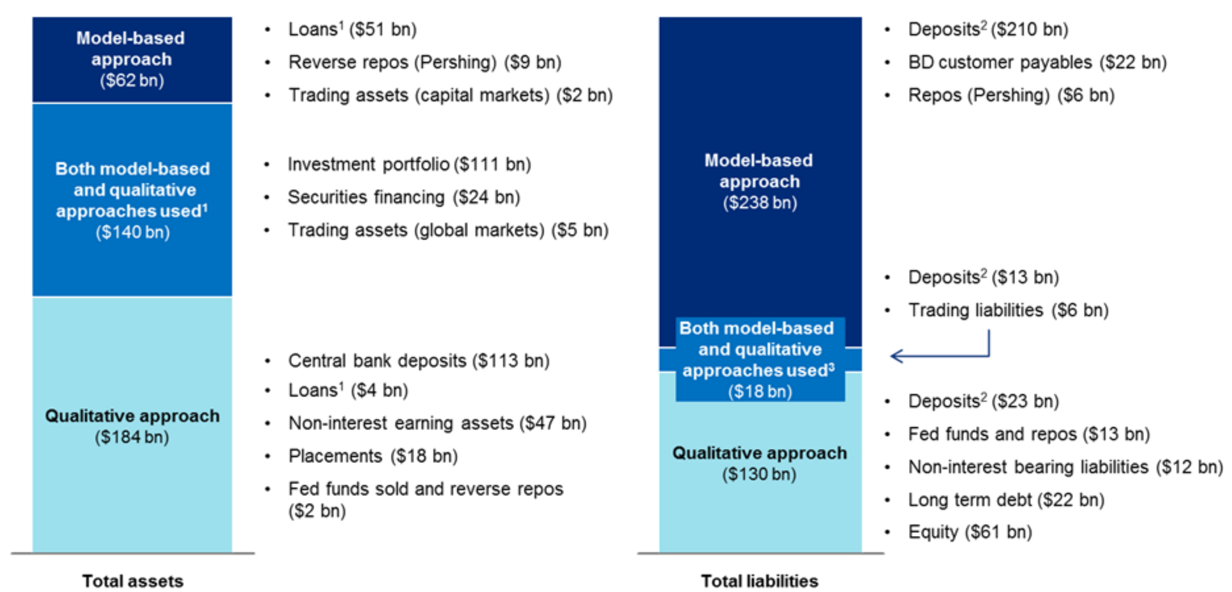
The development process was documented at the time of model development from June to September 2015. Model development was undertaken with development data up until March 2015, with the expectation that the models would be used to generate CCAR 2016 forecasts jumping off from December 2015. Thus, most language in the proceeding document refers and is based on the data available at the time of model development. However, if during the time of model review, changes to an approach were necessary or new, significant information came to light, more up-to-date data and language was incorporated.

1.3. Results overview

Based on the development approach and analysis described in this document, the modeling team developed a set of forecasting approaches for BNY Mellon's balance sheet, covering both balance and rate forecasts. A summary of the result of this process are included in this section, with additional detail on approach development for each segment included in Sections 5 to 12 of this document.

Figure 1 shows the final segmentation and the use of methodological approaches across the entire balance sheet:

Figure 1: Segmentation and Methodological Approaches, December 2015 Balances

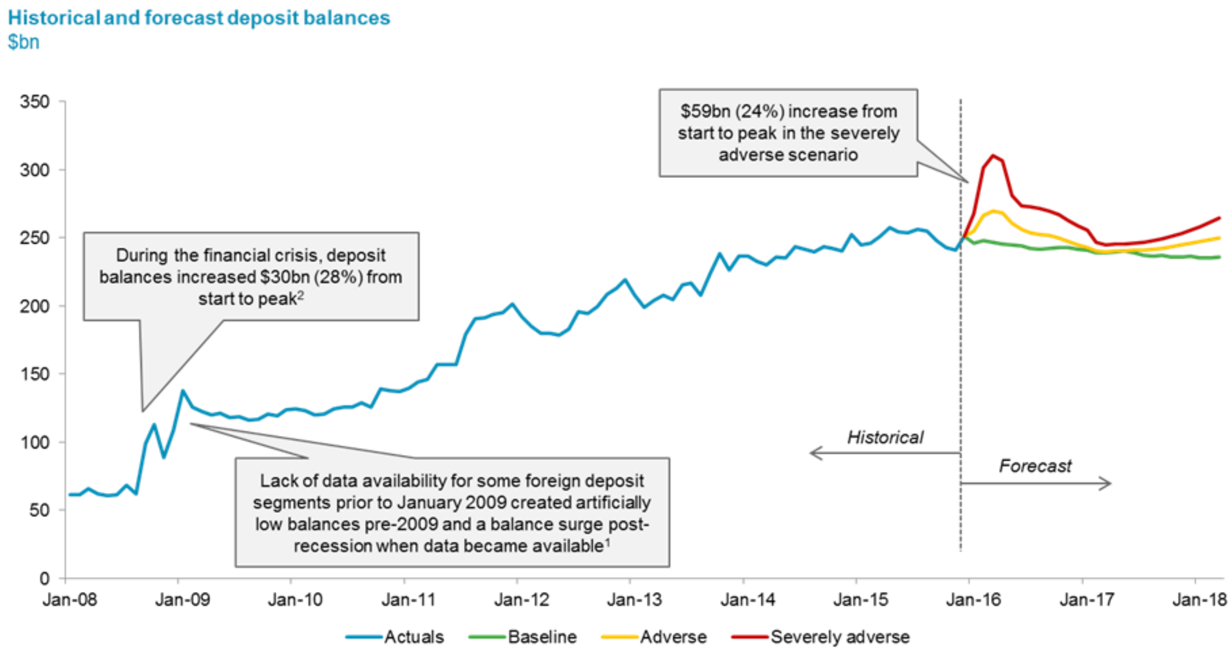


1. We are using a modeling approach for all loans except for HELOCs, lease financing , run-off mortgage loans, IHs, reverse mortgages and other loans
2. We are using a modeling approach for all deposits except for Corporate Treasury deposits and Foreign Deposits (Other), CT GBP balances and AIS/GCS IB rates
3. Different approaches used for rates and balances model, e.g., qualitative approach used for rates and model-based approach used for balances or vice versa

On aggregate, the statistical models and qualitative frameworkes produced intuitive results. In the following, this section describes the aggregate results of the statistical models for deposits and loans.

Figure 2 displays the aggregate forecast for BNY Mellon's total deposits under different economic scenarios using the paths of the CCAR 2016 supervisory scenarios. The forecast is aggregated across the 18 models that were developed for deposits. Model quality measured in terms of historical fit and intuitiveness of forecasts measured against business expectations varies from segment to segment, with some qualitative frameworkes. The management challenge and review process that is part of BNY Mellon's CCAR process will apply an increased level of scrutiny for the weaker models. Additional weaknesses might be identified during the model validation process that will also have to be addressed during the management review and challenge process.

Figure 2: Deposit forecasts for CCAR 2016 scenarios



1. AS USD foreign deposits data becomes available in January 2009; AS/TS GBP in January 2009; AIS/GCS IB in March 2009; Foreign Other in September 2013
2. Balance increase calculated assumes that foreign deposit segments without balance data in 2008 are held flat at earliest available balance for the segment

Overall, the results can be summarized as follows:

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant increase in deposits followed by a decline. This is directionally consistent with BNY Mellon's expectations for an economic crisis scenario. Clients are expected to increase their cash holdings and might seek out safer institutions such as BNY Mellon to hold their cash. A similar flight-to-safety was observed during the global financial crisis in 2008 to 2009
- **Moderate recession (Adverse) scenario**: The model predicts an increase in deposits followed by a decline, in a more tempered forecast than the severely adverse scenario. This is directionally consistent with BNY Mellon's expectations for a moderate recession. Clients are expected to increase their cash holdings and might seek out safer institutions such as BNY Mellon to hold their cash. A similar flight-to-safety was observed during the global financial crisis in 2008 to 2009.
- **Baseline scenario:** The baseline scenario forecasts balances that decrease very slightly. In this scenario, deposits are slightly driven down because the CCAR 2016 baseline scenario includes a moderate increase of interest rates

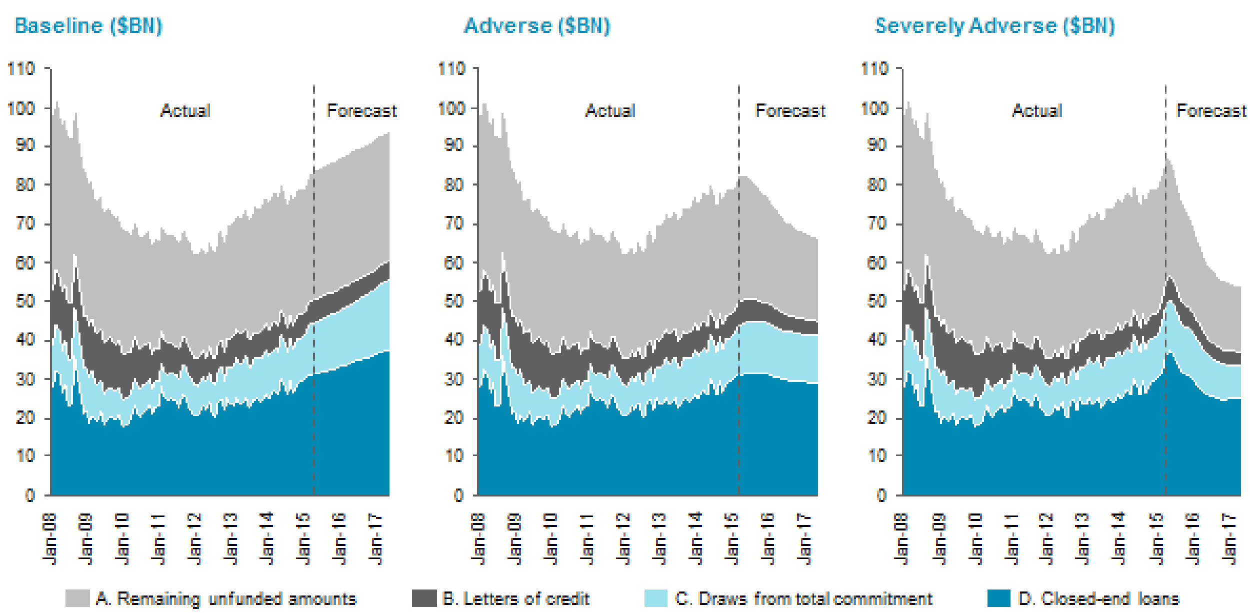
The deposit models capture merely the historical relationship between the balances and macroeconomic variables. The management review and challenge process that is part of BNY Mellon's CCAR process may identify additional dynamics. These will be captured in on-going monitoring. Examples are revised management strategies, changing client needs or demand, a changing business environment and regulatory constraints on growth that cannot be captured with a statistical model.

Figure 3 displays the aggregate forecast for BNY Mellon's loan segments under different economic scenarios using the paths of the CCAR 2015 supervisory scenarios (appended to the end point of the modeling period, which is March 2015). Note that only segments whose forecasts are based on statistical models are included. Similar to the model quality of deposit models, model quality measured in terms of historical fit and intuitiveness of forecasts measured against business expectations varies from segment to segment. The management challenge and review process that is part of BNY Mellon's CCAR process will apply an increased level of scrutiny for the weaker models. Additional weaknesses might be identified during the model validation process that will also have to be addressed during the management review and challenge process.

The estimation strategy used for the loan portfolio integrated the estimation of total commitment facility amounts with the estimation of on-balance sheet loans. This allowed a consistent estimation of unfunded commitment amounts (and letters of credit) along with the desirable split of the on-balance sheet loans into draws from facilities and closed-end loans.

The comprehensive and integrated loan balance estimation approach is applied to the path of the CCAR 2015 supervisory scenarios and results are displayed in Figure 3.

Figure 3: Integrated loan and commitment model forecasts for CCAR 2015



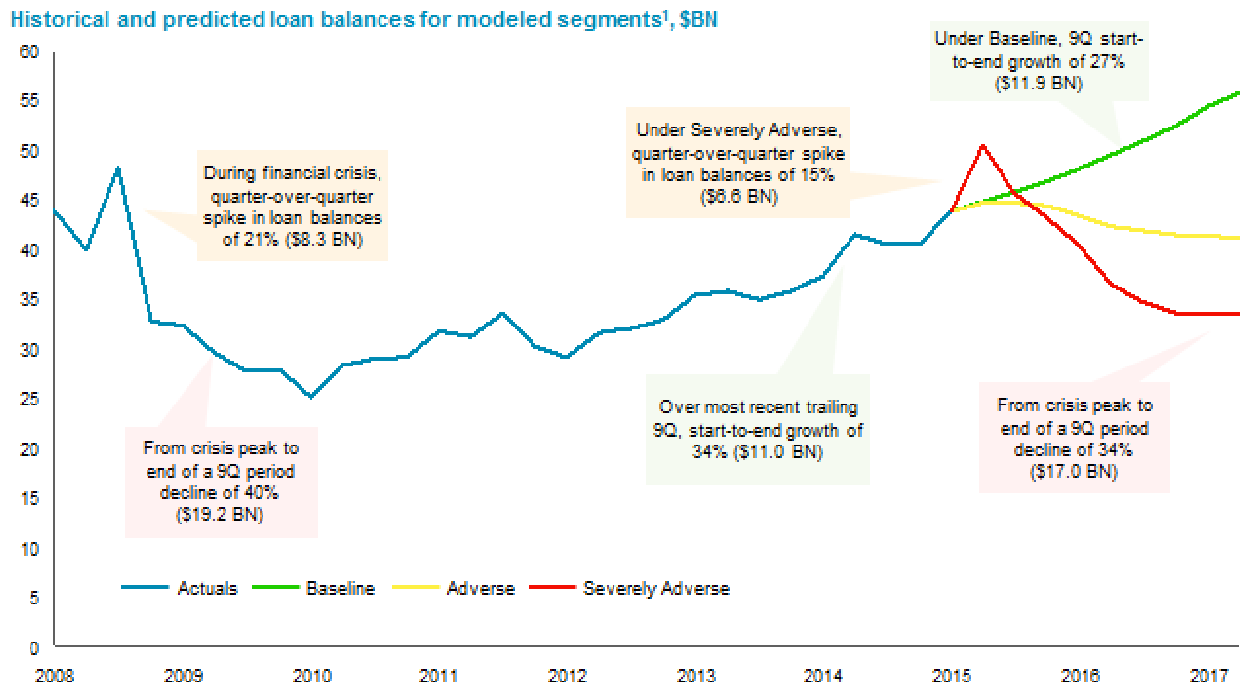
The results can be summarized as follows:

- **Severe recession (Severely Adverse) scenario:** In the beginning quarters of this stress scenario, the models predict an increase in total exposure followed by a large decline. The initial increase in total exposure is caused by higher drawn amounts from facilities and more closed-end loans. This is directionally consistent with BNY Mellon's expectations for an economic crisis scenario. Clients are expected to use existing facilities for their liquidity needs. The models also predict an increase in closed-end loans in the initial months of the crisis. This is consistent with the experience during the global financial crisis in 2008 and 2009 as BNY Mellon provided liquidity to its high-quality clients. However, overall across the entire 9-quarter forecast horizon, the bank's risk appetite decreases and total exposure is reduced. A similar dynamic was observed during the global financial crisis in 2008 to 2009
- **Interest rate shock (Adverse) scenario:** The model predicts a decrease in total exposure and closed end loans. This is consistent with business intuition as BNY Mellon expects client demand for funding to decline as it becomes relatively more expensive with the rising interest rates
- **Baseline scenario:** The baseline scenario forecasts increasing overall exposure. The increase is mainly driven by closed-end loans and drawn amounts from facilities, as both amounts increase under stable macroeconomic conditions. Unfunded commitments remain approximately constant

Note that only two out of the four components shown in Figure 3 are relevant for balance sheet projections, these are the closed-end loans and the drawn amounts from credit facilities. The unfunded commitments and letters of credits are not funded, but they impact capital ratios as they are included in the RWA.

Figure 4 shows the aggregate loan forecasts based on statistical models for the sum of the closed-end loans and the drawn amounts from facilities under different economic scenarios using the paths of the CCAR 2015 supervisory scenarios (appended to the end point of the modeling period, which is March 2015).

Figure 4: Loan model forecast for 2015 CCAR scenarios



The loan models capture merely the historical relationship between the balances and macroeconomic variables. The management review and challenge process that is part of BNY Mellon's CCAR process may identify additional dynamics. These will be captured in management on-going monitoring. Examples are revised management strategies, changing client needs or demand, a changing business environment and regulatory constraints on growth that cannot be captured with a statistical model.

For the Investment Portfolio a qualitative framework was developed that will guide the forecast under the different economic CCAR scenarios. It consists of a set of rules that will guide the forecasting process. The rules draw on existing policies and rely on the processes in place for the management of the Investment Portfolio. The Investment Portfolio is managed under various constraints such as the changes in deposit balances, the characteristics of the deposit balances currently on the balance sheet, compliance with a number of regulatory limits such as liquidity and leverage ratios, as well as the capital and OCI fluctuations due to the changes in market value of the securities. Moreover, some of these constraints were not in place for the historical data. Due to these considerations, the modeling team concluded that a qualitative framework was best taking into account how the portfolio is managed under these constraints to be conceptually more accurate compared to a statistical model based on historical data.

1.4. Input Data

To execute the models, input data in the form of scenario forecasts will be provided by Model #2399 from Moody's.

Model #2399 constructs a series of full macroeconomic scenarios. The Supervisory scenarios are based on a predetermined sub-set of macroeconomic drivers provided by the Fed, while the parameters for BHC scenarios are constructed by BNY Mellon. The model consists of two primary components: the Core Model and the Custom model. The Core model is a hybrid, structural and non-structural, macroeconomic framework provided by Moody's Analytics. The Core model utilizes an econometric approach - a large-scale multi-equation model mirroring the structural workings of the US economy - to project over 1,800 macroeconomic variables; it forecasts all key macro variable parameters for stress scenarios and also provides inputs for the Custom model. A set of individually built regressions then make up the Custom model, which is used to produce a tailored list of the remaining factors needed to run BNY Mellon's suite of CCAR models. A Nelson-Siegel framework, which considers three factors: the level, slope and curvature for the interest rates curve, is used to find the term structure for risk factors. Currently, the Bank has expanded its list of factors to build out more than 800 time series; the factors are broken down into Stock Factors (forecasts that are taken directly from Moody's Analytics' proprietary macroeconomic model) and Custom Factors (outputs of the regressions built specifically for the needs of BNY Mellon's models).

Due to the large number of variables, there is a range of quality in statistical methods used in the forecast models and a risk from lack of full transparency and reliance on a third-party vendor. To maintain a robust scenario forecast process, these models have therefore undergone a rigorous review and challenge process.

1.5. Key limitations of the models

The modeling team has identified two key limitations of the models:

- The modeling period covers only a few months during which short-term interest rates were very low. This means, that the sensitivities of the balances and rates are not well calibrated. The modeling team recommends re-estimation of the models once history in a higher rate environment is available
- Some models are not showing good historical fit. Often, the poor historical fit can be explained by balances that are not only a product of macroeconomic variables but also management decisions. For instance, deposit balances are actively managed by BNY Mellon and the bank might have decreased balances during the estimation period. Such changes in the balances cannot be explained with macroeconomic variables and therefore decrease the historical fit of the model

1.6. Outline of this document

This document is structured as follows.

- Section 2 addresses the governance of the project and describes the interaction of the various stakeholders in the development process of the forecasting approaches
- Section 3 details the methodology designed and employed for both the statistical models and the qualitative frameworkes
- Section 4 discusses the development data and the various data sources

- Sections 5 to 12 contain the detailed findings, results and the final specifications of the statistical and qualitative frameworkes: The deposits balance approaches (Section 5), the deposit rates models (Section 6), loan balance and unfunded commitment approaches (Section 7), loan rates models (Section 8), and the qualitative framework for the investment portfolio (Section 9) and approaches for other balance sheet items (Section 10) and other balance sheet items rates (Section 11). Net interest income approaches are discussed in Section 12.

2. Business and other stakeholder engagement and project governance

The development of the balance and rates models has been a joint effort between Oliver Wyman and BNY Mellon's Asset and Liability Management Group (jointly, the modeling team). Other BNY Mellon groups and departments that were frequently involved in the modeling process included other stakeholders within Treasury, Market Risk, Credit Risk, several Finance Department Management groups, the Corporate Strategy and Corporate Development team, as well as the lines of business (LOBs) responsible for the modeled balances.

Stakeholders engaged in the process in two main ways: through regular Working Group and Steering Committee discussions to provide ongoing project guidance and make key decisions on methodology and results, or as subject matter experts engaged to provide input on the analysis of a specific line of business.

The modeling team presented the proposed set of forecasting models and approaches to the Treasury Risk Committee. On Friday, September 11, 2015, the Treasury Risk Committee approved the use of the models for Treasury balance sheet forecasting by vote.

BNY Mellon's Model Risk Management Group will perform model validation on the models based on which the Model Certification Committee will decide to approve or not approve the models.

2.1. Working Group and steering committee

The project was driven by two governing bodies that met regularly to review the methodology, progress, results. Decisions on final models and approaches were made by the Steering Committee based on the recommendations of the Working Group:

Table 1: Working Group and Steering Committee details

Group	Responsibilities	Members
Working Group	• Discuss methodological approaches • Review of interim results and analyses • Recommendations to Steering Committee on all modeling decisions necessary to determine final model • Transfer of knowledge to modeling team • Resource and data sourcing • Meeting schedule: at least weekly, often bi-weekly	• Frank Austin, Head of Asset and Liability Management • David Gilhooley, Head of Global Markets and Treasury Market Risk • Randhir Ahluwalia, Head of Interest Rate Risk • Mengmeng Fu, Head of Model Validation • Patrick Buxton, EMEA Head of Market Risk • Avi Lopchinsky, Head of Treasury Market Risk • Cindy Summer, VP Asset and Liability Management • James Mangion, VP Asset and Liability Management • Taras Smetaniouk, VP Asset and Liability Management • Akshat Mittal, VP Asset and Liability Management • Nimit Doshi, VP Corporate Strategy and Corporate Development • Charlie Hart, VP Asset and Liability Management • Oliver Wyman team
Steering Committee	• Overall project guidance • Key decisions for all aspects of the project • Final approval of methodological approaches and individual models • Meeting schedule: every three to four weeks	• Todd Gibbons, Chief Financial Officer • James Wiener, Chief Risk Officer • Scott Freidenrich, Treasurer • Gary Gegick, Head of Office of Enterprise Capital Adequacy • Patrick Howard, Chief Market Risk Officer • Frank Austin, Head of Asset and Liability Management • Dominic Napolitano, Head of Model Risk Management • David Rich, Assistant General Counsel and MD Public Policy and Regulatory Affairs • Matthew Thornton, Head of Corporate Strategy and Corporate Development • Randy Ahluwalia, Head of Interest Rate Risk • Senior members of the Oliver Wyman team

2.2. Business and other stakeholder engagement

In order to ensure that the approaches developed across the balance sheet are consistent with business intuition, the modeling team engaged the lines of business and other stakeholders throughout the development phase. For every segment, the modeling team selected a group of representatives who would have expert knowledge and could provide support for the modeling process. For deposit models this included representatives of the lines of business as well as their representatives from the affiliated Financial Management and Analysis (FM&A) departments. For loan models, in addition to the lines of business and FM&A representatives, experts from BNY Mellon’s Credit Risk team joined the discussions. For the securities portfolio, the investment manager of the portfolio attended the meetings with the modeling team.

The business and other stakeholders met with the modeling team for three structured sessions during development:

1. The modeling team held an initial meeting with the lines of business to gain an understanding of the business specifics, their products and key client groups. This information served as an input into the initial segmentation hypotheses as well as the determination of the initial methodological approach for each segment
2. A second meeting was held prior to the actual development process of the model-based and qualitative frameworkes with two primary purposes: 1) to discuss balance and rate paid/charged data that the modeling team had obtained; and 2) to discuss candidate economic drivers. During these meetings, the modeling team reviewed the data it had sourced and posed questions with regards to irregularities in the data and explanations of the historical patterns. Further, the modeling team asked for information on macroeconomic drivers of the business's balances and how its clients are expected to react in times of economic stress with regards to their relationship with BNY Mellon, which were used to inform the set of candidate macroeconomic variables that were considered as part of statistical model development. Finally, the modeling team also discussed future expected changes in strategy and pending management decisions within the lines of business
3. After the completion of the statistical and qualitative frameworkes the modeling team met with each line of business for a segment-level review and challenge process of the model or the qualitative framework for the segment. Feedback was noted and incorporated where possible

Additionally, the modeling team reached out on occasions when business input was needed during the modeling process. For almost every segment, calls and meetings in addition to the three sessions described above were held. Oftentimes, the modeling team requested such meetings to follow up on investigations that the stakeholders and lines of business had offered in connection with question surrounding the data. During the model building phase, interim results were presented to the stakeholders and lines of business to gain additional input and information regarding results and intuitiveness of model estimations.

Table 2 contains a list of line of business meetings that the modeling team held during the balance sheet and rates development project.

Table 2: Summary of meetings with lines of business and stakeholders (without Working Group and Steering Committee meetings)

Meeting Type	Meeting Dates	Participants (all staff that attended at least one meeting)
Deposits	6/2/2015, 6/5/2015, 6/8/2015, 6/22/2015, 6/23/2015, 6/24/2015, 6/29/2015, 7/1/2015, 7/8/2015, 7/14/2015, 7/16/2015, 9/1/2015, 9/2/2015, 9/3/2015, 9/8/2015, 9/15/2015	Austin, Franklin; Ahluwalia, Randhir; Fink, James G; Mangion, James R; Mittal, Akshat; Hart, Charles; Demaio, Joseph; Meiman, Tom; Schwartzman, Sam M; Barber, Gerry; Tucker, Robert N; Koch, Robert K; Connor, Matthew M; Fu, Mengmeng; Napolitano, Dominic; Foglia, Carol; Wirth, John; Alexis, Stephen; Doshi, Nimit; Schultz, Karl; Borawski, Gary; Kennedy, Kim; Goldberg, Karen; Morik, John

Meeting Type	Meeting Dates	Participants (all staff that attended at least one meeting)
General	5/28/2015, 5/29/2015, 6/1/2015, 6/5/2015, 6/18/2015, 6/19/2015, 6/22/2015, 6/23/2015, 6/26/2015, 7/1/2015, 7/2/2015, 7/21/2015, 7/23/2015, 7/28/2015, 7/29/2015, 7/30/2015, 8/3/2015, 8/5/2015, 8/6/2015, 8/11/2015, 8/13/2015, 8/21/2015, 9/1/2015, 9/2/2015, 9/15/2015	Austin, Franklin; Ahluwalia, Randhir; Fink, James G; Mangion, James R; Mittal, Akshat; Hart, Charles; Smetaniouk, Taras; Summer, Cindy; Marwah, Pallavi; Schwartzman, Sam M; Demaio, Joseph; Nuttal, Andrew; Buxton, Patrick; Grinvald, Eliyahu; Lee, Hwidong; Dworzanski, Paulette; Lopchinsky, Avi; Gilhooley, David; Flannery, Michael; Malanga, George P; Meiman, Tom
Loans	6/1/2015, 6/3/2015, 6/8/2015, 6/10/2015, 6/15/2015, 6/16/2015, 6/30/2015, 7/1/2015, 7/8/2015, 7/14/2015, 7/15/2015, 7/16/2015, 7/29/2015, 8/5/2015, 8/6/2015, 8/20/2015, 8/27/2015, 8/28/2015, 8/31/2015, 9/1/2015, 9/4/2015, 9/9/2015, 9/10/2015, 9/11/2015, 9/14/2015, 9/15/2015, 9/16/2015	Austin, Franklin; Ahluwalia, Randhir; Fink, James G; Mangion, James R; Mittal, Akshat; Hart, Charles; Smetaniouk, Taras; Summer, Cindy; Marwah, Pallavi; Velkov, Stiliyan; Su, Hang; Dougherty, Edward J; Rogers, Mark T; Drexler, Alan P; Filip, Adrian; Radocaj, Robert; Stromoski, Scott; Zito, Michael; Chu, Kin; Schroeder, Michael; Clark, David; Malanga, George P; Elm, Kim D; Tucker, Robert N; Rawal, Manoj; Tippet, Bryan Baxter; Zhang, Jun; Zheng, Xiangyin; Ma, Weiman
Model Validation	7/20/2015, 7/29/2015, 8/3/2015	Austin, Franklin; Ahluwalia, Randhir; Mangion, James R; Fu, Mengmeng; Zhang, Wenhao; Liu, Jun; Zhang, Wenhao; Smetaniouk, Taras; Mittal, Akshat
Pershing	6/4/2015, 6/22/2015, 6/30/2015	Ahluwalia, Randhir; Mangion, James R; Sciabbarrasi, Rich; Rawal, Manoj; Summer, Cindy
Repos	8/17/2015	Tippet, Bryan Baxter; Kohad, Amit; Zheng, Xiangyin; Fu, Mengmeng; Ma, Weiman
Systems	8/17/2015	Summer, Cindy; Mangion, James R; Mittal, Akshat; Hart, Charles W; Ahluwalia, Randhir
Overdrafts	9/1/2015	Ahluwalia, Randhir; Hart, Charles W; Flannery, Michael; Malanga, George P; Mittal, Akshat
Risk	7/24/2015, 8/18/2015, 8/25/2015, 9/1/2015	Gegick, Gary; Hysenbegasi, Katie; Radocaj, Robert; Lamar, David T; Austin, Franklin; Ahluwalia, Randhir; Drexler, Alan P; Taylor, Rebecca; Tippet, Bryan Baxter; Karmarkar, Neel; Fu, Mengmeng; Kohad, Amit; Samara, Artan; Hart, Charles W; Mittal, Akshat; Knoll, Ryan
Investment Portfolio	6/8/2015, 6/15/2015, 6/17/2015, 6/25/2015, 7/16/2015, 7/27/2015, 8/28/2015	Austin, Franklin; Freidenrich, Scott; Ahluwalia, Randhir; Mittal, Akshat; Smetaniouk, Taras; Mangion, James R; Budd, Stephen; Swintek, Mark
Placements	7/1/2015	Drexler, Alan P; Mangion, James R
Central Bank Deposits	8/7/2015, 8/20/2015	Ellison, Robert M; Gesuele, Vincent; Ahluwalia, Randhir; Mittal, Akshat; Feazell, Joel; Hart, Charles W
Reverse Mortgages	8/20/2015	Ahluwalia, Randhir; Wilkinson, Timothy Sean; Mittal, Akshat
Iron Hound	8/7/2015	Passaro, George V; Ahluwalia, Randhir; Bansal, Malay; Mittal, Akshat
Securities Financing	8/7/2015	Bockian, Jeffrey A; Zito, Michael; Schroeder, Michael; Ahluwalia, Randhir; Hart, Charles W
Short term borrowings	8/20/2015, 8/19/2015	Bockian, Jeffrey A; Schultz, Karl R; Ahluwalia, Randhir; Hart, Charles W; Ferraioli, Donald; Mittal, Akshat
Trading Assets/Liabilities	8/19/2015, 8/26/2015	Mcfadden, Michael; Hart, Charles W; Ahluwalia, Randhir; Meredith-Carpeni, Regina; Fisher, EG; Curran, Michael; Samela, William; McAuliffe, James; Strumeyer, Gary; Donovan, Timothy; Costa, Fernando A

3. Methodology

This section describes the methodological approaches used for the development of statistical and qualitative frameworkes for balances. The approaches described in this section are applicable to all balance models described later in this document in Section 5 for deposits, Section 7 for loans and unfunded commitments, and Section 10 for other balance sheet segments. In addition, the methodology described in this section also applies to the statistical rate models presented in Section 6 for deposits, Section 8 for loans, and Section 11 for other balance sheet segments. However, certain adjustments to the methodology have to be made for the rates models, which are described in Section 3.5.

The requirements for the balance models are:

- The forecasting framework must be based on a robust set of quantitatively supported approaches for balances and rates. The framework must satisfy supervisory expectations as well as firm-specific requirements and standards
- The model development process must be rigorous, repeatable and transparent
- Where applicable, the models must use macroeconomic factors or other factors influenced by macroeconomic factors as inputs
- The models must be calibrated on monthly historical data as integration into the regular monthly business forecasting process is planned

This section covers the full methodology development process, including:

- The approach and criteria used to segment the bank's balance sheet for the purpose of balance sheet forecasting (Section 3.1)
- The approach and criteria used to determine the methodological approach to each segment. In particular, the segmentation of deposits and loans is addressed specifically in this section, as these represent significant portions of the balance sheet with many sub-segments (Section 3.2)
- The detailed procedure for each methodological approach described in Section 3.2, namely:
  - Model-based approaches, also referred to as statistical models or Simple Models in this document (Sections 3.3 3.4 and 3.5)
  - Qualitative frameworkes, which are customized for each segment they are applied to. Given the customized nature of each qualitative framework, this section provides a high-level summary of the principles that guided the development of qualitative frameworkes (Section **Error! Reference source not found.**). The details are described in subsequent sections in the context of the specific balance sheet components that the qualitative frameworkes are applied to

In the case of statistical balance models, the quantity forecast by these models (i.e. the dependent variable) is total balances for a given segment. This approach was taken for two main reasons:

- To simplify the forecasting approach and reduce the execution risk associated with a more complex suite of models to separately forecast inflows and outflows (e.g. new originations and prepayments for loans) for a given segment
- Because granular data on inflows and outflows (e.g. new origination and prepayments for loans) were not consistently available across segments or over time to support more granular modeling

The modeling period ends with the month March 2015. The reason is that at the time the modeling project started, the most recent observation for certain macroeconomic variables such as GDP was the first quarter value for 2015. The beginning of the modeling period differs by segment. The modeling team made an effort to obtain the longest available data series for each segment. As described in Section 4 on Development Data, this was January 2008 for most segments because of the merger between Bank of New York and Mellon in July 2007.

3.1. Balance sheet segmentation

As a first step in developing the overall forecasting approach, the modeling team reviewed BNY Mellon's balance sheet in detail and proposed to apply a set of criteria to divide the balance sheet into a set of segments for which balance projections will be developed. These criteria, and the resulting segmentation, were reviewed with a range of stakeholders, including members of the ALM team, other stakeholders in Treasury and Finance, Credit and Market Risk, and line of business representatives. The criteria used to determine segmentation are listed in Table 3. They are intended to produce segments that are aligned with business intuition and, where possible, other existing business-as-usual management applications.Aligning segmentation with business-as-usual management applications, including budgeting, planning, and ALM analytics ensures that the segmentation is consistent with the business logic that has been subject to rigorous vetting and applied by bank stakeholders (e.g. line of business, senior management) for business management purposes. In addition, the familiarity of the lines of business and management with the segmentation greatly enhances the communication between the modeling team and the lines of business during the model development phase. It further enhances the quality of the review and challenge process, an important element of the CCAR process. Finally, the alignment to existing business-as-usual management applications is an advantage as it greatly facilitates the ease of technical implementation of the models.

Table 3: Criteria used for balance sheet segmentation

Criteria	Description
Homogeneity of segments	The macroeconomic factors impacting the account balances within a segment are expected to be similar, and the sensitivities of account balances within a segment to a specific macroeconomic factor are expected to be similar.
Materiality of segments	Balances smaller than $2 BN dollars (or 0.5 percent of total balance sheet size) as of May 2015 and balances that exhibited historically low volatility may be consolidated with other balances unless the consolidation would significantly reduce the homogeneity of the resulting segment.
Data availability	Historical data must exist at a monthly frequency in order for a segment to be split from other segments. This reflects the requirement to produce monthly balance forecasts.

Other criteria	For certain account balances, segmentation at a more granular level was applied than what would be implied by the above criteria in order to satisfy other requirements or classification schemes. For example in certain cases additional segmentation was applied to align with management reporting systems or risk-weighted assets (RWA) classifications.

These criteria are used to create a set of homogeneous balance sheet segments, i.e. segments whose components can reasonably be expected to react to similar macroeconomic variables with a comparable sensitivity. The modeling team conducted a number of interviews with BNY Mellon's Treasury team and lines of business to gather information for the application of the criteria above. This resulted in the initial segmentation presented below.

The segmentation presented in the sections below was reviewed with the line of business representatives to ensure alignment to business-as-usual management practices, and served as the initial hypothesis for model development. This initial segmentation remained under review throughout the model development process. As more knowledge was acquired regarding the accounts and balances contained within an initial segment, the modeling team reassessed the initial segmentation. If the modeling team discovered that more granular segmentation or a realignment of certain account balances to different segments would benefit the forecasting quality, the initial segmentation was revised.

In the following sections contain a description of the final segmentation – which reflects application of the above logic as well as additional learnings during approach development.

3.1.1. Overview of BNY Mellon's balance sheet

As of April 30, 2015, BNY Mellon's liabilities were composed of the following balance sheet categories in the bank's regular ALM reporting: Deposits (76%), short-term borrowings (12%), long-term debt (6%), non-interest bearing liabilities (4%) and trading liabilities (2%). BNY Mellon's balance sheet is liability driven as it receives deposits from its customers as a function of its core businesses such as asset servicing, corporate trust and others. The level of these deposits determines the overall size of the bank's balance sheet. Given the volume of these deposits, as well as management's view on their nature (e.g. short-term versus long-term), management develops a strategy to monetize these deposits on the asset side of its balance sheet. The asset categories listed above are a natural starting point for the segmentation of assets as they consist of different funding sources for the bank's assets. The most important asset category is deposits, as deposits account for 76% of the bank's liabilities. Deposit segmentation is discussed in Section 3.1.2. The assessment of the homogeneity, materiality and data availability criteria for the remaining liability categories is provided in Table 5 below.

As of April 30, 2015, BNY Mellon's assets were composed of the following broad balance sheet categories: The investment portfolio (32%), Central Bank deposits in several currencies (25%), non-interest earning assets (14%), loans (13%), a securities financing portfolio (6%), placements at other banks (5%), Federal funds sold and repos (3%) and trading assets (2%). These balance sheet categories for assets align with how BNY Mellon reports its balance sheet in its regulatory filings and how the balance sheet is presented in investor reports and reflect fundamentally different asset classes. The sum of total assets is primarily determined by the level of total client deposits. Total client deposits are invested into the different asset categories, as listed above, where each category comprises a distinctively different asset class. These asset classes differ by:

- how easily they can be converted into cash (with central bank balances being the most easily convertible assets versus certain types of loans and securities being the hardest assets to convert); and
- how high their return on investment is (with central bank balances having a relatively low interest rate and certain securities in the investment portfolio and certain loans yielding relatively more).
- the structure of the instrument and source of repayment (for example with repayment sources from a US Treasury bond differning from those of a Wealth Management mortgage)

The asset categories as listed above are therefore a natural basis from which to further segment the assets. The assessment of the homogeneity, materiality and data availability criteria for the asset categories is provided in Table 4 below. The loans which are more heterogenous than the other asset categories are treated separately in Section 3.1.3.

Based on application of the criteria described above, as well as input from stakeholders including the ALM team, other members of BNY Mellon's Treasury Group, the balance sheet categories were split up into the segments described in Figure 5 below:

Figure 5: Balance sheet segmentation

Assets

Balance sheet category	Segmentation
Central bank deposits ($100bn) • Federal reserve bank ($70bn) • Foreign central bank ($30bn)	• Fed deposits • ECB deposits • BoE deposits
Placements ($20B)	• Nostro placements • Pershing placements • Treasury placements
Fed funds sold and repos ($11bn) • Reverse repos ($2bn) • Securities borrowing ($9bn)	• Securities borrowing and reverse repos (Pershing)
Securities financing portfolio ($24bn)	• Securities financing
Trading assets ($10B)	• Derivatives • Capital markets • FX
Investment portfolio ($129bn)	
Loans ($53bn)	• Loan segmentation covered in Section 3.1.2 below
Non-interest earning assets ($55bn) • Goodwill ($18bn) • Intangibles ($4bn) • Other non-interest earning assets ($33bn)	• Goodwill • Intangibles • Other non-interest earning assets

Liabilities

Balance sheet category	Segmentation
Deposits ($276bn) • Domestic ($152bn) • Foreign ($103bn) • LNI ($22bn)	• Deposit segmentation covered in Section 3.1.3 below
Trading liabilities ($8bn)	• Derivatives • Capital markets • FX
Short-term borrowings ($44bn) • BD customer payables ($24bn) • Fed funds purchase and repos ($15bn) • Floating rate commercial paper ($5bn)	• BD customer payables • Fed funds and Repos (Treasury) • Repos (Pershing) • Commercial paper
Long term debt ($20bn)	• Long term debt
Non-interest bearing liabilities ($14bn)	• Non-interest bearing liabilities

Equity

Balance sheet category	Segmentation
Equity ($40B)	• Equity

The supporting reasoning for these segments are described in Table 4 and Table 5 below, with the exception of the loan portfolio and deposits, which are described in separate sections.

Table 4: Balance sheet segmentation – Assets

Central bank deposits	Central bank deposits are homogenous by nature except for their currencies; as such these balances were segmented by major currency.
Placements	Bank placements are cash held at other banks. The behavior of bank placement balances in response to macroeconomic conditions is expected to depend on the purpose of the placements and they can therefore not be considered homogenous. Accordingly, the placements were segmented by purpose to create homogenous segments: • Nostro placements are local currency accounts held in a foreign country by a domestic bank and are used to facilitate settlement of foreign exchange and currency trading transactions. • Pershing placements are accounts that absorb excess funds of Pershing LLC (Pershing), a wholly owned subsidiary of BNY Mellon. As Pershing's balance sheet is managed separately from BNY Mellon's, Pershing's placements might respond differently to changing macroeconomic environments and will entirely depend on Pershing's balances. • Treasury placements are placements by BNY Mellon's corporate treasury. The volume of these placements is determined entirely by management discretion as part of the bank's overall discretionary Investment Portfolio strategy.
Federal funds sold and reverse repos	There are currently no Federal funds sold and none expected in the future. This balance sheet categories further contains reverse repurchase agreements and securities borrowing by Pershing. Both forms of lending are secured and are made to the same customer base, they are therefore expected to behave similarly under varying economic conditions and can therefore be considered homogenous. Consequently, they are modeled as a single segment.
Securities financing portfolio	This portfolio consists of term loans collateralized by investment securities. Although these transactions take different forms of lending such as loans, reverse repo or asset backed commercial paper, they are managed at the aggregate level and the underlying financial characteristics are the same. The securities financing portfolio is therefore deemed as homogenous and will be modeled as one segment.
Trading assets	BNY Mellon's trading assets stem from its trading in derivatives, foreign exchange and capital markets trading. The derivatives business is being wound down and will be treated separately. Capital markets and foreign exchange are treated as separate segments as the balances related to these two lines of business could potentially behave differently under changing macroeconomic conditions as they are related to different financial markets. At the business level, the trading assets were not segmented further.
Investment portfolio	BNY Mellon's investment securities portfolio, managed by Corporate Treasury, is composed of high quality liquid assets denominated in USD, EUR and GBP and primarily contains Treasuries, sovereign debt and Agency MBS. The portfolio also has investments in CMBS, ABS, municipal bonds, non-agency MBS, international non-agency MBS, and corporate bonds. The investment portfolio is treated as one segment given that it is managed holistically, with asset class composition dictated by the investment portfolio strategy defined by bank management. While this is considered a single segment, the approach taken (described in Section 9) will address all investment categories individually.
Loans	BNY Mellon's loan portfolio segmentation is addressed in Section 3.1.3 below.
Non-interest earning assets	NIEA will be split into goodwill, intangibles and other NIEA as both goodwill and intangibles are governed by accounting rules. The remaining NIEA are treated as one segment as review with subject matter experts suggested that there were no expected macroeconomic relationships for any sub-segments.

Table 5: Balance sheet segmentation – Liabilities

Trading liabilities	Trading liabilities are treated equivalent to trading assets with derivatives (being wound down), capital markets and Global Markets trading as separate segments.

Trading liabilities	Trading liabilities are treated equivalent to trading assets with derivatives (being wound down), capital markets and Global Markets trading as separate segments.
Short-term borrowings	The short-term borrowings are split into six different segments that correspond to different businesses that they relate to, these are Broker Dealer customer payables from Pershing, Fed funds and repurchase transactions by the Corporate Treasury, repurchase transactions by capital markets, repurchase transactions by Pershing, commercial paper, and other short-term borrowings. The Working Group in consultation with the lines of business deemed each of these segments as homogenous as they consist of a narrowly defined type of borrowing.
Long-term debt	Long-term debt is treated as one segment as BNY Mellon's issuances over the last few years have been similar in maturity and coupon type (fixed-rate coupon issuances have generally been swapped to floating rate coupons).
Non-interest bearing liabilities	Non-interest bearing liabilities are treated as one segment.

In addition, two segments do not appear on the balance sheet; rather, they are forecasted directly as net interest income. These segments are discussed in Section 12

3.1.2. Deposit segmentation

Deposit segmentation followed the criteria described in Section 3.1. As a starting point, the modeling team and the ALM team discussed how BNY Mellon's deposits are characterized for ALM management purposes. Deposits are separated along three characteristics:

- The line of business that generates the deposits
- Whether deposits are interest bearing or non-interest bearing
- By currency

This segmentation was adopted for the purposes of balance sheet forecasting as well to align the segmentation with those used for other business purposes. As mentioned above, segments aligned with business-as-usual management applications are preferred in order to be consistent with the business logic that has been vetted and implemented for business management purposes. Also, the familiarity of stakeholders with the model segmentation is an advantage for feedback during the development phase and the review and challenge process during execution.

This segmentation meets the homogeneity criterion discussed in the previous section:

- The line of business determines key deposit characteristics because it determines the client type, the nature of the underlying BNY Mellon business activity that generated these deposits, and the related deposit stability
  - Client type: Clients within a line of business are similar, and similar clients are expected to face similar exposures to macroeconomic conditions
  - Underlying business: BNY Mellon's business lines generate deposits in different ways (e.g. Asset Servicing deposits are related to global custody business, Corporate Trust deposits are related to issuance and servicing of debt instruments) and as such, are expected by business leaders to react differently to changes in the economic environment. In particular, the deposit stability will be expected to differ across different lines of business and be similar within a line of business as clients within a line of business face similar barriers and costs to switching banks.

Client type, underlying business and deposit stability are described in more detail for each line of business below.

- The interest bearing versus non-interest bearing split accounts for potentially different behavior when interest rates changes
- A split by currency accounts for the fact that different macroeconomic conditions could prevail across geographies

The line of business is the single most important factor for the behavior of deposits in response to changes in the macroeconomic environment. It is therefore the main attribute for segmenting deposits applying the homogeneity criteria described in Table 3 above. The line of business determines the type of service that a customer receives from BNY Mellon which implies the client type as well as the deposit stability. We explain how the client type, deposit stability and other factors affecting deposit balances differ between the lines of business in the following.

- Asset Servicing line of business: Provides global custody and related services to funds, ETFs, pensions, endowments, foundations, and other investment entities. Holding and processing of cash in connection with servicing securities portfolios is a core service for Asset Servicing. Asset servicing can only be provided after an initial set-up period of infrastructure that takes between six weeks and in excess of one year. The core deposits of asset servicing customers are therefore relatively stable, as similar set-up times would be required if a client were to switch custodians, but frictional deposits are present to a certain extent.
- Corporate Trust line of business: This line of business assumes trusteeships. Trust or agency agreements govern the uses and movements of funds within Corporate Trust structures and contribute to deposit stability. The large number and variety of deals and structures minimize the likelihood of a parallel runoff in deposits across deals, despite clients' ability to select investment options for the cash within the structure. Deposit balances are influenced by the underlying dynamics (e.g. the various roles and responsibilities within the structure) of the debt transactions including project financing, municipal, asset-backed/mortgage-backed securities and collateral debt obligations.
- Treasury Services line of business: Clients engage Treasury Services to assist in their working capital management and maintain liquidity in the form of deposits. As business-related cash inflows are not perfectly aligned with outflows, clients maintain cash balance buffers to be able to meet payment. Implementation of Treasury Services' products and solutions require significant time and financial commitments which implies that clients have some barriers to switch to another service provider. The prohibitively high cost of switching results in fairly captive balances.
- Wealth Management line of business: The Wealth Management business offers various financial services to high net worth individuals, families, endowments and foundations. Generally, agreements are in place to limit the number of withdrawals or outgoing transfers of funds per month but balances are less stable than those of the lines of business describe above.
- Alternative Investment Services (AIS) line of business: Deposits are obtained in the course of providing hedge fund, fund of hedge funds, and private equity clients with various products and services from trade execution to various middle office administrative tasks.

The level and stability of AIS deposits is a function of available investment opportunities, client and investor transactions as well as general market conditions as a portion of the deposits are held awaiting deployment in investments.

- Broker-Dealer Services (BDS) line of business: BNY Mellon's Broker-Dealer Services (BDS) line of business obtains deposits in the course of providing its Broker-Dealer clients with various products and services. These products and services include collateral and margin management as well as securities clearance. The level and volatility of BDS deposit balances is driven by market conditions and the level of transactions undertaken by clients. There is also a portion of the deposits which are relatively stable as they are comprised of balances with investment restrictions. The operational and contractual requirements associated with BDS deposit accounts are relatively low and result in few restrictions related to moving funds to and from the bank.

Based on this understanding of the lines of business, deposits are considered homogenous within a line of business as long as they are in the same currency and in the same type of account (interest bearing versus non-interest bearing).

The segmentation by line of business, interest versus non-interest bearing deposits, and currency defines the initial segmentation for deposits. Several revisions to this segmentation are made in accordance to the homogeneity and the materiality criteria discussed in the previous section to result in the final segmentation:

- GCS allocates its deposits to other business lines, primarily AIS. Deposits are booked via the General Ledger into GCS and are then allocated in post-closing via accounting entries to other business lines. Due to the similarities and re-allocation of deposits between the two lines of business, their balances are combined into a segment
- Non-interest bearing deposits (DDA accounts) in US Dollars from a number of lines of business did not meet the materiality threshold and were combined with the Asset Servicing DDA balances
- Interest bearing deposits in Euros and British Pounds from a number of lines of business did not meet the materiality threshold and were combined into the Asset Servicing interest bearing balances in the respective currency
- Interest-bearing deposits in the Wealth Management business were split into two segments given there are two distinctly heterogeneous types of balances – balances that are in overnight sweep accounts (contained in the Wealth Management Sweep segment) and balances that are in more traditional consumer deposit accounts (contained in the Wealth Management Personal segment)
- All deposits in non-US dollar, euro and pound sterling foreign currencies were combined into one segment (contained in the Foreign Other segment) and converted to US dollars as these balances did not meet the materiality threshold separately

Details on the final deposits segmentation and their major sub-components are listed in Table 6. There are 18 deposit segments.

The deposits data was sourced from the ALM team and the data sources are discussed in detail in Section 4.1.1.

Table 6: Details on Deposit Segmentation

Deposit segments	Component sub-segments	Modeling Currency	Size, avg monthly bal in Mar 2015 (BN)
Alternative Investment Services and Global Collateral Services Demand Deposit Accounts (AIS/GCS DDA)	AIS DDAs	USD	10.5
	GCS DDA	USD	7.4
Alternative Investment Services and Global Collateral Services Interest Bearing Deposits (AIS/GCS IB)	GCS Cash Reserves	USD	9.5
	GCS USD Foreign Deposits	USD	5.1
	AIS Cash Reserves	USD	1.9
Asset Servicing Demand Deposit Accounts (AS DDA)	Asset Servicing DDAs	USD	20.3
	Other LOB DDAs	USD	3.6
Asset Servicing Interest Bearing Deposits (AS IB)	Asset Servicing USD Foreign Deposits	USD	22.2
	Asset Servicing Cash Reserves	USD	14.6
	CIBC CWIs	USD	2.4
	Asset Servicing Trust Time	USD	2.0
	ADRs	USD	0.0
Broker Dealer Services Demand Deposit Accounts (BDS DDA)	BDS DDAs ex Allocation	USD	8.0
Corporate Treasury Interest Bearing Deposits (Corporate Treasury)	Corporate Treasury USD Foreign Deposits	USD	2.6
Corporate Trust Demand Deposit Accounts (CT DDA)	Corporate Trust DDAs	USD	22.9
Corporate Trust Interest Bearing Deposits (CT IB)	Corporate Trust Cash Reserves	USD	11.6
	Corporate Trust USD Foreign Deposits ex LNI	USD	3.5
Asset Servicing/Treasury Services EU Deposits (AS/TS EU)	Asset Servicing EUR Foreign Deposits	EUR	11.3
	Other LOB EUR Foreign Deposits	EUR	1.0
Asset Servicing/Treasury Services GB Deposits (AS/TS GB)	Asset Servicing GBP Foreign Deposits	GBP	8.6
	Other LOB GBP Foreign Deposits	GBP	0.3
Corporate Trust EU (CT EU)	Corporate Trust EUR Foreign Deposits	EUR	9.0
Corporate Trust GB (CT GB)	Corporate Trust GBP Foreign Deposits	GBP	1.5
Foreign deposits in currencies other than USD, Euro and GBP (Foreign Other)	Miscellaneous Currency	USD	11.1
Treasury Services Demand Deposit Accounts (TS DDA)	Treasury Services DDAs	USD	15.3
Treasury Services Interest	Total Company LNI	USD	19.2

Bearing Deposits (TS IB)	Treasury Services CWIs	USD	2.8
	Treasury Services USD Foreign Deposits ex LNI	USD	0.9
	IB DDAs	USD	0.6
	Treasury Services MMDAs	USD	0.0
	Rent Secured	USD	0.0
Wealth Management Demand Deposit Accounts (WM DDA)	WMs DDAs	USD	1.8
Wealth Management Personal Deposits (WM Personal)	WM Private Banking MMDAs	USD	2.4
	WM CWIs	USD	2.1
	WM CMAAs	USD	1.0
	WM Savings	USD	0.3
	WM Time Deposits	USD	0.0
Wealth Management Sweep Deposits (WM Sweep)	WM Sweep MMDAs	USD	7.1
	WM Escrows	USD	0.0

3.1.3. Loan segmentation

A large portion of BNY Mellon's lending is in form of credit facilities. Under a committed facility, clients have access to funding at their discretion up to the total facility amounts. Because draws from committed facilities are entirely client-driven decisions, the modeling team determined it to be important that an estimation strategy would capture the potentially different sensitivities to macroeconomic conditions of total facilities agreed between BNY Mellon and clients, amounts drawn under committed facilities, and closed-end loans. It is possible that while BNY Mellon reduces its overall exposure by not renewing committed facilities, its on-balance sheet loans still increase as clients increase their drawn amounts from committed credit facilities. This approach has the additional advantage that new segments and models important for the reporting of Risk Weighted Asset (RWA) are created. RWA reporting is part of the stress testing programs. Chosing an integrated estimation approach between credit facilities and on-balance sheet loans allows a forecast of unfunded commitments that is consistent with the loans forecasts. Unfunded commitments enterRWA and are therefore an element of the capital ratios under the stress testing programs.

A number of BNY Mellon data sources were evaluated for the modeling of loans. Of those considered that could be sourced in a timely manner – including MAQ, ALMIS, and CRDW – only CRDW included unfunded commitment data. As a result, CRDW was selected for modeling such that an integrated forecasting approach including facilities, amounts drawn from facilities and closed-end loans could be used.

The data source CRDW imposed practical constraints on how the loans (including the committed facilities, their drawn amounts and letters of credit) could be segmented. The modeling team engaged with CRDW data owners to source all available and reliably populated fields from CRDW such that homogenous segments could be created and a large number of information was accumulated. Nevertheless, the modeling team was limited to segment along dimensions that were historically available in the CRDW data – while the database has been augmented significantly since its inception, but given the time series nature of this modeling exercise, data were needed for the entire historical period, which limited the available data fields.[1] The fields available in CRDW include a Regulatory Group field which is used for regulatory reporting; Asset Description; Country of Risk; Customer SIC Description; General Ledger code, Legal Identity; and more granular customer information, all at the exposure level.

The modeling team determined that the Regulatory Group field produced segments that met the homogeneity criteria as described above. The details are provided in the next section.

3.1.3.1. Loan balance segmentation based on CRDW

CRDW data was obtained from the Basel and Capital Adequacy group (development data is discussed in further detail in Section 4).

The modeling team segmented loans using two fields in the CRDW data: The primary field for segmentation was Regulatory Group, which contains the following distinct values over the historical time period considered for modeling:

Regulatory Group
Commercial
Commercial Real Estate
Financial Institutions
Leasing Financings
Margin Loans
Other
Other Residential Mortgages
Overdrafts
Wealth Management
Wealth Management Loans and Mortgages

The Regulatory Group field aligns with the segmentation of the loan portfolio that is reported in BNY Mellon's Form 10-Q and Form 10-K filings.

The starting point for the loan segmentation was assigning one segment per regulatory group. Upon further evaluation of the historical balance data, two of these segments were discarded as final segments:

- "Wealth Management Loans and Mortgages" balances do not exist in the data after May 2008, and were determined to be an earlier label for balances that were later classified as Wealth Management. These balances were collapsed into the "Wealth Management" segment
- "Other" balances were not considered to be a segment for modeling, given that their miscellaneous nature violates the segmentation criterion of homogeneity

[1] The modeling team's initial preference was to segment along product and line of business to enable direct mapping into BNY Mellon's QRM system. There was however no field in the CRDW data that corresponded to line of business. Furthermore, examination of the historical monthly data, which spanned from January 2008 until May 2015, indicated that the General Ledger code – which is used to map to loan products – was not reliably populated.

In addition, two types of loan balances which the Working Group preferred to model separately were split across various Regulatory Group fields: Securities Financing balances and Residential Mortgages loans. Therefore, beyond the Regulatory Group field, the modeling team used an “Asset Description” field to identify these balances based on the following values:

- All exposures with the value “Margin loans from SFT” correspond to Securities Financing loan exposures; these were excluded from the data set. Since the Securities Financing portfolio includes other products such as reverse repos and asset-backed commercial paper that are not included in this data, the decision was made to use MAQ data instead for Securities Financing (see Section 4.5 on discussion of development data for other balance sheet items)
- All exposures in the Wealth Management segment with the value “Residential Mortgages” were separated out into a new Wealth Management Mortgages segment. This division was made to preserve segment homogeneity; Wealth Management mortgage balances have been steadily growing over the entire historical modeling period, while the remainder of the Wealth Management loans exhibit behavior that is more sensitive to macroeconomic factors

Finally, the “Asset Description” field was used to classify the majority of balances falling under the “Other” category in Regulatory Group. For these:

- Exposures with an Asset Description of “Overdrafts” were added to the Overdrafts segment
- Exposures with an Asset Description of “Lease” were added to the Leasing Financings segment
- Exposures with an Asset Description of “Residential Mortgages” were added to the Other Residential Mortgages segment

Applying these adjustments along with several data cleansing steps (see Section 4 for further details) resulted in the following segmentation for loans, as seen in Table 7. $9.1 BN in Securities Financing loans have been excluded, as they are part of a larger Securities Financing segment.

Table 7: Loan segments with April 30, 2015 on-balance sheet loan exposures

Segment	April 2015, $ BN
Financial Institutions	14.7
Margin loans	11.8
Wealth management	6.2
Overdrafts	6.2
WM Mortgages	5.7
Commercial Real Estate	3.1
Lease Financings	2.0
Commercial	1.8
Other	1.2
Other Residential Mortgages	1.2

These loan segments were deemed homogeneous in discussions with various stakeholders.

- Financial Insitutions loans: Broker Dealer loans, Trade Finance Loans and other commercial loans made to financial institutions, these are shorter dated loans with a weighted average maturity of around half a year
- Margin loans: Margin loans made by Pershing, all overnight loans
- Wealth management: Predominantly non-purpose loans made to high-networth individuals by the Wealth Management Bank, fully collateralized with a weighted average maturity of less than one year
- Overdrafts: Overnight loans that are made in connection with lines of business involving deposits, mainly related to custody and securities clearing business, they are happening on a daily basis but are generally repaid within two business days
- WM Mortgages: Mortgages issued to high-networth individuals by the Wealth Management Bank, mainly long-term mortgages
- Commercial real estate: Financing for commercial real estate related projects to a homogenous group of clients
- Commercial loans: Commercial and industrial loans as well as trade purchased loans, longer dated with a weighted average maturity of about four years, predominantly investment grade borrowers
- The Other loan segment consists of loans that were missing the required data in the fields used for segmentation. Further analysis of these loans indicated that they primarily consisted of commercial loan products (which are not necessarily overlapping with the Commercial Loans regulatory group) offered by Pershing
- The remaining segments are run-off portfolios that use a qualitative forecasting approach

Of the loans segments created, five included unfunded commitments. Table 8 shows the breakdown across each segment of total commitments, draws from commitments, Letters of Credit, unfunded commitments, and closed-end loans as of April 30, 2015. See Section 3.4 on the loan modeling methodology for further detail on these quantities and the relationships among them.

Table 8: Loan segments with April 30, 2015 volumes for unfunded and funded components of total exposure

Segment	Total Commitment	Draws from Commitments	Letters of Credit	Unfunded Commitments	Closed-end Loan
Financial Institutions	52.9	9.4	3.3	40.2	5.3
Commercial	20.1	1.3	1.3	17.5	0.6
Margin Loans	0.6	-	-	0.6	11.8
Wealth Management	2.6	0.9	0.3	1.4	5.3
Overdrafts	-	-	-	-	6.2
Commercial Real Estate	4.0	1.2	0.7	2.1	1.8
WM Mortgages	-	-	-	-	5.7
Leasing Financings	-	-	-	-	2.0
Other	-	-	-	-	1.2
Other Residential Mortgages	-	-	-	-	1.2

In addition to the above loan segments, there are three types of loans that were not distinguishable in CRDW data which are forecast using qualitative frameworkes based on MAQ data. These are the Iron Hound (IH) loans, Reverse Mortgages, and HELOCs, which are treated as separate segments with the following forecast logic, which is covered in more detail in Section 7:

- Iron Hound loans: consists of commercial real estate loans held for securitization by IH Capital. This is a growth segment, which will be grown at a constant rate until the management limit of $500 MM is reached
- Reverse Mortgages: consists mostly of FHA-insured Home Equity Conversion Mortgages (HECMs). This is a growth segment, which will be grown according to the company's operating plan in the baseline scenario; business will cease in the stress scenarios due to an expected seizure of securitization markets
- Home Equity Lines of Credit (HELOCs): offered to Wealth Management clients on a request basis. This is a runoff portfolio, with no new originations planned and balances set to decrease according to contractual terms

3.1.3.2. Loan rates segmentation

CRDW was selected as the data source for balance segmentation and modeling because it was the only available data source that contained granular data on unfunded commitments. However, neither rate data nor net interest income data could be sourced from CRDW. As a result, loan rates data was sourced from the MAQ, the management accounting system. The segmentation criteria for homogenous segments as discussed in Section 3.1 were applied here too.

From MAQ, loan rate data is available at the product and line of business level. The modeling team reviewed granular data as well as data aggregated to the product level. The rates data exhibited considerable volatility even at the product level. Because a more granular split by line of business produced more volatile historical time series for rates – and rate models are expected to be stronger across segments with less data volatility – it was decided to model loan rates at the product level.

Rates were forecast for the following loan products:

- Commercial loans
- Margin loans
- Mortgage loans
- Overdrafts
- Broker Dealer loans
- C&I loans
- Leases

- Commercial real estate

Balance forecasts from CRDW map to product based on the general ledger field at the level of individual exposures; therefore, it was determined that using this different segmentation scheme for rates would still enable balance and rate forecasts to be mapped into BNY Mellon’s QRM system. Table 9 below shows this mapping from CRDW balance segments to products; the rate forecasts from MAQ are applied to balance segments on a pro rata basis for each segment.

Table 9: Loan balance segmentation mapping to loan products

CRDW Balance Segmentation	Product	$ (BN)
Commercial	C&I loans	$1.6
	Commercial loans	$0.1
	Consumer loans	$0.0
	Total	$1.8
CRE	C&I loans	$0.5
	Commercial loans	$0.6
	CRE	$1.9
	Total	$3.0
FI	Banker's acceptance	$0.3
	BD loans	$3.2
	C&I loans	$0.3
	Commercial loans	$10.7
	Unknown	$0.2
	Total	$14.7
Lease Financings	Leases	$2.0
	Total	$2.0
Margin Loans	Margin loans	$11.8
	Total	$11.8
Other	Commercial loans	$1.2
	Total	$1.2
Residential Mortgages	Unknown	$1.2
	Total	$1.2
Overdrafts	Overdrafts	$5.9
	Unknown	$0.3
	Total	$6.2
WM	C&I loans	$0.3
	Commercial loans	$5.7
	Consumer loans	$0.0
	Unknown	$0.1
	HELOC	$0.1
	Total	$6.2
WM Mortgages	Mortgage loans	$5.6
	Total	$5.7
Total		**$53.7**

As with loan balances, no rates were forecast for the three segments being forecast using qualitative frameworkes: IH loans, Reverse Mortgages, and HELOCs.

3.1.4. Other balance sheet segmentation

Segmentation for “Other balance sheet (assets)” and “Other balance sheet (liabilities)” segments were constructed based on the April 2015 BNY Mellon Planning Tree, a management accounting hierarchy of balance sheet accounts utilized by BNY Mellon. These segments cover balances excluding deposits, loans, and the investment portfolio.

Starting with the most granular level available in the Planning Tree, balances that have similar characteristics were aggregated to produce a segmentation for balance sheet forecasting; these segmentations apply to both balances and rates. Given the wide variety of balance sheet items considered under the “Other balance sheet” category, the data for each item was reviewed to determine:

- Any groupings that could be applied to balance sheet items to arrive at homogeneous and material segments
- Feasibility of producing macroeconomic statistical regression models
- Usage of historical data to develop assumptions for qualitative frameworkes, if no reasonable macroeconomic regression model could be developed

The resulting segmentations used for “Other balance sheet” items are presented in the tables below.

Section 4.5 discusses the development data used for these “Other balance sheet” segments.

Table 10: "Other balance sheet" segments – Assets

#	Other assets	Description	Apr'15 Balance ($ BN)
1	Central bank deposits: Fed deposits	Central bank deposits at the US Federal Reserve	71
2	Central bank deposits: Foreign Central Bank deposits	Central bank deposits at foreign central banks	29
3	Placements: Nostro	Short-term unsecured deposits at foreign non-central bank accounts in foreign currency	5.1
4	Placements: Pershing	Short-term unsecured deposits held by Pershing at non-central banks	5.7
5	Placements: Treasury	Short-term unsecured deposits held by branches and subsidiaries of BNY Mellon at non-central banks, excluding Pershing and Nostro placements	9.5
6	Fed funds sold and reverse repos (Non-Pershing)	Fed funds sold and reverse repos of BNY Mellon excluding Pershing	0.5
7	Securities Borrowing & Reverse repos (Pershing)	Securities borrowing and reverse repos conducted by Pershing	11
8	Securities financing: ABCP, SF loans, Reverse repo	Term loans collateralized by investment securities; includes loans, reverse repos, and asset-backed commercial paper	24
9	Trading assets (Global Markets)	Debt, equity, and derivative instruments not designated as hedging instruments and held for short-term trading by Global Markets business	6.6
10	Trading assets (Capital Markets)	Debt, equity, and derivative instruments not designated as hedging instruments and held for short-term trading by Capital Markets business	3.0
11	Non-interest earning assets (excl. Goodwill, Intangibles)	Assets that do not accrue interest, excluding goodwill and intangibles	33
12	Non-interest earning assets: Goodwill	Goodwill resulting from acquisitions	18
13	Non-interest earning assets: Intangibles	Intangible assets with a finite useful life	4.0

Table 11: "Other balance sheet" segments – Liabilities

#	Other liabilities	Description	Apr'15 Balance ($ BN)
1	Trading liabilities (Global Markets)	Trading liabilities generated by the Global Markets business	6.6
2	Trading liabilities (Capital Markets)	Trading liabilities generated by the Capital Markets business	0.6
3	Short-term borrowings: Broker dealer customer payables	Funds awaiting re-investment and short sale proceeds payable on demand to Pershing clients	23
4	Short-term borrowings: Fed funds, Repos (Treasury)	Fed funds and repos held by BNY Mellon excluding Pershing	8.6
5	Short-term borrowings: Capital market repos	Repos used to fund Capital Markets HQLA activity	1.7
6	Short-term borrowings: Repos (Pershing)	Repos made by Pershing	6.4
7	Short-term borrowings: Commercial Paper	Commercial paper issued by BNY Mellon	4.8
8	Short-term borrowings: Other borrowed funds	Short-term borrowings other than Fed funds, repos, customer payables, and commercial paper; primarily consisting of Eurodollar deposits	1.1
9	Long term debt	Long term debt issued by BNY Mellon	21
10	Non-interest bearing liabilities	Liabilities that do not accrue interest	14

3.2. Determination of methodological approach for each segment

Following balance sheet segmentation, the modeling team determined the initial methodological approach for each segment. These initial approaches served as a starting point for developing segment-specific approaches. The modeling team's assumption was that the methodological approach could change as more information would become available and insights would be gained from analyses. However, to guide forecasting development, a target methodological approach was defined ex-ante for each segment. The modeling team considered two general methodological approaches for each segment – a model-based approach and a qualitative framework – defined further below.

3.2.1. Definition of the two methodological approaches

This section defines the two methodological approaches used to develop the forecasting framework for each segment:

- A model-based approach (used synonymously with statistical model, or used Simple Model), and
- A qualitative framework that describes a set of rules intended to guide the application of management input when developing a forecast for a segment.

The model-based approach consists of statistical models that describe the historical relationship between a segment's balances and selected macroeconomic variables. The statistical model is a linear regression model using ordinary least square (OLS) estimation. The details on the estimation procedure, the selection of the candidate variables and models, as well as the testing of the models, are described in Section 3.3 below.

The model-based approach also consists of "Simple Models". These models do not use linear regression; the forecastings of these segments are based on equations which linked the forecasting to other segments.

For segments for which a model-based approach is not suitable, a qualitative framework is developed. The qualitative framework is a set of rules intended to guide the application of management input when developing a forecast for a segment. The set of rules that define the forecasting is developed by relying on various sets of inputs:

- Empirical data that inform how the segment's balances have related to other segments historically
- Empirical data that inform how decisions are made or have been made in the past that affected the segment's balances
- Policies that are in place or rules that are adhered to in the normal course of business
- Explanations from experts regarding the logic behind the historical evolution of the segment's balances

In this document, the qualitative framework description is high level. Detailed qualitative approaches rationale and approaches are submitted in the "QFP" document in section 18.

The next section describes how the initial methodological approach for each segment was determined.

3.2.2. Initial methodological approach determination for each segment

The purpose of the balance and rate modeling project is to develop rigorous, quantitative models. A statistical model that is intuitive and sound is well suited to serve this purpose. The model-based approach is therefore preferred if the following key criteria are met:

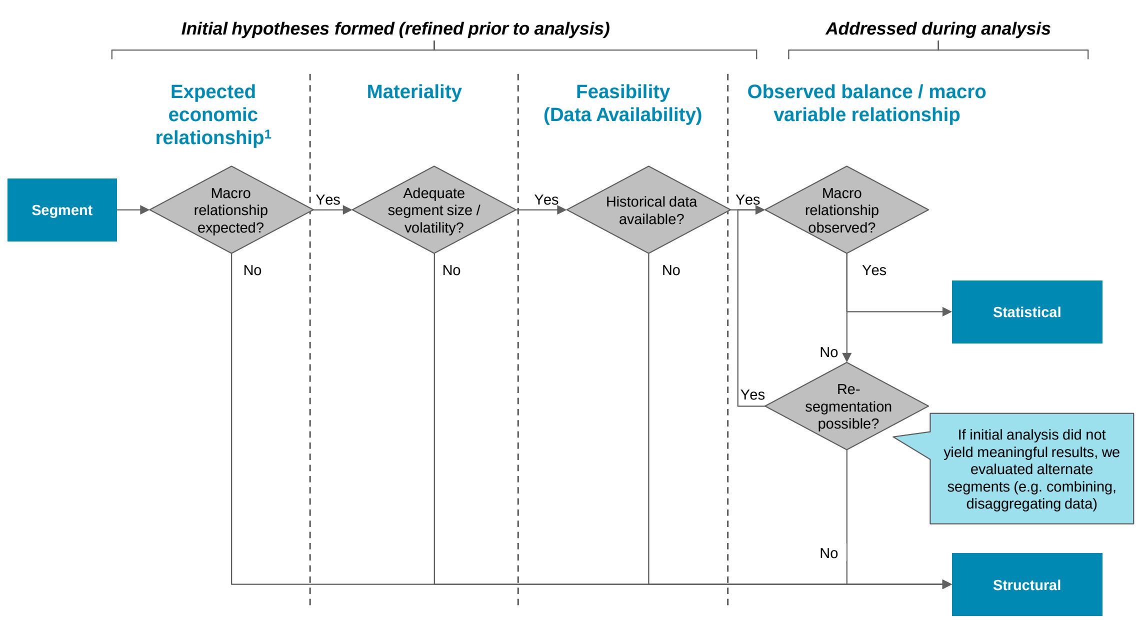
- Expectations of an economic relationship:
  - A segment's balances can reasonably be expected to have a relationship with macroeconomic variables that is supported by business intuition.
  - The relationship that is observed historically between a segment's balances and the macroeconomic variables can reasonably be expected to persist into the future.
- Materiality: A segment has balances larger than $2 BN as of April 2015 (0.5 percent of the balance sheet).
- Data availability: Historical monthly data is available.

For all other segment for which the above criteria were not met, a qualitative framework was assigned as the initial methodological approach. The specific reasoning varied by segment, but included:

- Cases where there is no ex-ante expectation of a relationship between balances and macroeconomic variables, for example goodwill and intangibles
- Cases where balance growth is dictated by management discretion, for example the Investment Portfolio
- Cases where historical data are not available, for example the bank's reverse mortgage products
- Cases where the size of the balance was below $2 BN as of April 2015 (related to the materiality criteria described in Section 3.1 above), though this applied to only a few segments

The decision process for the methodological approach starts with the assessment of expectations regarding an economic relationship as described above. The modeling team interviewed representatives from the lines of business and discussed the information obtained in the Working Group meetings. Segments without expectations of an economic relationship were assigned a qualitative framework. For those segments where a relationship was expected, the materiality and the data availability were considered and the segment's approach was reassessed if the segment's balance was smaller than $2BN or if monthly historical data was not available. During the development phase, the initial methodological approach remained under consideration. If new knowledge became available that suggested that a change in approach would result in a higher quality forecast approach for a segment, the changes to the approach were made. Figure 6 summarized the methodological approach determination process.

Figure 6: Methodological approach determination

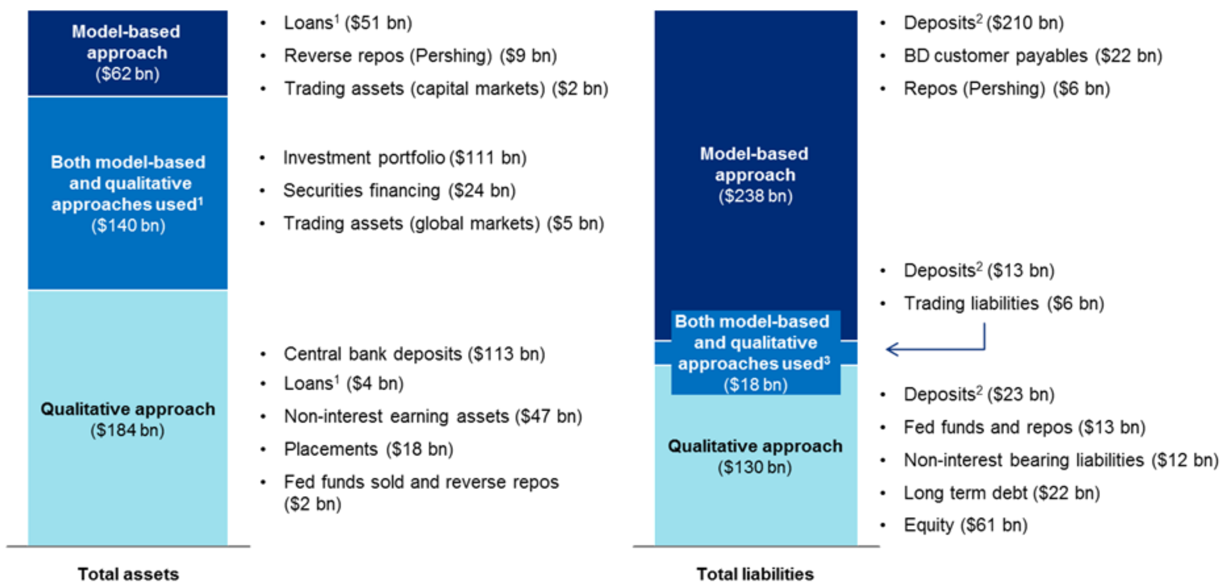


1. Relationship between balances and macro variables can reasonably be expected to be relevant for the future and can be explained using intuitive arguments

For each segment, the initial methodological approach determined based on the above criteria were reviewed with the project Working Group, Steering Committee and line of business experts to ensure support of the approach from the line of business and the Treasury group.

An overview of the balance sheet and the relative proportions of model-based versus qualitative framework is summarized in Figure 7 below, and described in additional detail in the following Table 12, which contains the assigned methodological approach as well as the reasons for the methodological approach decision.

Figure 7: Segmentation and Methodological Approaches, December 2015 Balances



1. We are using a modeling approach for all loans except for HELOCs, lease financing , run-off mortgage loans, IHs, reverse mortgages and other loans
2. We are using a modeling approach for all deposits except for Corporate Treasury deposits and Foreign Deposits (Other), CT GBP balances and AIS/GCS IB rates
3. Different approaches used for rates and balances model, e.g., qualitative approach used for rates and model-based approach used for balances or vice versa

Table 12: Model approaches by segment

					Reasons for qualitative framework			
#	**Segment**	**Model Category**	**Model Type**	**Model Approach**	**Lack of economic relationship**	**Materiality**	**Feasibility (data availability)**	**Other**
1	Commercial Loans (balance segment)	Assets (Loans)	Closed End Loan Balance	Statistical				
2	Commercial Loans (balance segment)	Assets (Loans)	Draw %	Statistical				
3	Commercial Loans (balance segment)	Assets (Loans)	LC Usage %	Statistical				
4	Commercial Loans (balance segment)	Assets (Loans)	Total Commitment	Statistical				
5	CRE Loans	Assets (Loans)	Closed End Loan Balance	Statistical				

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
6	CRE Loans	Assets (Loans)	Draw %	Statistical				
7	CRE Loans	Assets (Loans)	LC Usage %	Qualitative	X			
8	CRE Loans	Assets (Loans)	Total Commitment	Statistical				
9	Financial Institution Loans	Assets (Loans)	Closed End Loan Balance	Statistical				
10	Financial Institution Loans	Assets (Loans)	Draw %	Statistical				
11	Financial Institution Loans	Assets (Loans)	LC Usage %	Statistical				
12	Financial Institution Loans	Assets (Loans)	Total Commitment	Statistical				
13	Margin Loans	Assets (Loans)	Closed End Loan Balance	Statistical				
14	Margin Loans	Assets (Loans)	Total Commitment	Qualitative	X	X	X	
15	Other mortgage loans	Assets (Loans)	Balance	Qualitative	X	X		
16	Overdrafts	Assets (Loans)	Balance	Statistical				
17	Reverse mortgages	Assets (Loans)	Balance	Qualitative	X	X	X	
18	Wealth Management Loans	Assets (Loans)	Balance	Statistical				
19	Wealth Management Loans	Assets (Loans)	Draw %	Statistical				
20	Wealth Management Loans	Assets (Loans)	LC Usage %	Qualitative	X	X		
21	Wealth Management Loans	Assets (Loans)	Total Commitment	Statistical				
22	Wealth Management Mortgage	Assets (Loans)	Balance	Statistical				
23	HELOCs	Assets (Loans)	Balance	Qualitative	X	X		
24	Iron Hound Loans	Assets (Loans)	Balance	Qualitative	X	X	X	
25	Lease Financing	Assets (Loans)	Balance	Qualitative	X			
26	Central bank deposits: Fed deposits	Assets (Other BS)	Balance	Qualitative	X			
27	Central bank deposits: Foreign Central Bank deposits	Assets (Other BS)	Balance	Qualitative	X			
28	Fed Fund Sold and Rev Repos: Non-Pershing	Assets (Other BS)	Balance	Qualitative		X		

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
29	Investment Portfolio	Assets (Other BS)	Balance	Qualitative	X			
30	Non-interest earning assets (excl Goodwill, Intangibles)	Assets (Other BS)	Balance	Qualitative	X			
31	Non-interest earning assets: Goodwill	Assets (Other BS)	Balance	Qualitative	X			
32	Non-interest earning assets: Intangibles	Assets (Other BS)	Balance	Qualitative	X			
33	Placements: Nostro	Assets (Other BS)	Balance	Simple model	X		X	
34	Placements: Pershing	Assets (Other BS)	Balance	Simple model	X	X		
35	Placements: Treasury	Assets (Other BS)	Balance	Qualitative	X			
36	Reverse Repos: Pershing	Assets (Other BS)	Balance	Statistical				
37	Securities Financing	Assets (Other BS)	Balance	Statistical				
38	Trading Assets: Capital Markets	Assets (Other BS)	Balance	Statistical				
39	Trading Assets: Global Markets	Assets (Other BS)	Balance	Statistical				
40	Alternative Investment Services and Global Collateral Services Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
41	Alternative Investment Services and Global Collateral Services Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
42	Asset Servicing Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
43	Asset Servicing Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
44	Asset Servicing/ Treasury Services EU	Liabilities (Deposits)	Balance	Statistical				
45	Asset Servicing/ Treasury Services GB	Liabilities (Deposits)	Balance	Statistical				
46	Broker Dealer Services Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
47	Corporate Treasury Interest Bearing Deposits	Liabilities (Deposits)	Balance	Qualitative	X			
48	Corporate Trust Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework			
					Lack of economic relationship	Materiality	Feasibility (data availability)	Other
49	Corporate Trust Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
50	Corporate Trust Interest Bearing Deposits EU	Liabilities (Deposits)	Balance	Statistical				
51	Corporate Trust Interest Bearing Deposits GB	Liabilities (Deposits)	Balance	Simple model			X	
52	Foreign deposits in currencies other than USD, Euro and GBP	Liabilities (Deposits)	Balance	Simple model			X	
53	Treasury Services Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
54	Treasury Services Interest Bearing Deposits	Liabilities (Deposits)	Balance	Statistical				
55	Wealth Management Demand Deposit Accounts	Liabilities (Deposits)	Balance	Statistical				
56	Wealth Management Personal Deposits	Liabilities (Deposits)	Balance	Statistical				
57	Wealth Management Sweep Deposits	Liabilities (Deposits)	Balance	Statistical				
58	Broker Dealer Payables	Liabilities (Other BS)	Balance	Statistical				
59	Long term debt	Liabilities (Other BS)	Balance	Qualitative	X			
60	Non-interest bearing liabilities	Liabilities (Other BS)	Balance	Qualitative	X			
61	Repos: Pershing	Liabilities (Other BS)	Balance	Statistical				
62	Short-term borrowings: Commercial Paper	Liabilities (Other BS)	Balance	Qualitative	X	X		
63	Short-term borrowings: Fed funds, Repos (Treasury)	Liabilities (Other BS)	Balance	Qualitative	X			
64	Short-term borrowings: Other borrowed funds	Liabilities (Other BS)	Balance	Qualitative	X	X		
65	Trading Liabilities: Capital Markets	Liabilities (Other BS)	Balance	Simple model				Modeled off of Trading Assets
66	Trading Liabilities: Global Markets	Liabilities (Other BS)	Balance	Simple model				Modeled off of Trading Assets

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework			
					Lack of economic relationship	Materiality	Feasibility (data availability)	Other
67	Broker Dealer Loans	Rate: Assets (Loans)	Rate	Statistical				
68	C&I Loans	Rate: Assets (Loans)	Rate	Statistical				
69	Commercial Loans (rates segment)	Rate: Assets (Loans)	Rate	Statistical				
70	CRE Loans	Rate: Assets (Loans)	Rate	Statistical				
71	HELOCs	Rate: Assets (Loans)	Rate	Qualitative	X	X		
72	Iron Hound Loans	Rate: Assets (Loans)	Rate	Qualitative	X	X	X	
73	Lease Financing	Rate: Assets (Loans)	Rate	Qualitative	X			
74	Margin Loans	Rate: Assets (Loans)	Rate	Statistical				
75	Mortgage Loans (Wealth Management)	Rate: Assets (Loans)	Rate	Statistical				
76	Other mortgage loans	Rate: Assets (Loans)	Rate	Qualitative	X	X		
77	Overdrafts	Rate: Assets (Loans)	Rate	Statistical				
78	Reverse mortgages	Rate: Assets (Loans)	Rate	Qualitative	X	X	X	
79	Central bank deposits: Fed deposits	Rate: Assets (Other BS)	Rate	Qualitative				Use Moody's forecast
80	Central bank deposits: Foreign Central Bank deposits	Rate: Assets (Other BS)	Rate	Qualitative				Use Moody's forecast
81	Fed Fund Sold and Rev Repos: Non-Pershing	Rate: Assets (Other BS)	Rate	Qualitative			X	
82	Placements: Nostro	Rate: Assets (Other BS)	Rate	Qualitative			X	
83	Placements: Pershing	Rate: Assets (Other BS)	Rate	Qualitative			X	

					Reasons for qualitative framework			
#	**Segment**	**Model Category**	**Model Type**	**Model Approach**	**Lack of economic relationship**	**Materiality**	**Feasibility (data availability)**	**Other**
84	Placements: Treasury	Rate: Assets (Other BS)	Rate	Qualitative			X	
85	Reverse Repos: Pershing	Rate: Assets (Other BS)	Rate	Statistical				
86	Securities Financing	Rate: Assets (Other BS)	Rate	Qualitative	X			
87	Trading Assets: Capital Markets	Rate: Assets (Other BS)	Rate	Statistical				
88	Trading Assets: Global Markets	Rate: Assets (Other BS)	Rate	Qualitative	X			
89	Alternative Investment Services and Global Collateral Services Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Qualitative			X	
90	Asset Servicing Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
91	Asset Servicing/ Treasury Services Deposits EU	Rate: Liabilities (Deposits)	Rate	Statistical				
92	Asset Servicing/ Treasury Services Deposits GB	Rate: Liabilities (Deposits)	Rate	Statistical				
93	Corporate Treasury Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Qualitative	X		X	
94	Corporate Trust Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
95	Corporate Trust Interest Bearing Deposits EU	Rate: Liabilities (Deposits)	Rate	Statistical				
96	Corporate Trust Interest Bearing Deposits GB	Rate: Liabilities (Deposits)	Rate	Statistical				
97	Foreign deposits in currencies other than USD, Euro and GBP	Rate: Liabilities (Deposits)	Rate	Qualitative			X	
98	Treasury Services Interest Bearing Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
99	Wealth Management Personal Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				
100	Wealth Management Sweep Deposits	Rate: Liabilities (Deposits)	Rate	Statistical				

#	Segment	Model Category	Model Type	Model Approach	Reasons for qualitative framework: Lack of economic relationship	Materiality	Feasibility (data availability)	Other
101	Broker Dealer Payables	Rate: Liabilities (Other BS)	Rate	Statistical				
102	Long term debt	Rate: Liabilities (Other BS)	Rate	Qualitative	X			
103	Repos: Pershing	Rate: Liabilities (Other BS)	Rate	Statistical				
104	Short-term borrowings: Commercial Paper	Rate: Liabilities (Other BS)	Rate	Qualitative	X	X		
105	Short-term borrowings: Fed funds, Repos (Treasury)	Rate: Liabilities (Other BS)	Rate	Qualitative			X	
106	Short-term borrowings: Other borrowed funds	Rate: Liabilities (Other BS)	Rate	Qualitative	X	X		
107	Trading Liabilities: Capital Markets	Rate: Liabilities (Other BS)	Rate	Statistical				
108	Trading Liabilities: Global Markets	Rate: Liabilities (Other BS)	Rate	Statistical				
109	Other Loans	Assets (Loans)	Balance	Qualitative	X	X		
110	Loan Fees	Net Interest Income	NII	Qualitative	X	X		
111	Interest Income from Specials	Net Interest Income	NII	Qualitative	X	X		
112	Short Term Borrowings: Capital Markets	Balance: Liabilities (Other BS)	Balance	Qualitative			X	
		Rate: Liabilities (Other BS)	Rate	Qualitative			X	

As described in Figure 6 above, the decisions of a model-based versus a qualitative framework might be revised during the execution process of the methodological approaches. As an example, segments for which a model-based approach failed to result in a sound statistical model might be switched to a qualitative framework that is quantitatively informed by the data sourced for potential model development.

For each of the model-based and qualitative frameworkes, the modeling team then follows a standard set of steps to further develop the approach for each segment. These steps are explained in Section 3.3 for the model-based approach and in Section 3.4 for the qualitative framework.

3.3. Model-based approach

This section describes the model-based approach. The model-based approach consists of five steps:

- Data review (involving project stakeholders and lines of business) (Section 3.3.1)
- Driver identification and development of driver hypotheses (involving project stakeholders and lines of business) (Section 3.3.2)
- Application of econometric guidelines to modeling (Section 3.3.3)
- Model diagnostics and sensitivity tests (Section 3.3.3.3)
- Model selection (involving Working Group, Steering Committee and lines of business) (Section 3.3.4)

Each step is described in the following sub-sections.

3.3.1. Data review

Together with the Working Group, the Treasury group, the ALM team and various representatives of the lines of business, the modeling team collected data for each of the segments as presented in Section 3.1. The sources are described in Section 4 below.

As described in the Section 1.1 above, all data – both balances and interest payments made or received (for rate analysis) – were obtained on a monthly frequency. Modeling on monthly data is a requirement as the ALM team produces monthly balance sheet forecasts as part of the CCAR process. In addition, developing models on a monthly time step may allow these models to be in the monthly business forecasting process conducted by the Treasury group in the future.

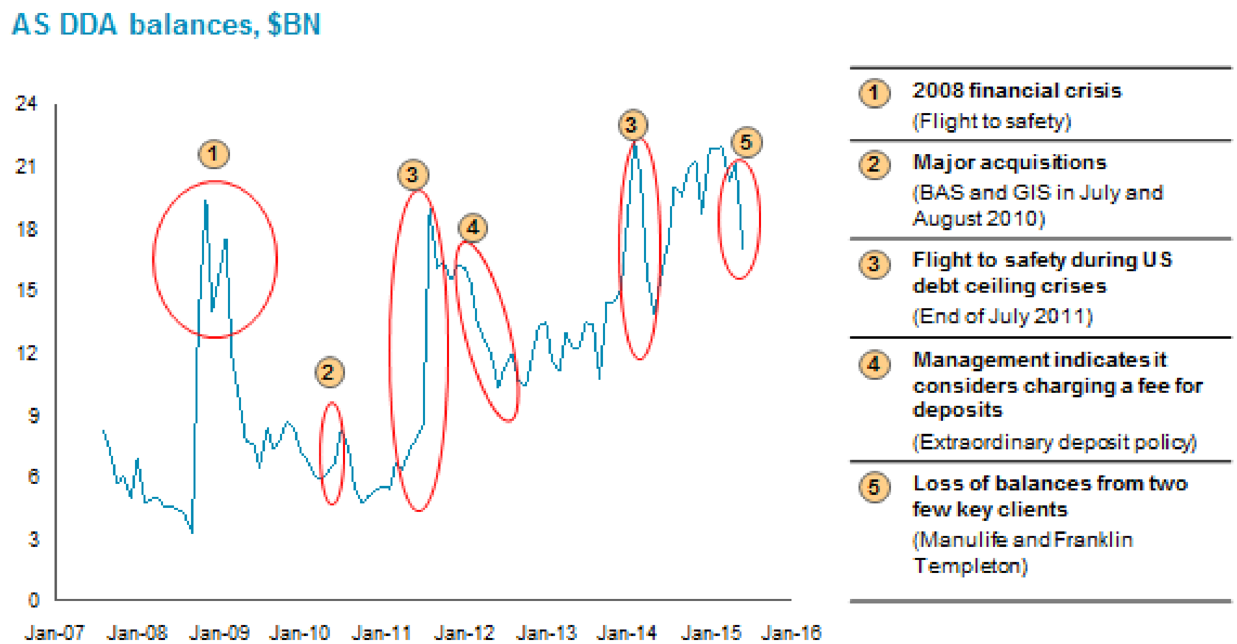
Once the balances and the interest payments made or received were obtained for a segment, the modeling team reviewed the data. The review focused on identifying unusual patterns in the data, such as sudden or exceptionally large spikes and drops, and seasonal patterns both quarterly and annual.

For the balances, the modeling team conducted a comparison against a snapshot of the balance sheet as of April 30, 2015, to confirm that all account balances identified for a segment were included in the data received. The modeling team had obtained a balance sheet snapshot that was extracted at the highest granularity of BNY Mellon’s accounting system and therefore allowed the recreation of an independent spot balance number for each segment.

The modeling team reviewed the balance and rate data with the lines of business or their representatives. The modeling team sought explanations for all unusual patterns identified that would inform the modeling process and to identify data issues.

Figure 8 contains an example of an exhibit shared with the Asset Servicing line of business to facilitate the data review along with a legend on the right that lists the information received during the conversation.

Figure 8: Example chart for data discussion with LOBs



The data review meetings for deposit balances and rates did not suggest that any cleaning or scrubbing of the data was necessary. The data was aligned with the expectations of the lines of business regarding balance sizes at various points in time as well as general trends. Moreover, no unexpected spikes or outliers were detected that would suggest that the historical data was changed by accounting adjustments that would require further review and correction.

However, for one of the loan segments, the Wealth Management loans, a data irregularity in connection with the post-merger harmonization of Bank of New York's and Mellon's systems was discovered. The details are described in the section on this segment below.

The loan rates were consistently more volatile than expected, most likely due to accounting adjustments. The modeling team was not able to obtain information that would have allowed a correction of the data. The modeling team recommends an effort to complement the management accounting system data with additional data sources to test whether they could replace the accounting system data in the future.

3.3.2. Driver identification and development of driver hypotheses

After data collection was completed and the data was reviewed with the lines of business or their representatives, the modeling team worked with all stakeholders to identify macroeconomic drivers (driver hypotheses) that may have an impact or a relationship with the balances and rates.

The main input for the driver hypotheses was collected during meetings with the lines of business of their representatives. For the discussions the modeling team provided the lines of business with the balances and rates data as well as a list of historical, political and economic events during the modeling period.

Example questions that were asked to the lines of business are:

1. What macroeconomic factors are linked to your clients' decision to increase or decrease their deposit balances at BNY Mellon? (adapted for loan segments)
2. What macroeconomic factors do you consider when setting deposit balance targets for budgeting or forecasts for business purposes? (adapted for loan segments)
3. How, if at all, do these considerations change at times of severe economic stress (e.g. during the 2008 financial crisis)?
4. If the 2008 crisis happened today, what would happen to current deposit balances? (adapted for loan segments)

The modeling team also asked questions related to changes in the regulatory environment, changes in BNY Mellon's management strategy, and changes in the competitive environment that could have affected the balances during the modeling period. Similar questions were asked regarding future expected changes.

Based on these conversations, the modeling team compiled a preliminary list of driver hypotheses for each segment. Those were reviewed with the Working Group; the Working Group, including members of the ALM team, then had the option to add additional hypotheses and suggest exploring for further research, such as the review of academic research. The extended list of driver hypotheses were then reviewed again and discussed with the Steering Committee for the segments with the largest balances.

The driver hypotheses are presented in the individual sections below on the model results for each segment.

Once segment-level drivers were confirmed, the modeling team collected candidate variables for each driver hypothesis. For instance, for the Asset Servicing DDA segment, one of the driver hypotheses was that as uncertainty in equity markets increases, the AS DDA balances would increase. The business had reasoned that the higher the uncertainty and perceived risk in the equity market, the more clients would gravitate towards safer investments and the more deposits would be held. The candidate variables collected for the driver hypothesis of perceived equity market risk is the variable VIX, a common measure of equity market volatility.

The candidate variables collected for each driver hypothesis are described in Section 4 on the development data for the models.

3.3.3. Econometric guidelines to modeling

A requirement for the balance and rate model development is that the process be rigorous, transparent and repeatable. The modeling team developed estimation procedures that are consistent with this requirement. The procedure uses standard econometric techniques and builds on business intuition and knowledge regarding the modeled balances and rates.

Three choices define the forecasting approach:

- The choice of the functional form of models: The modeling team recommended a forecasting approach that builds on linear, multivariate regression models.
- The choice of an estimation method: The choice of the estimator is OLS.
- The choice of a procedure that selects the variables used in the models: This is covered in the remainder of this section on econometric guidelines.

Linear regressions using OLS estimation is the most straightforward type of regression analysis and therefore provides the highest degree of transparency. The OLS estimator has been found to be robust to violations of classical linear model assumptions to which other methods are more sensitive. Over decades of research, the OLS estimator has stood up remarkably well against other estimation methods.[2]

To assure statistically sound models, however, a few considerations have to be made in order to avoid the problem of spurious correlations. To accomplish this, the modeling team followed the three steps below:

- Testing all dependent and independent variables for unit roots and time trends and transform the variables accordingly if warranted (Section 3.3.3.1)
- Estimate models using only candidate variables as identified in the driver hypotheses and review models regarding statistical fit and intuitiveness (see Section 3.3.3.2)
- Perform model diagnostics on each model and only allow for models that satisfy all assumptions or correct for violations of assumptions (Section 3.3.3.3)

The following sub-sections contain the details of these three steps.

[2] See p. 324 of J. Scott Armstrong, *Principles of Forecasting: A Handbook for Researchers and Practitioners*, New York: Springer, 2001.

3.3.3.1. Unit root and stationarity testing

The terms "spurious correlation" and "spurious regression" apply to two situations:[3]

- A regression model estimates a statistically significant relationship between two independent variables that are related through their correlation with a third variable. This situation may apply to time series that are not detrended prior to estimation through actual detrending or inclusion of time trends in the models.
- A regression model estimates a statistically significant relationship between two variables that may or may not be trending even though the variables are independent. This situation occurs with a high probability when time series are highly persistent,[4] or in other words, contain a unit root. For such variables the probability of a spurious regression increases with sample size and typically yields highly significant coefficients along with large R^2 even though the variables are independent time series processes.

For these reasons the regressions are only run on variables for which a unit root can be rejected or stationarity (including trend-stationarity[5]) cannot be rejected (henceforth stationary variables). Stationary variables are time series whose mean, variance and covariances amongst equidistant elements are independent of time.[6] A nonstationary series is a series that is not stationary, for instance, random walks are non-stationary (random walks are one class of the more general class of unit root processes). In every period, a random walk's value is the prior month's value plus a random and possibly a deterministic element. It is intuitively clear that many macroeconomic variables as well as account balances might fall into the category of unit root processes.

Because many macroeconomic variables are expected to have unit roots and be non-stationary, the modeling team created transformations of the macroeconomic variables. All transformations are tested for stationarity along with the untransformed variables. Only stationary variables and transformations are used in the estimation of models.

Table 13 lists the transformations created and tested for stationarity.

[3] See, e.g. Chapters 10 and 18 in Jeffrey M. Wooldridge, *Introductory Econometrics, A Modern Approach*, Cengage Learning, 2013.

[4] Highly persistent series violate the weak dependence assumption necessary for the OLS estimator to be consistent, see, e.g. Chapter 11 in Jeffrey M. Wooldridge, *Introductory Econometrics, A Modern Approach*, Cengage Learning, 2013.

[5] For the definition of a series that is stationary around a time trend, that is, trend-stationary, see, e.g. Chapter 11 in Jeffrey M. Wooldridge, *Introductory Econometrics, A Modern Approach*, Cengage Learning, 2013.

[6] See, e.g. for a formal treatment Chapter 3 in James D. Hamilton, *Time Series Analysis*, New Jersey: Princeton University Press, 1994, and, e.g. for an intuitive discussion Chapter 11.1. in Jeffrey M. Wooldridge, *Introductory Econometrics, A Modern Approach*, Cengage Learning, 2013.

Table 13: Variable transformations created and tested for stationarity

	Growth rates (incl. CPI)		Interest rates		All other variables	
	Unlagged	1-month lag	Unlagged	1-month lag	Unlagged	1-month lag
Month over month difference	✓	✓	✓	✓	✓	✓
Month over month percent change	✗	✗	✗	✗	✓	✓
Three month over month difference	✓	✗	✓	✗	✓	✗
Three month over month percentage change	✗	✗	✗	✗	✓	✗
Year over year difference	✓	✗	✓	✗	✓	✗
Year over year percentage change	✗	✗	✗	✗	✓	✗

The remainder of the section explains the stationarity testing procedure for all dependent and independent variables (transformed and un-transformed).

Three standard tests are used to assess the presence of unit roots in a series: The Augmented Dickey Fuller (ADF) test and the Phillips Perron (PP) test that test the null hypothesis that a time series follows a unit root process, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test that tests the null hypothesis that a time series is stationary.[7]

All three tests allow for a variety of alternative hypotheses, that is, different types of tests. As an example, the Dickey-Fuller test equation in its most general form can be written as:[8]

$$dy_t = a + b \times y_{t-1} + c \times t + u_t$$

The term *a* is the drift term of the process and the term *c*t* is the time trend. By including these terms separately or in combination different types of tests can be applied:

[7] See, e.g. In Choi, *Almost All About Unit Roots*, Edited by Peter C. B. Phillips, New York: Cambridge University Press, 2015.

[8] For a thorough treatment of Dickey-Fuller, Augmented Dickey-Fuller and Phillips-Perron tests as well as the different types of alternative hypotheses, see James D. Hamilton, *Time Series Analysis*, New Jersey: Princeton University Press, 1994, Chapter 17.

- The test equation includes a drift term and a time trend which allows to test the null hypothesis of a unit root series against a trend-stationary series
- The test equation includes a drift but no time trend which allows to test the null hypothesis of a unit root series against a series that is stationary around a single mean
- The test equation includes no drift and no time trend which allows to test the null hypothesis of a unit root series against the alternative hypothesis of a stationary series around zero

The test equation is estimated for the variable under consideration. A unit root can be rejected if the coefficient *b* is statistically different from zero according to the Dickey-Fuller critical values.

Both the Phillips-Perron and KPSS tests allow for the equivalent types of tests, for the KPSS tests on the null hypothesis of stationarity.

The selection procedure for the type of test used for each variable follows the approach by Elder and Kennedy.[9] The Elder and Kennedy estimation strategy relies on two simplifying assumptions. The assumptions are:

- A model of a random walk with a drift plus a time trend is unrealistic for economic variables due to this model's explosive nature, so this model can be excluded
- A model of a stationary variable around exactly zero is highly unlikely, so this model can be excluded

These assumptions are generally considered as appropriate for economic time series.[10] As a consequence of these assumptions, the type of test can be determined based on the following classification of the tested variable:

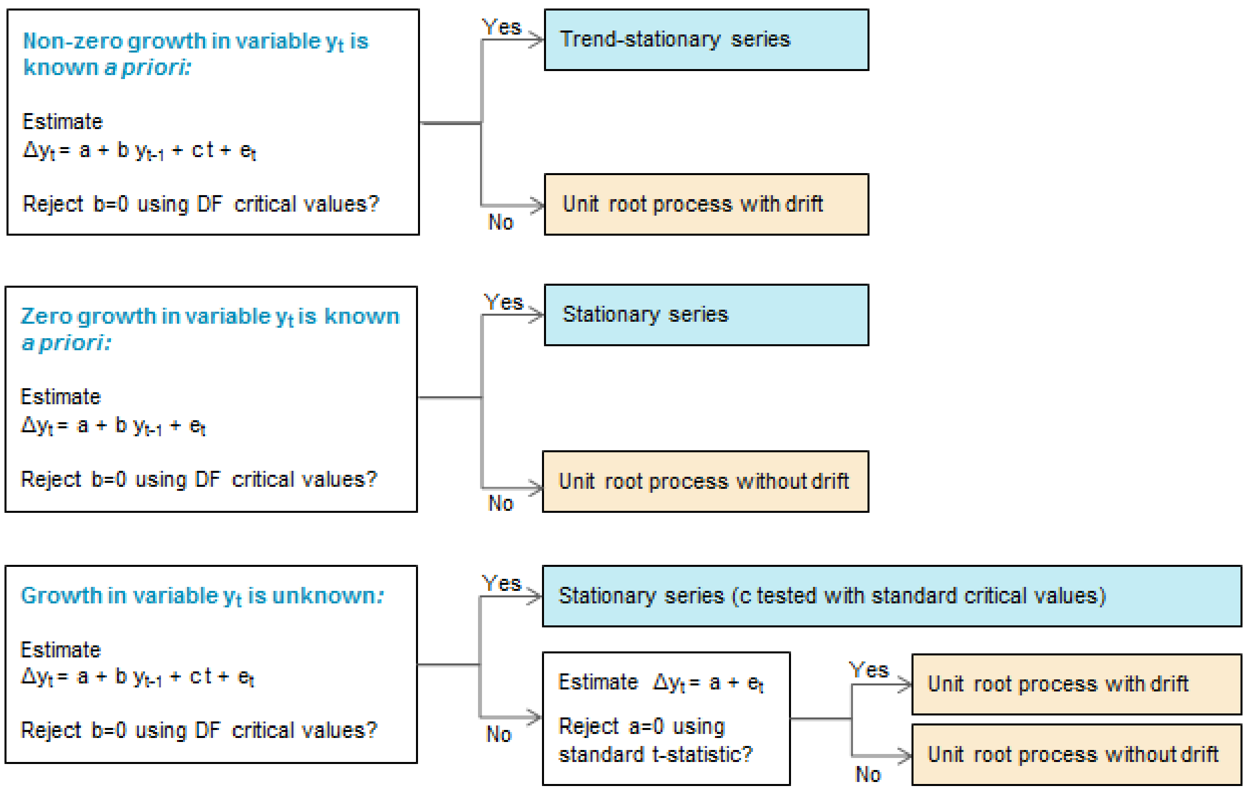
- A "growth variable", that is, a variable that can potentially exhibit unlimited growth, such as GDP or deposit balances, can either be a unit root process with a drift, or a process that is stationary around a deterministic trend (trend-stationary). As a consequence, the test used for growth variables is a unit root test including a time trend and a constant (trend test) that allows for the distinction between these two hypotheses for a given series
- A "zero-growth variable", that is a variable that cannot grow indefinitely, such as interest rates or inflation, can either be a unit root process without drift and trend, or a stationary process around a non-zero constant. As a consequence, the type of test used is a unit root test with a constant but without a time trend (single mean test) that allows for the distinction between these two hypotheses for a given series

[9] J. Elder and P. E. Kennedy (2001), "Testing for Unit Roots: What Should Students Be Taught?" *Journal of Economic Education*, 32(2): 137–46. R. S. Hacker and J. A. Hatemi (2001), "The Properties of Procedures Dealing with Uncertainty about Intercept and Deterministic Trend in Unit Root Testing". *CESIS Electronic Working Paper Series*, Paper No. 214.

[10] See, e.g. R. S. Hacker and J. A. Hatemi (2001), "The Properties of Procedures Dealing with Uncertainty about Intercept and Deterministic Trend in Unit Root Testing". *CESIS Electronic Working Paper Series*, Paper No. 214.

When growth is unknown, a multi-step procedure is followed. The following figure shows the selection procedure for the type of unit root or stationarity test:

Figure 9: Elder and Kennedy unit root testing strategy



For the independent variables, the modeling team determined the growth versus zero-growth status of variables as displayed in Table 14.

Table 14: Determination of growth versus zero-growth variable status based on the Elder and Kennedy unit root testing procedure

Variable classification	Description of assessment	List of variables
Growth variables:	A variable is considered a growth variable if there is no economic reason for the variable to have bounded values and no economic reason for the variable not to grow steadily. Growth variables mainly exist because of a positive equilibrium growth rate of an economy or a positive equilibrium inflation rate.	• Monetary supply variables • Equity and hedge fund indices • Bond price indices • Housing and real estate price indices • Mutual fund cash flow measures • Debt issuance measures • Assets under custody at BNY • Fed balance sheet size • Import and export measures • Industrial production measures
Zero-growth variables	Variables were considered zero-growth variables when there are economic reasons that will prevent these variables from growing indefinitely. A sustained growth of these variables is not consistent with a long-term equilibrium of an economy. For instance, it is not reasonable to expect interest rates to grow continuously over time.	• Income and economic output growth rates • Unemployment and inflation rates[11] • Equity and fixed income markets volatility measures • Interest rates and bond yields • Credit spreads and spreads between different interest rates or yields • Debt versus equity ratios • Exchange rates[12] • Any transformations created according to Table 13 of both growth or zero-growth variables

The growth variables were tested using the Augmented Dickey-Fuller, the Phillips-Perron and the KPSS tests, all of which included a time trend, consistent with the Elder and Kennedy procedure.

The zero-growth variables were tested using the Augmented Dickey-Fuller, the Phillips-Perron and the KPSS tests, all of which included a constant and no time trend, consistent with the Elder and Kennedy procedure.

The modeling team assessed the results for both the growth and zero-growth untransformed variables in the following manner:

[11] Note that none of the inflation rates considered as candidate variables were from economies that experienced periods of hyperinflation, a state of the economy where the inflation rate can show the behavior of a growth variable. See, e.g. M. Hashem Pesaran, Til Schuermann and L. Vanessa Smith, "Forecasting Economic and Financial Variables with Global VARs," *Federal Reserve Bank of New York Staff Reports*, 317, 2008.

[12] None of the exchange rates involved currencies from economies with hyperinflation episodes, see Footnote 11.

- The Augmented Dickey-Fuller and Phillips-Perron test results were reviewed first. If there was no disagreement between the tests, a conclusion was drawn. The reason for the preference of the unit root tests over the KPSS test is that the macroeconomic variables tested here are often thought of as unit roots processes in the academic literature. The unit root tests use this ingoing hypothesis as the null hypothesis and are therefore preferred over the KPSS which tests the null hypothesis of stationarity[13]
- Whenever the ADF and the PP unit root tests provided conflicting results, the modeling team reviewed the series manually. In general, the ADF test was preferred over the PP test as a basis for a decision unless it conflicted with the visual assessment of the data.[14] The modeling team erred on the side of concluding a unit root when test results conflicted as over-differencing the data has less severe repercussions for the OLS estimator than estimating on non-stationary series

The results for the growth and zero-growth untransformed variables are listed in the Appendix. The notes on the visual assessment are included when necessary.

Variables that are assessed to be trend-stationary are allowed to enter the modeling stage after detrending.

As indicated in Table 14 above, the transformations of both growth and zero-growth variables were determined to be zero-growth variables. The reason is that percentage growth rates and month-over-month changes are not expected to grow continuously.[15] Accordingly, their unit root and KPSS tests included a constant and no time trend, consistent with the Elder and Kennedy procedure. The assessment of the results differed from untransformed variables though.

[13] The KPSS test is known to suffer from serious size distortions in the vicinity of a unit root, see In Choi, *Almost All About Unit Roots*, Edited by Peter C. B. Phillips, New York: Cambridge University Press, 2015, p. 127. The modeling team decided to use the test when the ingoing hypothesis was that a series would not contain a unit root or be near a unit root.

[14] The Augmented Dickey-Fuller test is often assessed to have less distortions under a variety of underlying data generating processes, see, e.g. In Choi, *Almost All About Unit Roots*, Edited by Peter C. B. Phillips, New York: Cambridge University Press, 2015, p. 127.

[15] Steadily growing transformations would imply an explosive behavior of the original macroeconomic variables. This is not observed historically for any of these variables over sustained periods of time.

- A transformed variable for which the KPSS did not reject the stationarity was assessed to be stationary and allowed into the estimation procedure. The reason for the preference of the KPSS test is that the transformed variables, being the growth rates and changes of macroeconomic variables, are expected to be stationary. First differencing as well as transformations into percentage changes is expected to result in stationary processes for most macroeconomic variables. The KPSS test is a direct test of this ingoing hypothesis as it uses stationarity as the null hypothesis.[16] If the KPSS test contradicted the results of both the Augmented Dickey-Fuller and the Phillips-Perron test, the variable was reviewed anually
- Additionally, the modeling team reviewed the outcome of the Augmented Dickey-Fuller and Phillips-Perron tests alongside the KPSS test whenever the unit root couldn't be rejected for an untransformed variable and none of its transformations passed the KPSS test. In addition to the ADF and PP tests, the modeling team reviewed these series manually and assessed on a case by case basis if one of the transformations should be allowed into the independent variable set based on the Augmented Dickey-Fuller and Phillips-Perron test results

The results of these tests are listed in the Appendix, including notes on the visual assessment when necessary.

The list of all independent variables assessed to be stationary along with their transformations assessed to be stationary is referred to as the set of independent variables in the following.

For the dependent variables the unit root and stationarity test results are summarized in the respective sections on the model segments. The procedure was the same as for the independent variables. The rationale for decisions in cases of conflicting test results are described in each segment section.

All deposit and loan balances were assessed to be growth variables and therefore tested with trend tests. The reason is that monetary variables could grow steadily in an economy with a positive equilibrium inflation rate. The modeling team recommended to the Working Group to use the first difference transformation of balances should unit root tests fail to reject the null hypothesis of a unit root. The modeling team's recommendation was based on the consideration of a consistent and transparent forecasting process across all variables. Moreover, the non-linearity of percentage and logarithmic changes would pose increased complexity for the potential correction of forecasting biases.

[16] In order to conclude that a variable is stationary based on a unit root test, one has to rely on the test to reject the null hypothesis of a unit root when the alternative hypothesis of stationarity is in fact true. This means, one has to rely on the power of the unit root test. It has been argued frequently, that the power of unit root tests can be low, see, e.g. In Choi, *Almost All About Unit Roots*, Edited by Peter C. B. Phillips, New York: Cambridge University Press, 2015, p. 38.

3.3.3.2. Estimation of models on candidate variables

The modeling team categorized the independent variable set described in Section 3.3.3.1 into groups of candidate variables that correspond to different macroeconomic drivers.

Based on the driver hypotheses that were developed in collaboration with the Working Group and the lines of business, the modeling team identified the list of candidate variables that would be used to model each segment. A variable becomes a candidate variable for a specific segment if it represents one of the driver hypotheses for that segment. For instance, if a driver hypothesis for a segment is that its balances will positively depend on the performance of equity markets, then any stationary transformation of equity indices such as the Dow Jones Index will be a candidate variable. Table 15 presents the candidate variables for a consolidated list of driver hypotheses across all segments.

Table 15: Driver hypotheses and related candidate variables across all segments

Driver	Variable name
Assets under custody	BNY Mellon AUC
Corporate credit	Baa Corporate Yield
	Baa to Treasury Spread (Baa minus Treasury)
Debt issuances	Corp Debt Outstanding
	Debt Share of Asset Financing
	Total Bond Issuance (ex MBS, treasuries)
	Total Bond Issuance (ex MBS, gov)
	ABS Issuance
	EU Outstanding debt (ex gov)
	EU Gross debt issuances (ex gov)
	UK debt (ex MBS)
	UK debt (ex MBS, gov)
Equity markets	DJI
	MSCI WORLD Index
	KBW Bank Index
	FTSE 100 Price Index
	FTSE All Price Index
	Euro Stoxx Price Index
Exports	Nominal Exports
Financial stability of US government	1M-3M Treasury Spread (1month minus 3 month)
FX rates (to USD)	USD/EUR
	USD/GBP
	Weighted Avg USD FX rate
General economic health	Real GDP growth
	Nominal GDP growth
	Unemp rate
	Real Disposable Income
	Nom Disposable Income
	EU Real GDP
	UK Real GDP
Hedge fund index	HFRX NA Index
	Eurekahedge NA HF Index
	Eurekahedge NA FoF Index
Housing prices	HPI
	Com Real Estate Price Index
Imports	Real Imports
	Nominal Imports
Industrial production	Industrial Production

Driver	Variable name
Long-term rates	1Y Treasury
	2Y Treasury
	3Y Treasury
	5Y Treasury
	7Y Treasury
	10Y Treasury
	20Y Treasury
	30Y Treasury
	Mortgage Rate
	Germany 10yr bond
	S&P Euro Sov Bond Index
	5Y EUR Swap
	10Y EUR Swap
	5Y UK Swap
	10Y UK Swap
	5Y US Swap
	10Y US Swap
	12 Month USD LIBOR
	12 Month EUR LIBOR
	12 Month GBP LIBOR
Market volatility/uncertainty (equity)	S&P Vol (30D MAVG)
	Market Vol
	FTSE 100 Volatility Index
	Euro Stoxx Volatility Index
Market volatility/uncertainty (rates)	10 Year US T-Note Volatility Index
MF Cash Flow	Bond and Income Mut Fund Cash Flow
	Money market fund Cash Flow
	Stock Mut Fund Cash Flow
Monetary base	Inflation
	EU inflation
	UK inflation
	US M1
	EUR M1
	EUR M2
	EUR M3
	UK M0
	Fed balance sheet
Banking system risk	Ovrnt LIBOR-1wk OIS spread (LIBOR minus OIS)
	1 week LIBOR 1 week OIS spread (LIBOR minus OIS)
	TED Spread
Real estate loans	Real estate loans
Relative creditworthiness of BNY Mellon	BNY Mellon – Peer Group Debt Yield Spread (peer minus BNY Mellon)
	BNY Mellon – Peer Group Debt Yield Ratio (peer divided by BNY Mellon)

Driver	Variable name
Short-term rates	Prime rate
	1M Treasury rate
	3M Treasury
	Ovrnt LIBOR
	Federal Funds Rate
	Ovrnt Repo Rate
	SONIA
	EONIA
	T spread with Fed Funds (Fed Fund minus T bill index)
	3M EUR Swap
	3M UK Swap
	3M US Swap
	Fed Funds Target Rate
	ECB Marginal Lending Rate
	BoE Clearng Base Rate
	1 Month USD LIBOR
	3 Month USD LIBOR
	6 Month USD LIBOR
	1 Month EUR LIBOR
	3 Month EUR LIBOR
	6 Month EUR LIBOR
	1 Month GBP LIBOR
	3 Month GBP LIBOR
	6 Month GBP LIBOR
Yield spread	3M to 5Y T Spread (5 year minus 3 month)
	3M to 10Y T Spread (10 year minus 3 month)

For every segment, only its candidate variables are used in the actual modeling procedure. So for every segment, only variables that were supported by business judgment or economic theory entered the modeling procedure. As a consequence, the variable selection described subsequently is done on this pre-selected set of candidate variables. This process is therefore different from a data mining approach to model selection, the drivers and their supporting variables are chosen prior to the model selection and the model selection is focused on finding the appropriate candidate variables for the drivers as well as the appropriate transformation.

Dummy variables are used to correct for data problems. The use of dummy variables in model development was discussed with the Working Group and the following principles regarding the use of dummy variables were applied during model development:

Table 16: Principles for the use of dummies

Principle	Reason
Dummy variables should not be used to neutralize the effect of idiosyncratic events or management driven movements in balances and rates	• The Working Group decided not to create variables that are overly difficult to forecast, such as, for instance, dummy variables for political events such as the debt ceiling crises • The Working Group believed that supporting dummy

	variables for management driven movements in balances would be challenging as management actions are always made in context of macroeconomic environments and can therefore not be separated from the macroeconomic environment in a clean manner
Dummy variables can be used to control for changes in the dependent variables due to data problems	• A few data series had issues that could not be corrected and the Working Group decided to include dummy variables in these instances in order to obtain unbiased coefficients

There are five models that include a dummy variable:

Table 17: Models using dummy variables

Segment	Months in which dummy=1	Reason for dummy
Asset Servicing Interest Bearing Deposits (AS IB)	January 2009	Data for one component of the segment (AS USD Foreign Deposits) only becomes available starting in January 2009
AIS/GCS Interest Bearing Deposits (AIS/GCS IB)	July 2011	Data for one component of the segment (GCS Cash Reserves) only becomes available starting in July 2011
Wealth Management Loans – Total Commitments	April 2009	Large volume of draws from facilities were reclassified as closed-end loans due to integration of legacy Mellon balances into BNY Mellon systems
Wealth Management Loans – Draw Percentage	April 2009	
Wealth Management Loans – Closed End Loans	April 2009	

The modeling team used SAS software to estimate the multivariate, linear regression models. In order to avoid over-fitting, a maximum of three macroeconomic variables was allowed in each model.

The modeling team used SAS/STAT's capabilities to select a set of models with the best historical fit within the set of all possible models that include up to three independent variables. The goodness-of-fit measure used to identify the best fitting models is R^2.[17] The model selection function is available within SAS/STAT's regression procedure REG, where the method RSQUARE can be used to select a pre-specified number of models with highest R^2 out of all models.

For each segment, the modeling team extracted all one-variable models and between 1,000 and 5,000 models with two and three variables, respectively, depending on the segment. The models were rank-ordered by R^2.

For every model, the p-values based on a two-sided t-test are calculated. For a t-statistic of a coefficient, both the coefficient estimate as well as its standard deviation are used. The bigger

[17] R^2 is defined as the explained sum of squares (sum of squared distances between predicted values and sample mean) divided by the total sum of squared (sum of squared distances between variable values and sample mean, a measure of total sample variation). R^2 is the ratio of the explained variation compared to the total variation in the data, that is, it can be interpreted as the fraction of the sample variation in the dependent variable that is explained by the independent variables. See, e.g. Chapter 2 in Jeffrey M. Wooldridge, *Introductory Econometrics, A Modern Approach*, Cengage Learning, 2013.

the absolute value of a coefficient and the smaller its standard deviation, the bigger is the t-statistic. The p-value is the probability that a higher t-statistic would be obtained under the null hypothesis that the true coefficient is zero. Consequently, the smaller the p-value of a coefficient, the stronger is the support to reject the null hypothesis that the coefficient is equal to zero. The modeling team uses a significance threshold of 10 percent. So for coefficient with a p-value of less than 10 percent, the hypothesis that the coefficient is equal to zero will be rejected, that is, the coefficient estimate is considered statistically significant.

Similarly, for every model the coefficient estimates are tested jointly against the null hypothesis that they are all equal to zero. This joint test uses an F-statistic. With a significance threshold of 10 percent, a p-value of less than 10 percent provides enough support to reject the null hypothesis that all coefficient estimates are equal to zero. In this case, the model is considered statistically significant.

Further, both the R^2 and the adjusted R^2 are calculated for each of the models. The R^2 can be interpreted as the proportion of the variation in the dependent variable that is explained by the independent variables in the model. The adjusted R^2 is adjusted for the number of explanatory terms in a model relative to the number of data points. The R^2 is used to rank models that are produced through the model selection function in SAS/STAT. Everything else equal, a model with a higher R^2 is preferred over a model with a lower R^2. The selection procedure of the models is described in Section 3.3.4 below after the discussion of the model diagnostic and sensitivity tests in Section 3.3.3.3.

3.3.3.3. Model diagnostics and sensitivity tests

This section discusses the diagnostic tests considered for each model and the actions taken when violations of assumptions are detected for a model. In particular, this section describes the treatment of serial correlation in the residuals of estimated models. The section further discusses the sensitivity tests applied to the final models.

For every model that was extracted through the SAS/STAT model selection procedure for the highest R^2 models, a set of diagnostic tests were executed. Table 18 lists the diagnostic tests used:

Table 18: List of diagnostic tests

Test	Definition	Application in modeling approach
VIF	The Variance Inflation Factor is a measure of the correlation among the independent variables.	A VIF in excess of 5 indicates that a model's selection of independent variables should be reviewed and the model dropped unless there is strong intuition for the selection of independent variables.
Breusch-Pagan test	The Breusch-Pagan test is a test used to assess heteroskedasticity in a linear regression model, that is, it tests whether the variance of the residuals are dependent from the values of the independent variables.	A detection of heteroskedasticity indicates that a heteroskedasticity robust estimation should be used to obtain significance tests with the correct size.
Breusch-Godfrey test	The Breusch-Godfrey test is a test used to assess serial correlation in the residuals of a model, i.e. it tests whether residuals dependent on past residual values.	A detection of serial correlation indicates that a heteroskedasticity and autocorrelation consistent estimation should be used to obtain significance tests with the correct size.
RESET test	The RESET test is designed to detect misspecifications in the estimated model.	A detection of a misspecification will result in a review for omitted variables and functional form of the model. As such misspecifications are often not easily corrected for, a failure of this test is most likely resulting in an exclusion of the model.

For models for which the hypotheses of no serial correlation or no heteroskedasticity were rejected by the Breusch-Pagan and the Breusch-Godfrey tests, a heteroskedasticity and autocorrelation consistent (HAC) estimator is used for the standard error of the regression. This is a standard technique to account for these violations of the classical model assumptions.[18] This approach is preferred as it avoids the shortcomings of alternative methods such as Feasible Generalized Least Squares (FGLS) estimation.[19] While the modeling team considered FGLS estimation, the OLS approach combined with a consistent estimator for the standard error was preferred.[20]

The modeling team used Newey-West estimation for the heteroskedasticity and autocorrelation consistent standard error, the Newey-West estimator is the most commonly used estimator to correct standard errors for the bias due to serial correlation in the residuals. The Newey-West truncation parameter that needs to be determined was set based on the sample size of each of the segments, consistent with the recommendations made in Stock and Watson (2011).[21] It resulted in a truncation parameter of 4 for all segments after rounding up to the closest integer.

[18] See, e.g. p. 201 in William H. Greene, *Econometric Analysis*, Prentice Hall, 5th Edition, 2002.

[19] See p. 417 in Jeffrey M. Wooldridge, *Introductory Econometrics, A Modern Approach*, Cengage Learning, 2013.

[20] There were three reasons for this choice. First, the strict exogeneity assumption might be violated if changes in certain macroeconomic variables are anticipated by clients. This is a crucial assumption needed for FGLS estimation, the FGLS estimator is not consistent or efficient (or unbiased) under less stringent assumptions (e.g. contemporaneous exogeneity) under which OLS is still consistent (OLS is the more robust estimation procedure). Second, FGLS estimation requires the specification of the serial correlation process while the HAC approach is robust to general forms of serial correlation. Third, residuals from the estimation period do not impact stress scenario forecast under the HAC approach, which is consistent with stress testing. Stress tests are not a forecast based on the "natural" continuance of the historical time series used in estimation, but a deliberate shock to those.

[21] See p. 599 in James H. Stock and Mark W. Watson, *Introduction to Econometrics*, Addison-Wesley, 3rd Edition, 2011.

All p-values based on t-statistics and F-statistics will be based on the Newey-West estimated standard errors for models with heteroskedastic or serially correlated residuals. The model result sections in Sections 5 to 11 for models with residuals for which heteroskedasticity or serial correlation was detected refer to the use of the Newey-West estimator. The tables which display the statistical significance test results identify the P-values as “HAC P-values” in the column header whenever the P-values are based on a heteroskedasticity and autocorrelation consistent estimator for the standard error of the regression.

The SAS code that was provided by the modeling team along with this documentation relies on a GMM estimation for the Newey-West estimator. For one segment, the SAS optimization procedure of this GMM estimation did not converge due to the numerical size of the dependent variable in combination with certain independent variables. The modeling team therefore recommends transforming all balances to USD million instead of using USD.

For all final models, the modeling team calculated standard residuals, leverage values, DFFITS as well as Cook’s distance to evaluate the influence of each data point on the regression. Large absolute standard residual means higher chance of being an outlier; heavier leverage value hints an observation having more impact to the fitted regression models; DFFITS measures when left one point out of the regression, the studentized or standardized change in the predicted value for that point. It could be converted to Cook’s distance, aligned with standard residual, and also has direct relationship with leverage value. Points with large DFFITS values are identified with corresponding vintage month in the influential point charts; Cook's distance measures the effect of omitting a given observation from the modeling period on the predicted value of the dependent variable. Data points with large residuals (outliers) and unusually large independent variable values (high leverage points) will have larger Cook’s distances and have a larger influence on the estimated coefficients. Those observations with Cook’s distances greater than 1 are considered highly-influential points and are investigated to determine the cause and to assess whether the high-Influential point would suggest a model’s weakness.

For each segment, the data points used for estimation were plotted in a chart. The y-axis depicts the standardized residual of the observations. The x-axis is the leverage, a measure of how much the independent variable value of an observation deviates from other observations in the sample. The two dotted red lines indicate where the Cook’s distance equals 0.5 and 1 – observations lying outside these lines have Cook’s distances that are larger than 0.5 and 1, respectively.

3.3.4. Model selection

The list of estimated models with highest R^2 that was extracted through SAS/STAT’s model selection capabilities (described above), was filtered using the following criteria:

1. Models with coefficients that are statistically insignificant at the 10 percent confidence level are eliminated
2. Models that fail the RESET tests are eliminated
3. Models that contain more than one variable representing a single driver hypothesis are eliminated. The reason is that models that capture two or three driver hypotheses were preferred as CCAR scenarios will differ along several economic quantities.

The first filter was used to limit the model review to models with variables for which the observed data rejected the null hypothesis that the variables had no impact on the dependent variable. The second filter was used to exclude models for which evidence existed that the linear specification might be mis-specified. The third filter was used to eliminate models that were very similar to each other in terms of their macroeconomic variables. The modeling team attempted to provide the Working Group with models that were based on different driver hypotheses in order to foster discussions around a broad range of driver hypotheses and to assess the intuitiveness of different combinations of driver hypotheses. The model selection process was discussed with the Working Group and the trade-off between the review of more diverse models and the omission of models with similar macroeconomic variables was transparent and considered acceptable by the Working Group.

The list of models that passed the above filters was reviewed by the modeling team. For some segments, only a small number of models were left, while for others several hundreds of models passed all the filters. For a small number of segments, no models could be found after the above three filters were applied. In these cases, the modeling team relaxed the second and the third filter and noted RESET test failures as a model weakness.

The modeling team created a short-list that was presented to the Working Group generally referred to as the candidate models. In general, the modeling team attempted to present models to the Working Group that covered different combinations of driver hypotheses.

The modeling team used an excel spreadsheet to which filtering capabilities had been added for efficient review and selection of models, generally referred to as the Model Selection Tool. In addition to filtering capabilities, the Model Selection Tool also automatically created the charts as described below.

When selecting models, the modeling team reviewed the following charts containing information on historical fit and information on the forecasting behavior of the model tested on the CCAR 2015 scenarios. The same charts were then presented to the Working Group.

Figure 10 contains information on the historical fit of the model.

- The top left panel shows the independent variables in the model, their coefficient estimates, the P-values and the standardized coefficients.
- The top right panel shows the dependent variable over time and the predicted values of it, this usually is a transformation of the balances or rates
- The bottom left panel shows the untransformed balances or rates along with a back-test of the model over the first nine quarters of the modeling period which covers the global financial crisis in 2008 and 2009. The back-test is anchored at the value of the balances in the first month of the modeling period and uses the model predictions to calculate the balances or rates over nine quarters
- The bottom right panel shows a back-test covering the entire period. It shows the errors of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted

were highlighted and investigated to ensure the modeling team understood the reason for the deviation

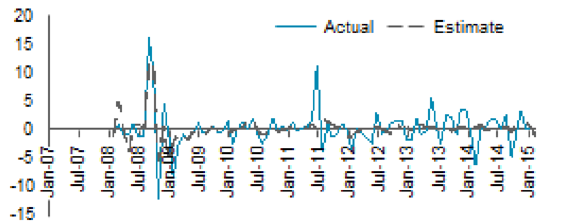
Figure 10: Information on historical fit reviewed for model selection

Drivers used in selected model

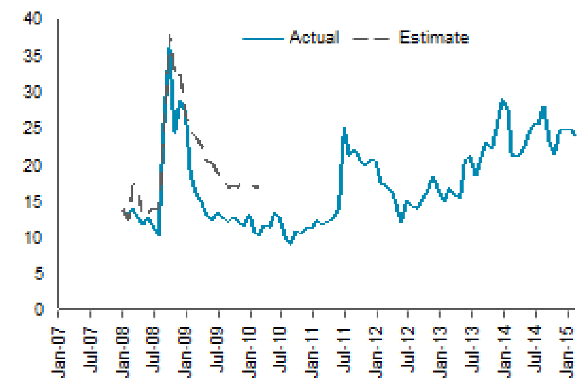
Driver	Variable	Coefficient	Unit of coefficient	P-value	Std Coef
Short-term rates	Ovrnt Repo Rate (Diff MoM)	-3,615.10	$MM /% diff	0.05	-0.20
Market volatility/ uncertainty (equity)	S&P Vol (30D MAVG) (Diff QoQ)	658.40	$MM /index diff	0.07	0.16
Banking system risk	TED Spread	6,344.16	$MM /% diff	<0.01	0.48
	Intercept	131.22	$MM		N/A

R-squared (first differences): 44%; P > F: <0.001

Month over month difference in balances, $BN



Historical balances for asset servicing DDA
$BN



Average predicted vs. actual balances over 9Q windows
$BN, Starting months = Jan 08 – Dec 12 (60 observations)

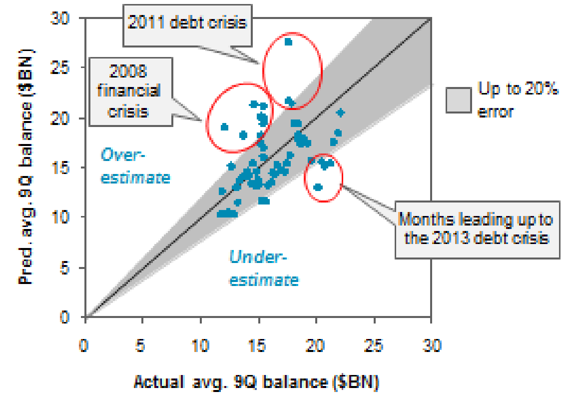
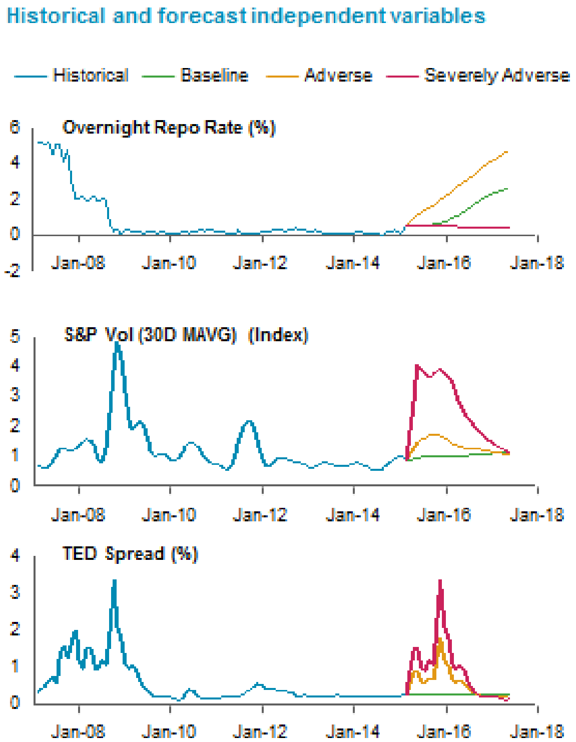


Figure 11 contains information regarding the model's forecast behavior under different macroeconomic scenarios. The scenarios are based on the Federal Reserve's supervisory CCAR 2015 scenarios. Section 4.7 describes how the independent variable forecasts under the different scenarios are derived.

- The left hand side shows the independent variable forecasts for the different macroeconomic scenarios
- The right hand side shows the forecast behavior of the model for the balances or rates modeled

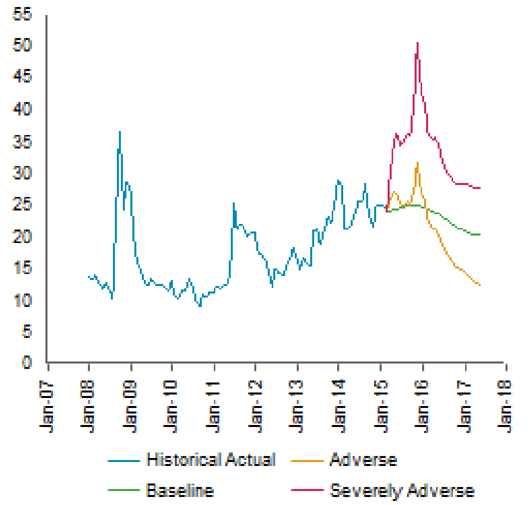
The forecast is obtained by using the models to predict the dependent variable for nine quarters (27 monthly observations) based on the scenario values of the independent variable. These 27 monthly predicted changes are then added to the "jumping off point", which is the last historical data point in the estimation period (March 2015).

Figure 11: Information on forecasting behavior reviewed for model selection



Historical and forecast balances for asset servicing DDA
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-3.77 (-16%)	-11.7 (-49%)	3.78 (16%)	-
Start to peak	0.87 (4%)	7.46 (31%)	26.61 (111%)	22.79 (168%)
Start to trough	-3.77 (-16%)	-11.7 (-49%)	N/A	-3.37 (-25%)



In general, the modeling team presented between three and five models to the Working Group. For the two to three most promising model candidates, the above charts were discussed in model review sessions with the Working Group.

Generally, there was an iterative process between the Working Group meetings and model estimation. The Working Group would suggest additional drivers or candidate variables to the modeling team that would be tested and the new results presented. For some segments several rounds were necessary to converge to a final model.

The Working Group recommended a model to the Steering Group for review. In general, the Working Group considered all information contained in Figure 10 and Figure 11 in combination with the intuitiveness of the models. For every segment, the Working Group's decision to recommend a model was preceded by a thorough discussion of each candidate model's intuitiveness, that is, the intuitiveness of its independent variables and their coefficients.

3.4. Additional details on the loan modeling approach

For certain loan segments, a modified version of the model-based approach described above is used for balances, in order to establish a direct quantitative linkage between the modeling of unfunded commitments and funded loans. This modified approach applies to segments where BNY Mellon offers commitments to clients in the form of facilities, in addition to closed-end loans that are fully funded at origination. Modeled loan segments that do not have unfunded commitments, e.g. Overdrafts, follow the approach described above.

Clients may draw down loans from their committed lines up to the total facility limit, or take Letters of Credit out from their unfunded commitments. The total exposure for any segment that has unfunded commitments can therefore be decomposed into the following components:

A. Unused unfunded commitments

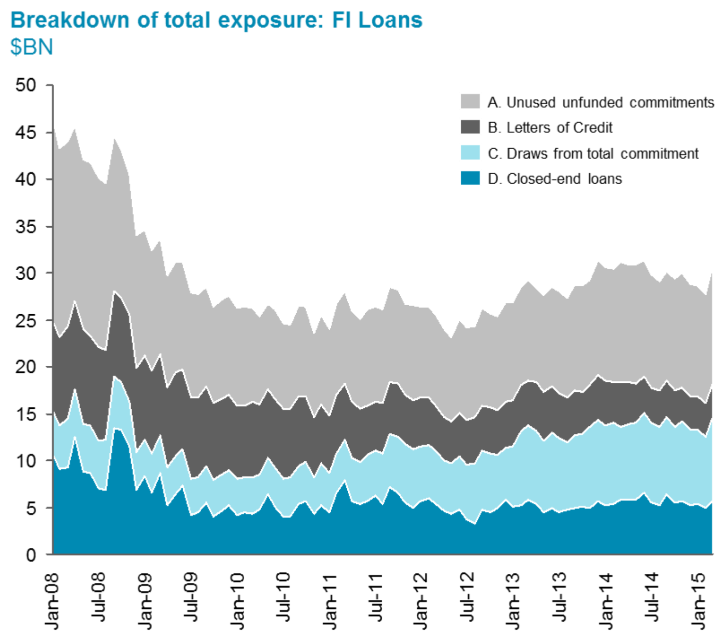
B. Unfunded Letters of Credit

C. Funded draws from commitments

D. Closed-end loans (fully funded at origination)

Figure 12 shows the breakdown of total exposure into these components for an example loan segment.

Figure 12. Breakdown of total exposure for example loan segment (FI Loans)



In order to produce forecasts for these four components of the total exposure, the following quantities are modeled:

- Total commitment amount
- Draw percentage, i.e. total drawn amount divided by total commitment amount (modeled as a percentage)
- Letter of Credit usage percentage, i.e. total amount in unfunded Letters of Credit divided by total commitment amount (modeled as a percentage)
- Closed-end loan balance

By forecasting these quantities, a direct quantitative link is established between unfunded commitment amounts and total funded loan balances. One of the components of funded loan balances is draws from commitments, which typically moves inversely to unfunded commitments unless new commitments are growing faster than draws. This link ensures that the forecasts for unfunded commitments are consistent with the forecasts for funded loan balances. For example, under sudden severe stress, clients may increase the draws on their lines to access liquidity as alternate sources of credit dry up. In such a situation, total funded loan balances would rise while unfunded commitments would decrease. Such relationships would not be adequately captured through modeling if the total funded loan balances were modeled independently from the unfunded commitments.

Only committed lines are considered for the purposes of CCAR when considering unfunded commitments; advised and guidance lines are not included because BNY Mellon has the discretionary power to cancel them, for example when the bank is under stress. However, any loans that have been funded from advised and guidance lines are included for the purpose of modeling under closed-end loans, since they represent realized on-balance sheet exposures. Similarly, Letters of Credit from advised and guidance lines are included for the purpose of modeling in the numerator of Letter of Credit percentage, even though the denominator does not include unfunded commitments from these lines.

Draws and Letters of Credit are modeled as percentages in order to ensure that the forecast drawn balances and Letter of Credit amounts are consistent with the total commitment amount. In addition, modeling these percentages separates purely client-driven behaviors (drawing from lines or taking out Letters of Credit) from changes in total commitment, which are driven by both client behavior and BNY Mellon discretion. Since draw percentage and Letter of Credit usage percentage are by definition bounded between 0% and 100%, a logit transformation was first applied to these quantities to obtain a dependent variable for modeling that has a continuous unbounded range. The logit transformation is given by:

$$Logit(x) = 1n\left(\frac{x}{1-x}\right)$$

As x approaches 0%, the logit-transformed value approaches negative infinity. As x approaches 100%, the logit-transformed value approaches infinity. Therefore, the logit-transformed variable has a continuous unbounded range, which enables usage of the same modeling approach as for balances since there are no restrictions on the forecast value for the logit-transformed variable.

To convert back into a percentage, the inverse transformation is used:

$$Logit^{-1}(y) = \frac{e^y}{1+e^y}$$

All references to the dependent variable for these percentage quantities in subsequent sections refer to the logit-transformed versions.

The loan segments that have unfunded commitments are FI loans, Commercial loans, CRE loans, Wealth Management loans (excluding mortgages), and Margin loans. In a few cases, certain quantities for these segments have been forecast using an assumption-based qualitative framework, either based on business input or due to short historical time series. These exceptions are described in more detail in the sections for each loan segment.

3.5. Additional details on the rates modeling approach

3.5.1. Rates modeling segmentation

Segmentation for balance modeling and rate modeling was kept consistent for most of the Balance Sheet items. However, segmentation used for balance modeling and rate modeling differed for loans. Details are described in Section 4.

3.5.2. Rates modeling approach

The rates modeled for each segment are blended rates: This means that the rates being estimated for a given month is a weighted average of the rates on balances carried over from the previous time period and on new balances originated that month. This is especially important to note for loans, as there can be differences in the rates charged for loans originated years before and those originated more recently.

The rate models are developed following the methodology described in Section 3.3 that is also applied to model the balances.

However, two adjustments to the methodology were applied for the rates models:

- Rates models consider a broader set of independent variable transformations (Details in Section 3.5.2.1).
- Deposit rate models estimate separate coefficients for rising and falling rate environments using a set of specifically constructed independent variables (Details in Section 3.5.2.2).

3.5.2.1. Additional transformations of independent variables for rate models

The rates BNY Mellon pays on deposits and similar products and the rates BNY Mellon receives on loans and other type of lending (rates, or customer rates) are either directly based or tightly linked to a benchmark interest rate. This strongly suggests driver hypotheses that are limited to the benchmark rate for each segment, resulting in lists of candidate variables that are therefore limited to the benchmark rates and their transformations specific to each segment. For the loan and loan-related rate models, several additional variables and their transformations were included: credit spreads, market volatility/uncertainty, and yield spreads.

Due to the very narrow driver hypotheses that were specified for the rates models, two specific restrictions in the methodology as presented above are relaxed to allow for more flexibility in rates modeling:

1. The speed of adjustment in response to a change in the benchmark rate can differ across segments. To allow for a precise description of the adjustment process, the following adjustments are necessary to the methodology as described in Section 3.3
   A. Transformations in addition to those listed in Table 13 were created for the benchmark rates. Specifically, up to three lags were considered for month-over-month difference transformations
   B. Models that contain more than one transformation of the same benchmark rate are considered as candidate models
2. Because of the established link between the customer rates and the benchmark rates there was little concern for omitted variables or misspecification of the functional form of the estimated regression. As a consequence, for certain segments, the modeling team considered candidate models with P-values below the 10% threshold for the RESET test

3.5.2.2. Special case approach for certain deposits rate models

The ALM team and lines of business representatives have indicated that the deposit rate sensitivity to changes in the benchmark rate could be different in rising and falling rate environments. To incorporate this feedback, deposit rate models are constructed to estimate different coefficients for rising and falling rate environments whenever rate data could be sourced that covered a rate cycle.

Generally, US short-term interest rates were rising from the second quarter in 2004 to the third quarter in 2006. For selected deposit rate segments rate data was available that covered this period entirely or partially (details on data availability and the limitations for the data sources used are discussed in Section 4).

For these segments, the deposit rate paid is estimated in multivariate linear regression models of the form illustrated in Figure 13.

Figure 13: Functional forms of select deposit rate models

$y = \beta_0 + \beta_1 x_{rising1} + \beta_2 x_{falling1} + \varepsilon$ (1)

OR

$y = \beta_0 + \beta_1 x_{rising1} + \beta_2 x_{falling1} + \beta_3 x_{falling2} + \varepsilon$ (2)

OR

$y = \beta_0 + \beta_1 x_{rising1} + \beta_2 x_{rising2} + \beta_3 x_{falling1} + \varepsilon$ (3)

In Figure 13, the dependent variable y is a difference month-over-month transformation of the customer rate. The variables on the right hand side of the equation are:

- $x_{rising1}$ is a stationary transformation of the appropriate reference rate that has zeroes replaced for observations when the reference rate is declining. In Equation 3, $x_{rising2}$ is a different transformation of the same reference rate as $x_{rising1}$ (e.g. if $x_{rising1}$ is constructed based on a difference month-over-month transformation of the Fed Funds Target rate, $x_{rising2}$ may be constructed based on a difference quarter-over-quarter transformation of the Fed Funds Target rate)
- $x_{falling1}$ is a stationary transformation of the same reference rate that has zeroes replaced for observations when the reference rate is increasing. β_0 is the intercept estimate and ε is the error term. In Equation 2, $x_{falling2}$ is a different transformation of the same reference rate as $x_{falling1}$

An illustrative example of the construction of the $x_{rising1}$ and $x_{falling1}$ variables is shown in Table 19. In this example, both $x_{rising1}$and $x_{falling1}$ are month-over-month difference transformations of the reference rate. When $t = 2$and $t = 3$, the reference rate is rising, and hence the $x_{rising1}$ variable is non-zero while the $x_{falling1}$ variable is zero. Conversely, when $t = 5\ and\ 6$, the reference rate is falling, so the treatment reverses.

Table 19: Illustrative example of $\boldsymbol{x_{rising1}}$ and $\boldsymbol{x_{falling1}}$ variables

t	Reference rate (levels)	Reference rate (month-over-month differences)	$x_{rising1}$	$x_{falling1}$
1	0.1	N/A	N/A	N/A
2	0.2	0.1	0.1	0
3	0.3	0.1	0.1	0
4	0.3	0	0	0
5	0.2	-0.1	0	-0.1
6	0.1	-0.1	0	-0.1

Using this estimation equation, β_1 in Equation 1 of Figure 13 can be interpreted as the sensitivity of BNY Mellon's deposit rate per unit change in the reference rate in a rising rate environment, while β_2 can be interpreted as the sensitivity of BNY Mellon's deposit rate per unit change in the reference rate in a falling rate environment.

Models containing three independent variables that contain at least one x_{rising} variable and one $x_{falling}$ variable were also considered as candidate models (i.e. Equations 2 and 3 of Figure 13). For some rate segments, a model with three independent variables is preferred over the simpler case of the models specified in Equation 1 as they can capture different adjustment dynamics.

The details on deposit rate models are discussed in Section 6, the details on loan rate models in Section 8 and the other balance sheet rate models in Section 11. In these sections, for example, the Fed_Funds_t1 is referring to the rising rate transformation of Fed Fund Target rate as illustrated here, and Fed_Funds_t2 is the corresponding falling rate variable.

3.6. Qualitative framework

For segments that are assigned a qualitative framework, including those for which there is not an ex-ante expectation of a macroeconomic relationship, we will develop data-driven conceptual frameworks to guide forecasts of balances and rates under different macroeconomic scenarios. Each segment will be built on its own framework that is tailored to the specific factors and relationships that are relevant to forecasting the segment (e.g. depreciation/amortization schedules). The considerations for developing a particular qualitative framework will be appropriately documented as part of this effort.

In this document, the qualitative framework description is high level. Detailed qualitative approaches rationale and approaches are submitted in the "QFP" document in section 18.

The modeling team identified four different categories of qualitative frameworks which are shown in Table 20.

Table 20: Categories of qualitative frameworkes

#	Category	Description	Example segments covered
1	Other management driven	• Changes in balances heavily influenced by management decision • Qualitative framework may rely on statistical model to produce starting point for forecasts, or use data-driven assumptions	• Iron Hound loans • Reverse mortgages • Investment Portfolio (covered separately) • Treasury placements (treated as part of Investment Portfolio) • Non-interest earning assets (excl. Goodwill, Intangibles) • Non-Interest bearing liabilities • Long term debt
2	Direct quantitative relationship with other segments	• Balances can be calculated using other segments' balances, either mathematically or with a simplified model	• Corporate Trust GBP • Pershing placements • Trading liabilities (Global Markets) • Trading liabilities (Capital Markets)
3	Accounting	• Forecasts are determined by accounting treatment	• Goodwill • Intangibles
4	Runoff	• No new origination planned • Balances to decrease according to contractual terms	• Commercial paper • Other mortgage loans

3.7. Key assumptions for model-based and qualitative frameworkes

Several assumptions were necessary to develop the models.

The assumptions made for the model-based approach are:

- The developed models rely on the assumption that the historical relationships between the balances and rates and the macroeconomic drivers continue to hold in the future.
- The regression models use the ordinary least squares (OLS) estimator. In order for the OLS estimator to have the desired properties (consistent estimator) certain statistical properties on data and modeled relationship have to hold. Not all of those assumptions can be tested explicitly. The assumptions are:

- The dependent and independent variables have to be stationary and weakly dependent
  - The modeling team tested all dependent and independent variables for stationarity and weak dependence
  - Only stationary variables and weakly dependent variables were included in the modeling process
- The independent variables have to be exogenous, that is, unexplained portions of the dependent variable in a model cannot be correlated with the independent variables
  - This assumption is on the underlying data generating process and cannot be tested for explicitly
  - The modeling team tested for omitted variables as omitted variables are one of the most common causes for this assumption to be violated
- The independent variables cannot be perfectly collinear
  - The modeling team did not include any perfectly collinear independent variables in models

As every qualitative framework will be tailored to the segment it is applied to, the assumptions will be specific to the segment and listed in the model documentation for these segments.

3.8. Key limitations of model-based and qualitative frameworkes

The key limitations of the model-based approach are as follows:

- The chosen approach is dependent on the existence of a sufficient number of observations in the balances and rates data as well as the quality of the data. Short time series data or data with measurement errors may reduce the robustness of conclusions drawn from a statistical model
  - While measurement error has not emerged as a concern for any segments, the development data period is short as it starts in January 2008 due to the merger between Bank of New York and Mellon Financial in 2007. This period covers a recession period (per NBER, the latest recession started in December 2007 and ended in June 2009 – the development data covers all months but one in this period) and post-recession environment. However, some macroeconomic factors are subject to cycles that behave somewhat differently from business cycles that are based on economic growth, and therefore the development data does not cover a full cycle for some macroeconomic factors. This is particularly the case for interest rates given the prevailing initially decreasing and subsequently low rate environment since 2008. As a result, models might not fully capture balance and rates responses to interest rate movements
  - The modelling team recommends that interest rate effects are given special consideration during the management review and challenge process that is part of BNY Mellon's CCAR process

- It might not be always possible to find an intuitive and statistically significant relationship between the balances or rates and the macroeconomic variables. In some segments macroeconomic factors are not drivers of balances and rates, in particular if they have been driven by management decisions or idiosyncratic events over extended periods in the past
  - The developed models are subject to the same rigorous statistical process but differ in their statistical significance and/or the intuitiveness of their forecasted behavior
  - The weaker models should be treated with higher scrutiny during the management review and challenge process. For models where no model could be developed with intuitive relationships, a qualitative framework was developed
- Both balances and customer rates are driven by macroeconomic drivers which are explicitly captured in the developed models for balances and customer rates
  - It is possible that BNY Mellon might have chosen (or will choose in the future) to incentivize or dis-incentivize certain customer behavior by increasing or decreasing customer rates
  - This strategic interaction between balances and rates is not captured in the models. However, when there were such customer rate actions in the past, the Working Group considered the implications in the model selection process
- A small number of macroeconomic variables, e.g. GDP, do not exist as monthly frequency. For these variables a cubic-spline interpolation method was used to derive the monthly data from the historically available quarterly data. This is based on the assumption that a cubic-spline function approximates the actual historical part of these variables reasonably well

The key limitations of the qualitative framework are as follows:

Qualitative frameworkes, just like statistical models, rely on historical relationships and patterns, and they could fall short of predicting balances and rates in changing environments.

4. Development data

This section describes the development data used for the balance and rate models. The development data consists of internal BNY Mellon data as well as external macroeconomic data. Specifically, in the case of the model-based approach, internal data are used to create the dependent variables (balance and rate data) while external macroeconomic data are used to create the independent variables.

All historical balances and customer rates are sourced internally at a monthly frequency. They are the basis for both the statistical model-based approaches and qualitative frameworkes:

- For statistical models, the internal data serves as the dependent variables in the regression analyses
- For the qualitative frameworkes, the internal data are used as the basis for the projection process and any associated analyses

The use of internal balance data will ensure that subsequent balance and rate forecasts are reflective of the bank's own historical experience. There are several data systems that are used. The most prominently used data system is Management Analytics Qube (MAQ), the accounting data system that is linked to BNY Mellon's General Ledger. The modeling team complemented the MAQ data where necessary with transaction level data from other BNY Mellon systems, including Credit Risk Data Warehouse (CRDW) (for loan balances) and ALMIS. Details on the data sourcing process for balance and rate data are described in the following sections of this chapter.

Macroeconomic variables are the independent variables in the statistical models. The bases for the collected macroeconomic variables are the driver hypotheses that were developed for each segment as described above in Section 3.3.2. BNY Mellon's list of macroeconomic variables that it obtains from Moody's was reviewed, and variables that were applicable to the identified drivers were included in the set of macroeconomic variables tested. Additional data sources were used when a desired variable for the driver hypotheses was not readily available from Moody's (though most variables are likely obtainable from Moody's, time permitting). The following sources were used: Government and Federal Agencies, national exchanges, Nationally Recognized Statistical Rating Organizations (NRSRO) such as Moody's, and other data vendors such as Bloomberg L.P. Details on the data sourcing process for macroeconomic variables are described in the following sections.

When a variable from a source other than Moody's was included in a potential final model, the modeling team consulted Market Risk to ensure that they were comfortable that Moody's can produce a reliable forecast for the variable. Some variables, such as the US Money Supply, were deemed to be too difficult to forecast and therefore were not included in any of the final models. Details of such cases are discussed in Sections 5 through 11.

The data sourcing of bank internal data is split by segment groups:

- Data sources for deposit balances and rates are described in Section 4.1.1
- Data sources for loan balances and loan rates are described in Sections 4.2.1 and 4.3.1 respectively
- Data for the investment portfolio are discussed in Section 4.4
- Data sources for the other balance sheet segment balances and rates are in Section 4.5.

The data for the bank external data, that is the macroeconomic variables used as explanatory variables, are described in Section 4.6.

4.1. Deposit balance and rates data

4.1.1. Description of data sources

Deposit balance and rates data is sourced entirely from internal systems. Three data sources are used for modeling deposits: MAQ, Microstrategy and Pre-Merger Deposits Rates Database. All data was sourced from members of the ALM team.

Table 21: Deposit data source descriptions

Data source name	Description
Management Analytics Qube (MAQ)	• MAQ is BNY Mellon's business performance management system that supports BNY Mellon's enterprise budgeting, forecasting and performance measurement and reporting. This system is the primary data source used for deposit balances and rates. • MAQ data on deposits is available starting from January 2008, following the merger of Bank of New York and Mellon in 2007. • Data for foreign deposits (deposits denominated in USD and other foreign currencies that are managed outside of the US), however, can only be broken out by currency starting from September 2013. • MAQ data is considered reliable as it is used for financial reporting purposes and analysis.
Microstrategy	• This is a legacy system that was sunset in July 2014. • It was a web-based reporting tool for enterprise performance management and allowed reports on customer and product information including actuals, allocations and forecasts. • The ALM team has preserved historical data from Microstrategy for certain deposit segments by currency, including offshore balances and foreign currencies with some segments extending back to 2008.
Pre-Merger Deposit Rates Database	• This dataset has been managed by the ALM team since before the merger. It contains historical rates for select deposit products dating back to as far as 2004.

4.1.2. Description of data for deposit balance segments

Table 22 outlines the data source used for each deposit balance segment. The balances are end-of-day balances averaged across all days in a month. Interest rate data is calculated as the total monthly interest expense divided by the average monthly balance, annualized. See the Appendix for details on the data sources by component sub-segments (sub-segments are more granular breakouts of deposits than the modeling segments that are aggregated up to form the modeling segments). For deposit balances, MAQ data is the preferred source given it is a controlled system source. Moreover, it also is the dataset from which forecasts are likely to be generated during model execution.

In some cases, the modeling team uses data from the alternate data sources. These cases are:

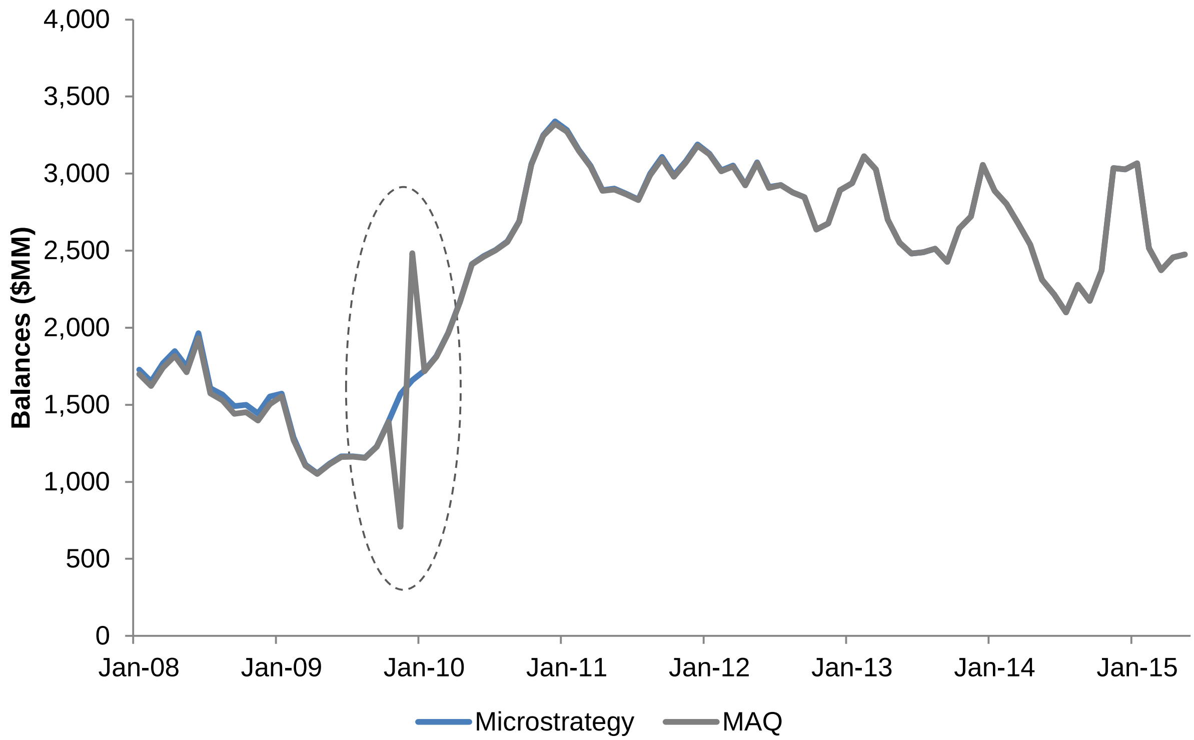
- **Asset Servicing and Corporate Trust interest bearing deposit segments** – The Asset Servicing and Corporate Trust businesses manage deposits outside of the US denominated in multiple currencies. The segmentation as described in Section 3.1.2 requires that the foreign USD-denominated deposits are pooled with the domestic USD deposits – which is aligned to the way in which these deposits are managed by the Bank – to form the AS IB and CT IB segments. Also, the selected segmentation requires balances for the two largest non-USD currencies for the Asset Servicing and Corporate Trust businesses – Pound Sterling and Euros – to be modeled in their own segments (AS/TS EU, AS/TS GB, CT GB and CT EU). As MAQ is only able to split these balances by currency starting September 2013, Microstrategy is preferred as the data source for modeling for these balances
- **Wealth Management Personal segment** – One of the products in the Wealth Management Personal segment, the Private Banking MMDAs, has a significant accounting adjustment in November and December 2009 in MAQ. Given data for the same series is available from Microstrategy and the two data series align except for the months with the accounting adjustment, the Microstrategy data is used for modeling. A comparison of the corresponding balances in the two data sources are illustrated in **Figure 14**. The difference in data in 2008 and 2009 is attributable to changes in the accounting hierarchy and/or adjustments to historical data made in MAQ that are not reflected in Microstrategy. This was confirmed with the ALM team

Table 22: Data sources used by segment (balances)

Deposit segments	Sub-segment data name	Data Source	File Name	Modeling Currency	Size, avg monthly bal in Mar 2015 (BN)
Alternative Investment Services and Global Collateral Services Demand Deposit Accounts (AIS/GCS DDA)	AIS DDAs	MAQ	Deposit Data_OW_v2	USD	10.5
	GCS DDA	MAQ	Deposit Data_OW_v2	USD	7.4
Alternative Investment Services and Global Collateral Services Interest Bearing Deposits (AIS/GCS IB)	GCS Cash Reserves	MAQ	Deposit Data_OW_v2	USD	9.5
	GCS USD Foreign Deposits	MAQ	Deposit Data_OW_v2	USD	5.1
	AIS Cash Reserves	MAQ	Deposit Data_OW_v2	USD	1.9
Asset Servicing Demand Deposit Accounts (AS DDA)	Asset Servicing DDAs	MAQ	Deposit Data_OW_v2	USD	20.3
	Other LOB DDAs	MAQ	Deposit Data_OW_v2	USD	3.6
Asset Servicing Interest Bearing Deposits (AS IB)	Asset Servicing USD Foreign Deposits	Microstrategy	Regression_AS_USD_May15	USD	22.2
	Asset Servicing Cash Reserves	MAQ	Deposit Data_OW_v2	USD	14.6
	CIBC CWIs	MAQ	Deposit Data_OW_v2	USD	2.4
	Asset Servicing Trust Time	MAQ	Deposit Data_OW_v2	USD	2.0
	ADRs	MAQ	Deposit Data_OW_v2	USD	0.0
Broker Dealer Services Demand Deposit Accounts	BDS DDAs ex Allocation	MAQ	Deposit Data_OW_v2	USD	8.0

(BDS DDA)					
Corporate Treasury Interest Bearing Deposits (Corporate Treasury)	Corporate Treasury USD Foreign Deposits	MAQ	Deposit Data_OW_v2	USD	2.6
Corporate Trust Demand Deposit Accounts (CT DDA)	Corporate Trust DDAs	MAQ	Deposit Data_OW_v2	USD	22.9
Corporate Trust Interest Bearing Deposits (CT IB)	Corporate Trust Cash Reserves	MAQ	Deposit Data_OW_v2	USD	11.6
	Corporate Trust USD Foreign Deposits ex LNI	Microstrategy	Regression_CT_USD_May15	USD	3.5
Asset Servicing/Treasury Services EU Deposits (AS/TS EU)	Asset Servicing EUR Foreign Deposits	Microstrategy	Regression_AS_EUR_May15	EUR	11.3
	Other LOB EUR Foreign Deposits	MAQ	Deposit Data_OW_v2	EUR	1.0
Asset Servicing/Treasury Services GB Deposits (AS/TS GB)	Asset Servicing GBP Foreign Deposits	Microstrategy	Regression_AS_GBP_May15	GBP	8.6
	Other LOB GBP Foreign Deposits	MAQ	Deposit Data_OW_v2	GBP	0.3
Corporate Trust EU (CT EU)	Corporate Trust EUR Foreign Deposits	Microstrategy	Regression_CT_EUR_May15	EUR	9.0
Corporate Trust GB (CT GB)	Corporate Trust GBP Foreign Deposits	Microstrategy	Regression_CT_GBP_May15	GBP	1.5
Foreign deposits in currencies other than USD, Euro and GBP (Foreign Other)	Miscellaneous Currency	MAQ	Deposit Data_OW_v2	USD	11.1
Treasury Services Demand Deposit Accounts (TS DDA)	Treasury Services DDAs	MAQ	Deposit Data_OW_v2	USD	15.3
Treasury Services Interest Bearing Deposits (TS IB)	Total Company LNI	MAQ	Deposit Data_OW_v2	USD	19.2
	Treasury Services CWIs	MAQ	Deposit Data_OW_v2	USD	2.8
	Treasury Services USD Foreign Deposits ex LNI	MAQ	Deposit Data_OW_v2	USD	0.9
	IB DDAs	MAQ	Deposit Data_OW_v2	USD	0.6
	Treasury Services MMDAs	MAQ	Deposit Data_OW_v2	USD	0.0
	Rent Secured	MAQ	Deposit Data_OW_v2	USD	0.0
Wealth Management Demand Deposit Accounts (WM DDA)	WMs DDAs	MAQ	Deposit Data_OW_v2	USD	1.8
Wealth Management Personal Deposits (WM Personal)	WM Private Banking MMDAs	Microstrategy	PWM MMDAs_May15	USD	2.4
	WM CWIs	MAQ	Deposit Data_OW_v2	USD	2.1
	WM CMAAs	MAQ	Deposit Data_OW_v2	USD	1.0
	WM Savings	MAQ	Deposit Data_OW_v2	USD	0.3
	WM Time Deposits	MAQ	Deposit Data_OW_v2	USD	0.0
Wealth Management Sweep Deposits (WM Sweep)	WM Sweep MMDAs	MAQ	Deposit Data_OW_v2	USD	7.1
	WM Escrows	MAQ	Deposit Data_OW_v2	USD	0.0

Figure 14: Comparison of WM Private Banking MMDA balances by data source



4.1.3. Description of data for deposit rate segments

Table 23 illustrates the data source used for each rates segment. Interest rate data is calculated as the total monthly interest expense divided by the average monthly balance, annualized. The deposit rates were annualized by multiplying the calculated monthly rates by 12, which is slightly different from the method used to calculate rates for loans and other balance sheet items described in Sections 4.2.5 and 4.5. When the deposit rate models are redeveloped in the future, the modeling team recommends addressing this inconsistency by annualizing deposit rates using the same method as currently used for loans and other balance sheet items.

For deposit rates, the Pre-Merger Deposits Rate Database is in some cases preferred over rates from MAQ. The reason is that the modeling team received feedback from the lines of business as well as the wider Treasury group that data capturing a full rate cycle was preferred due to potential differences of the deposit rate sensitivity to interest rates in rising and falling rate environments. This choice is further discussed in Section 3.5 (on deposit rate methodology). Therefore, for segments where rates data is available for an extended period of time in the Pre-Merger Deposits Rate Database, the MAQ data is not used given that it only starts in 2008.

As with the balances, Microstrategy is preferred for the non-USD denominated segments, since this data is not available in MAQ and is not available for an extended time period in the Pre-Merger Deposits Rate Database.

Table 23: Deposit rates development data by segment (rates)

Interest bearing balance segment	Data source used for rates
AS IB Deposits	Pre-Merger Deposit Rates Database
Fgn AS/TS EUR	Microstrategy
Fgn AS/TS GBP	Microstrategy
CT IB Deposits	Pre-Merger Deposit Rates Database
Fgn CT EUR	Microstrategy
Fgn CT GBP	Microstrategy
TS IB Deposits	MAQ
WM Personal	Pre-Merger Deposit Rates Database
WM Sweep	Pre-Merger Deposit Rates Database
AIS/GCS IB	MAQ
Corp. Treasury	MAQ
Foreign Other	MAQ

Figure 15 illustrates the data available in the Pre-Merger Deposits Rates Database. The figure illustrates a mapping of the rates data series available in the Pre-Merger Deposits Rates Database and the balance segments and its component sub-segments. Key points on the data availability are listed below:

- As discussed earlier, not all balance sub-segments are represented in the Pre-Merger Deposits Rates Database (e.g. the GCS USD Foreign Deposits balances does not have a corresponding series in the Pre-Merger Deposits Rates Database)
- Not all data in the Pre-Merger Deposits Rates Database extend back to cover a sufficient portion of the rate cycle. Any series that is available starting only after 2007 is not considered as sufficient history to diverge away from MAQ data, which starts in 2008 (e.g. GCS Cash Reserves rate data was in the Pre-Merger Deposits Rates Database, but only available from August 2010)
- Due to the limited availability of extended rates data, for certain segments the modeling team chooses to estimate a model on a component or product contained in the segment (e.g. the rates model for the AS IB segment is estimated on the rates for the Asset Servicing Cash Reserves sub-segment). The rationale and limitations of assuming the proxy relationships are discussed in Section 6 (deposit rates results)

Figure 15: Rates data available in the Pre-Merger Deposits Rates Database by sub-segment

Balance Segmentation	Balance sub-segment	% of segment balance (3/2015)	Corresponding sub-segments from Pre-Merger Deposits Rates Data	Data covering raising interest rate period?
AIS/GCS IB Deposits	GCS Cash Reserves	58%	Glob Liq Svcs Cash Reserve	-
	GCS USD Foreign Deposits	31%		
	AIS Cash Reserves	11%	AIS Cash Reserve	-
AS IB Deposits	Asset Servicing Cash Reserves	32%	Asset Servicing Cash Reserve	✓
	Asset Servicing Trust Time	4%		
	CIBC CWIs	5%	Asset Servicing CWI (CIBC)	✓
	Asset Servicing USD Foreign Deposits	59%	Asset Servicing USD	-
	ADRs	0%		
Fgn AS/TS EUR	Asset Servicing EUR Foreign Deposits	92%	AS_EUR	-
	Other LOB EUR Foreign Deposits	8%		
Fgn AS/TS GBP	Asset Servicing GBP Foreign Deposits	96%	AS GBP	-
	Other LOB GBP Foreign Deposits	4%		
Corporate Treasury	Corporate Treasury USD Foreign Deposits	100%		
CT IB Deposits	Corporate Trust Cash Reserves	77%	Corp Trust Cash Reserve	✓
	Corporate Trust USD Foreign Deposits ex LNI	23%	Total Corporate Trust USD	-
Fgn CT EUR	Corporate Trust EUR Foreign Deposits	100%	CT_EUR	-
Fgn CT GBP	Corporate Trust GBP Foreign Deposits	100%	CT_GBP	-
Fgn Deposits Other	Total JPY Foreign Deposits	56%		
	Total HKD Foreign Deposits	15%		
	Misc Currency	29%		
TS IB Deposits	Treasury Services CWIs	12%	Cash Mgmt CWIs	✓
	Treasury Services USD Foreign Deposits ex LNI	4%		
	Treasury Services MMDAs	0%	Cash Mgmt MMDAs	✓
	Total Company LNI	82%	LNI	-
	IB DDAs	2%		
	Rent Secured	0%		
WM Personal	WM CWIs	36%	WMB CWIs	✓
	WM Private Banking MMDAs	41%	WMB Private Banking MMDAs	✓
	WM Savings	6%	WMB Savings	-
	WM CMAAs	17%		
	WM Time Deposits	1%		
WM Sweep	WM Sweep MMDAs	100%	WMB Sweep MMDAs	✓
	WM Escrows	0%		

Legend Selected proxy segments

4.1.4. Data cleansing

Data adjustments were made for several rates segments in their MAQ data.

- **IT error in February 2008** – There was an IT error in February 2008 that caused BNY Mellon to incorrectly charge/overpay customers for their deposits, thereby resulting in an offsetting the following month. The affected segments are
  - Asset Servicing IB (Asset Servicing Trust Time)
  - Wealth Management Personal (Wealth Management Personal MMDAs)
  - Wealth Management Sweep (Wealth Management Sweep MMDAs)
- **IT error in January 2010 –** There was a similar IT error in January 2010, which affected one segment:
  - AIS/GCS IB (For GCS Foreign Deposits)

In all four cases, the adjustment is to replace the two months with a linear interpolation of the month prior and after (e.g. for Asset Servicing IB, the February and March 2008 values are replaced with a linear interpolation of the January 2008 and April 2008 rates).

The historical rates for these segments are illustrated on Figure 16 -Figure 19.

Figure 16: Historical AS IB Rates (MAQ/Microstrategy)

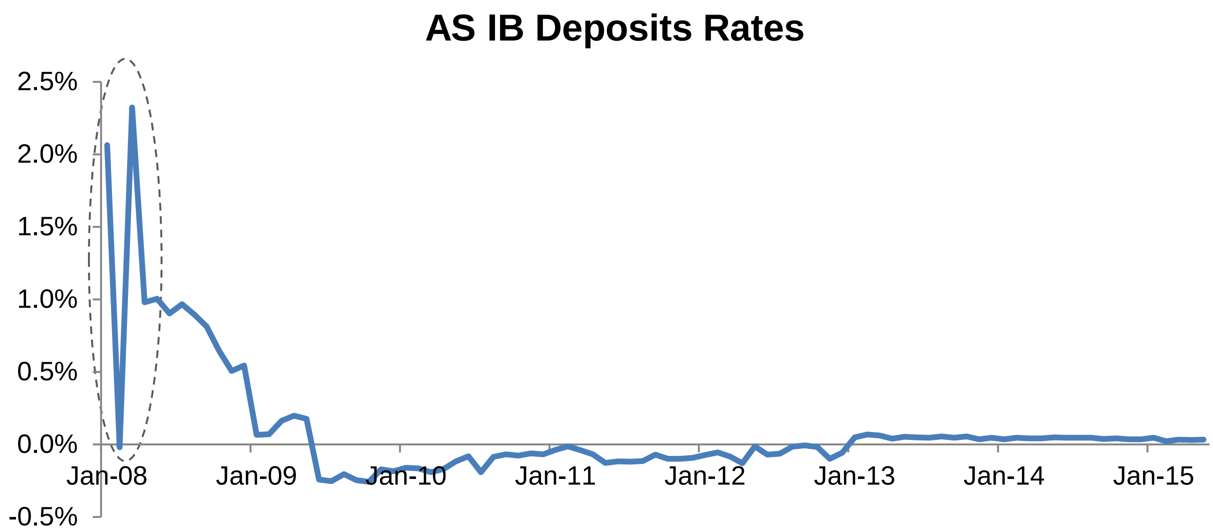


Figure 17: Historical WM Personal Rates (MAQ)

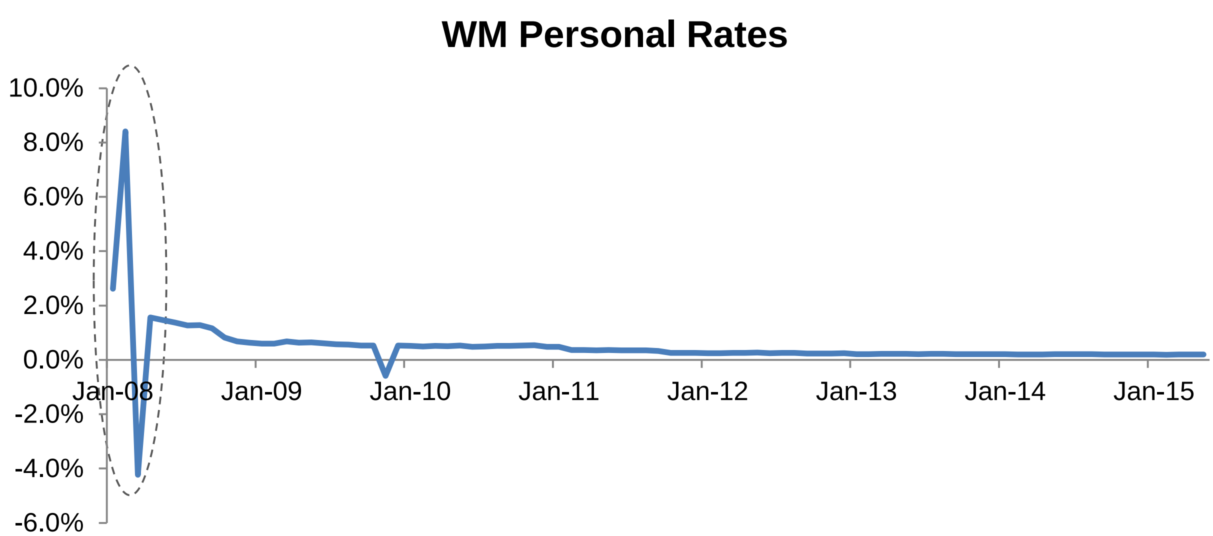


Figure 18: Historical WM Sweep Rates (MAQ)

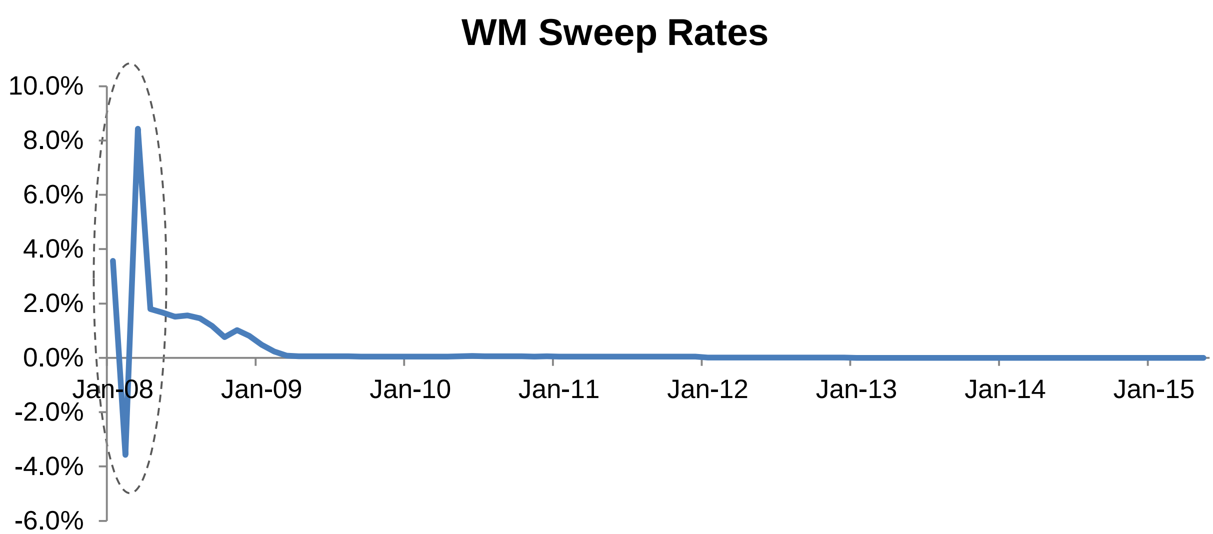
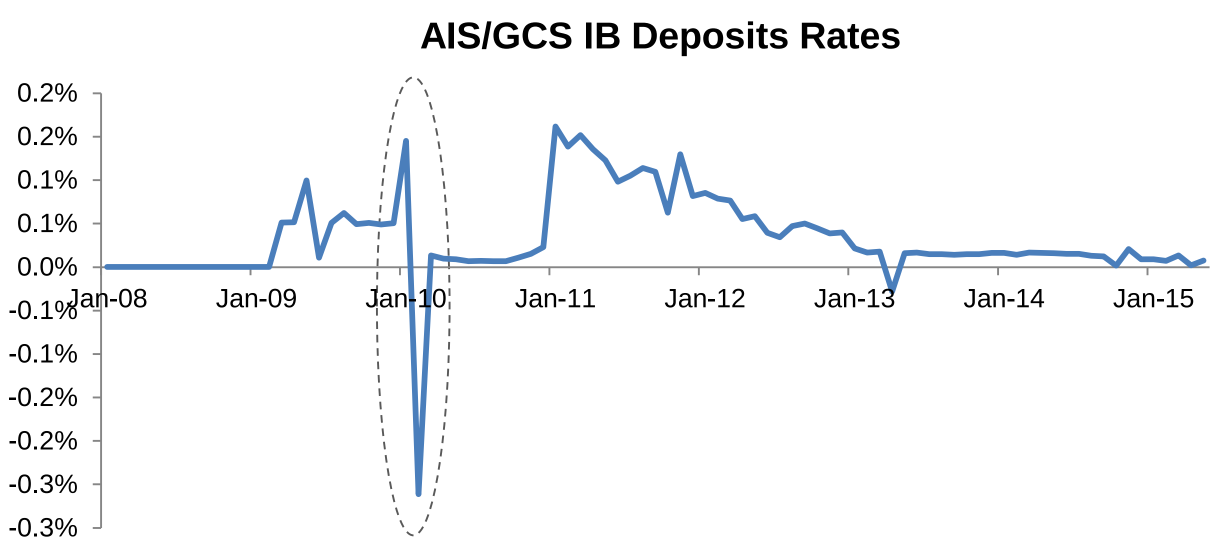
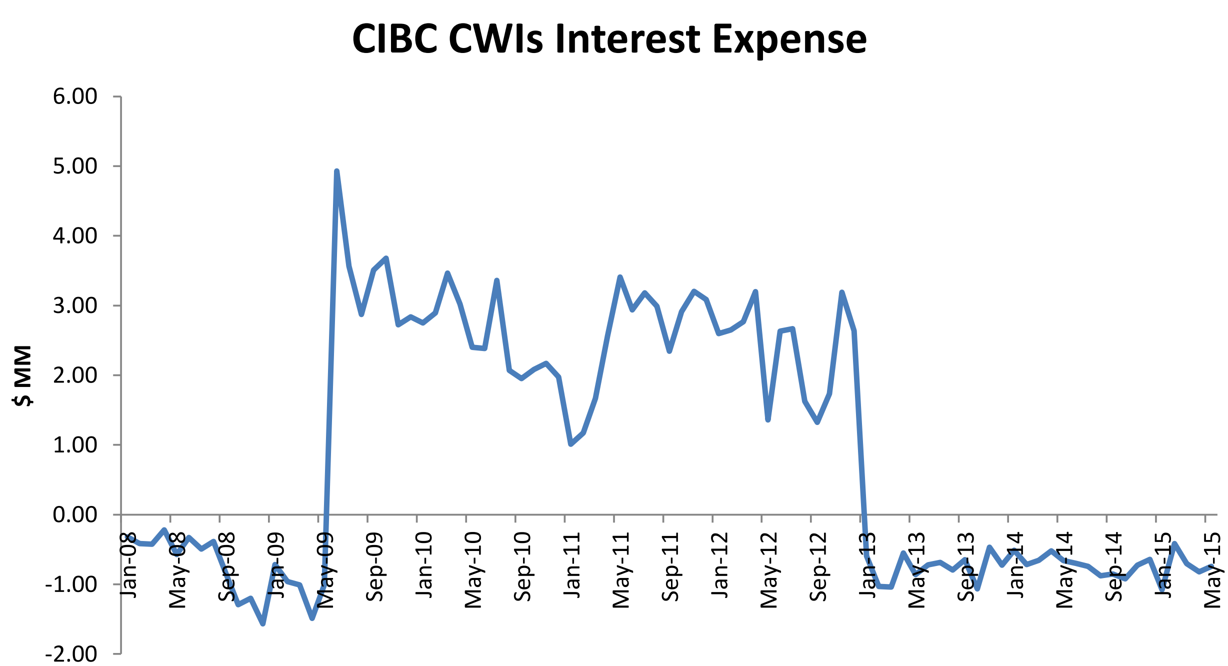


Figure 19: Historical AIS/GCS Rates (MAQ)



Also, the rates for the AS IB deposits segment using the MAQ data were calculated without including the balances and interest expense for CIBC CWIs, a joint venture product that BNY Mellon offers with CIBC. This is because both the balance and interest expense data for observations prior to January 2013 is not indicative of actual values. Prior to that date, the balances were allocated under AS DDAs, and the interest expense recorded represented payments/reimbursements exchanged between BNY Mellon and CIBC for these deposits, and not the actual interest paid to customers. Between June 2009 and December 2012, this resulted in a net interest income for BNY Mellon (shown in Figure 20; positive interest expense on the figure represents interest income). Starting January 2013, the net payment/reimbursements have been registered as non-interest income, meaning the interest expense data represents the actual interest BNY Mellon pays the clients. The CIBC CWI sub-segment accounts for 5% of the AS IB segment balance as of April 30, 2015. The final rate model selected for the AS IB segment does not use this MAQ data and uses the Pre-Merger Deposits Rates database instead.

Figure 20: CIBC CWIs Interest Expense



4.1.5. Data limitations

MAQ, the primary deposit data source, has several limitations.

- MAQ data only extends back to 2008, meaning it only captures the end of the most recent rate cycle followed by an extended period of very low interest rates. Therefore, the models are developed with a limited number of observations during which interest rates fluctuate, and may not fully capture the key relationship between deposit balances and the rate environment
- Deposit balances and associated interest expense data of deposits managed outside of the US can only be broken out by native currency from September 2013 onwards in MAQ. Given off-shore balances for the Asset Servicing and Corporate Trust businesses are segmented by currency, this significantly limits the number of observations available for modeling. Therefore, data from Microstrategy was used for the segments that contain off-shore balances (AS IB, AS/TS EU, AS/TS GB, CT IB, CT EU, CT GB)
- Some deposit rates series (i.e. the interest expense series from which rates are calculated) exhibit sudden large swings in consecutive months due to accounting system errors/misclassifications and their corresponding corrections the following month. The ingoing preference was to limit the amount of data adjustments as much as possible, so only the most material data issues that significantly impacted the segment rates were altered for the final models. An example of where a data issue was identified but the data was not modified was for a one time IT glitch in the data in November 2009 for Wealth Management CWIs (part of WM Personal). This data issue was not addressed, as altering this data point did not affect the overall segment rates series and therefore the estimated coefficients

Due to these limitations, the modeling team supplemented the MAQ data using two alternative data sources, Microstrategy and the Pre-Merger Deposit Rates Database. There are several limitations to these alternative data sources:

- Unlike MAQ, these data sources are managed primarily in Excel. The modeling team acknowledges this shortcoming. However, the modeling team, incorporating the strong feedback from lines of business and Treasury, believes capturing longer series is an important factor for development of a robust model for deposit rates
- They do not reflect any adjustments and corrections to historical data periods that may occur in MAQ. Both sources are extended every month with the most recent data from MAQ, but historical adjustments that may occur in MAQ are not reflected, so a full reconciliation of historical balances may not yield perfectly matching series
- They do not comprehensively cover all deposit segments that exist at BNY Mellon today

In addition to the limitations of the data sources used, there are some segments with unique data limitations. These limitations are discussed in the following section.

4.1.5.1. Data limitations for the Corporate Treasury segment

The Corporate Treasury segment balances and rates data sourced from MAQ contains significant volatility introduced by accounting adjustments. This is due to an allocation process applied to MAQ. At month end, all Late Night Investment deposits ($22 BN on April 30, 2015) are first allocated to the Corporate Treasury account, and then reallocated to the lines of business that are the actual owners of these deposits.

This allocation is conducted prior to closing the balance sheet and any discrepancies between when the allocation is made and when the final balance is booked are left under the Corporate Treasury account. The discrepancies can amount to billions of dollars. This creates significant noise in both the balance and rates data for this segment, and the existence of this noise was confirmed both by data experts and by the business during the review of historical data.

Figure 21 and Figure 22 show the historical deposit balances and rates data from MAQ respectively. Especially in the rates, the accounting noise can be observed clearly, as there are periods when the rate paid falls below -20%, which the business confirmed did not occur.

Data for the Corporate Treasury segment is not available in the alternative data sources. Hence, modeling for the Corporate Treasury segment is significantly challenged by this data limitation in MAQ.

Figure 21: Historical Corporate Treasury deposit balances

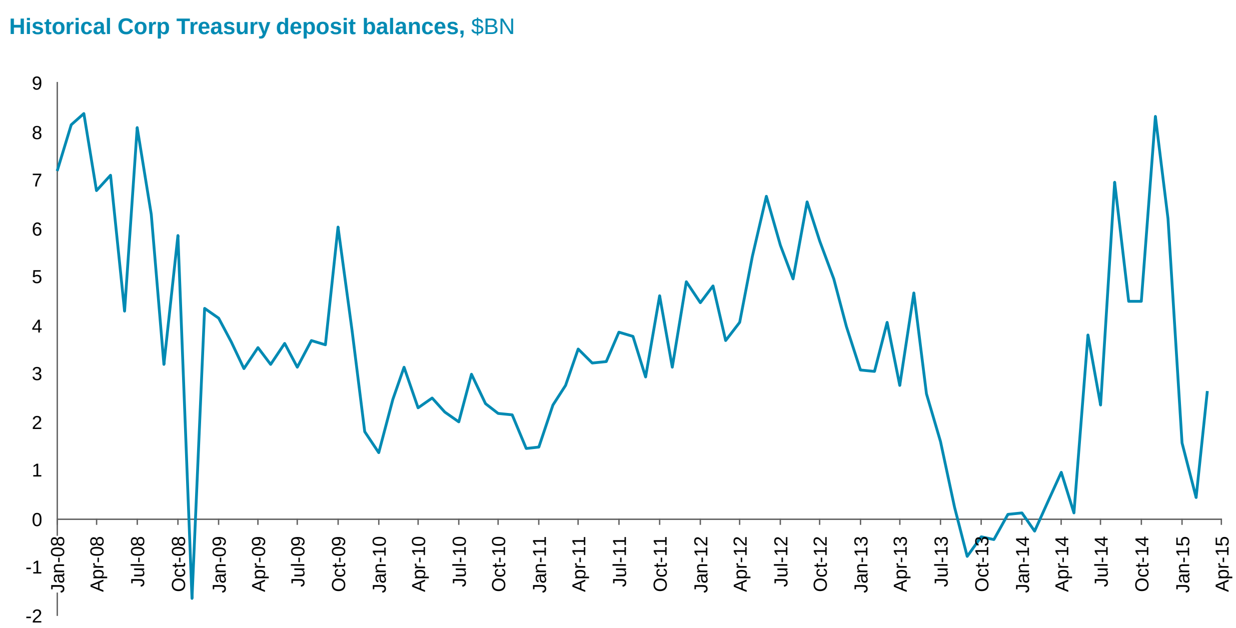
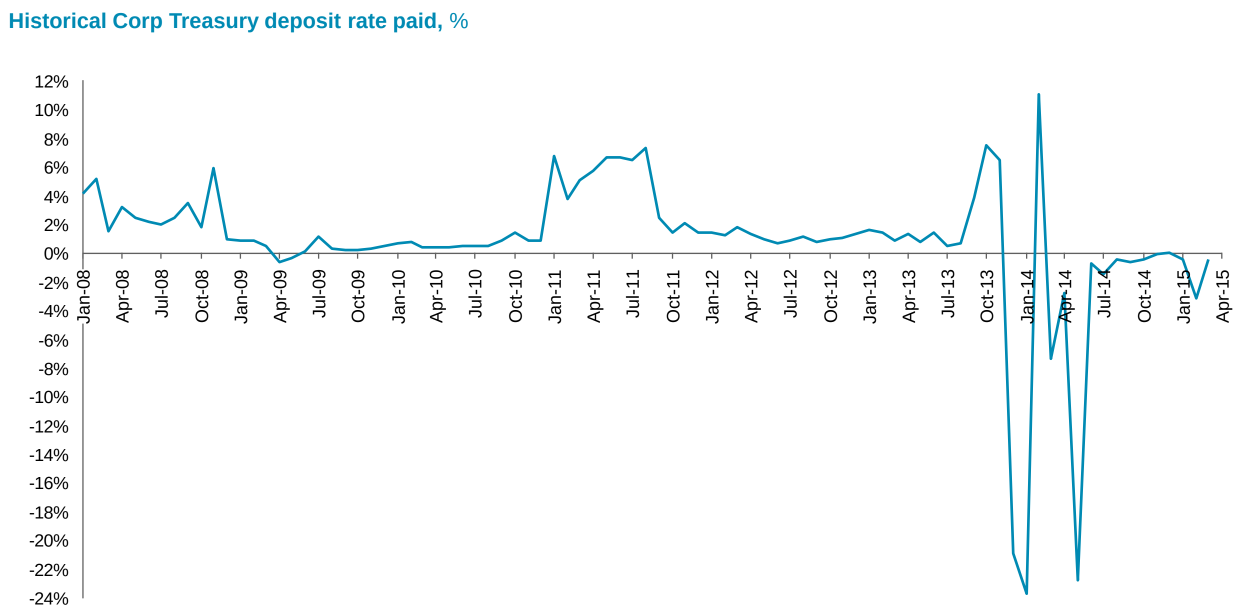


Figure 22: Historical Corporate Treasury deposit rates



4.1.5.2. Data limitations for the Deposits in the Other Foreign Currencies segment

The data for Deposits In Other Foreign Currencies segment is particularly limited. As discussed in Section 4.1.5, MAQ is only able to report balances by currency starting September 2013. In addition, Microstrategy, the alternative data source that is used for some foreign deposits, only reports balances by currency for US Dollar, GB Sterling and EU Euro. Therefore, the only data source available for non-USD, GBP and EUR balances is from MAQ, starting on September 2013. As a result, the dataset contains a limited number of observations over a short period of time, which places a limitation on the resulting model. More details are discussed in Section **Error! Reference source not found.** (foreign other deposits balance model section).

4.1.6. Process for sourcing data

The ongoing maintenance plan for the balance sheet forecasting models requires regular performance monitoring, re-estimation and re-development of the models. As a result, deposit and rates data will have to be sourced in the appropriate segmentation on a continuous basis going forward. The ALM team has implemented automated processes to reduce the risk involved in expanding the existing data set over time. In particular, the following steps were implemented:

1. The ALM team has built Excel templates to match the segment definition of each deposit model and linked them to MAQ, the source of the data used in the balance forecasting models for deposit balances and rates:

    a. Templates are programmed to systemically retrieve actuals each month by refreshing the links to MAQ Management Accounting’s reporting application

   b. Results from the templates are loaded into a database monthly to build the data repository

2. Modifications were made to QRM to mimic the deposit models, QRM is the system that executes the balance sheet forecast during CCAR exercises:

   a. Copies of existing leaf-level accounts were made in the account hierarchy

   b. Parent accounts were added to the hierarchy with the new leaf-level accounts to segment the deposit accounts as per the models

   c. Testing was completed to validate the account links work on the new deposit accounts

   d. Adjustments were made to look-up tables to discontinue splitting deposit forecasts between “fixed” and “variable” accounts

   e. Volume forecasting will be done at the parent-account level to be consistent with the model output

Step 1 resulted in a complete check of the development data. Step 2 was used during a dry-run that the ALM team performed after the model development and the QRM implementation was found to be fully consistent with the deposit segmentation as used by the balance sheet forecasting models.

4.2. Loan balance data

The loan balance estimation approach is described in detail in Section 3.4. In summary, the modeling team is using an approach that integrates the estimation of closed-end loans, amounts drawn from facilities and unfunded commitments to account for the linkages between these balances. The choice of estimation approach determined the data source, as only one system, CRDW, contained information on all these balances on a granular level.

The data used in the estimation approach are described below:

- Section 4.2.1 describes the data system that was used to source the data
- Section 4.2.2 describes the data
- Section 4.2.3 describes the data cleaning steps
- Section 4.2.4 discusses the data limitations

4.2.1. Description of data source

The dependent variable data series used for loans modeling come from the Credit Risk Data Warehouse (CRDW) system. CRDW collects all credit positions, associated attributes, and mitigants for use in regulatory, risk, and economic credit model reporting. The system is primarily used for Credit Risk reporting and is built to support the reports that contain the financial information for BNY Mellon’s Form 10-Q and Form 10-K filings with the Securities and Exchange Commission. The Basel and Capital Adequacy group prepares reports based on

CRDW data, augmenting it with additional fields such as Regulatory Group. These reports are the direct source of the data used for loan segmentation and modeling.

CRDW was selected as the data source for modeling loans and unfunded commitments after discussions with the Working Group, Steering Committee, and BNY Mellon Corporate Treasury and Market Risk groups. CRDW was the only viable BNY Mellon data source identified during the development exercise which contained data for unfunded commitments.

4.2.2. Description of data used

Data for loans, Letters of Credit, and unfunded commitments were provided to the modeling team by the Basel and Capital Adequacy group in monthly files spanning from January 2008 until May 2015. Each data file contains data at the exposure level, with each data row being identified by a unique Exposure ID. The exposure is as of the last calendar day of the month as no monthly average data was available. Borrowing behavior is not expected to change at the end of the month, however, and as a result, the modeling team does not expect significant deviations between spot and average balances. Month-end data for exposures was therefore deemed to be suitable for modeling. Each exposure falls into one of the following three categories:

- Unfunded commitments
- Unfunded Letters of Credit
- Funded loans (including draws from committed facilities and closed-end loans)

In addition to funded and unfunded amounts, additional variables are populated for each exposure, relating to both the borrowing customer and the loan product. Specifically, the data contains, among others:

- Facility numbers
- Legal entities
- General ledger codes
- Customer names
- Customer SIC codes
- Asset descriptions
- Maturity dates
- Country of risk
- Regulatory grouping

To inform the loans segmentation as described in Section 3.1.3, Regulatory Group was used as the primary field with some additional adjustments made based on the Asset Description field.

CRDW did not have any fields indicating whether a loan was funded at origination or a draw from a committed facility. In line with the modeling plan to produce models for both loans funded at origination and draw percentages, it was necessary to develop a way to identify this distinction based on the existing data fields listed above. The CRDW dataset included a facility number field which was consistent across both unfunded commitments and draws from those facilities; therefore, to distinguish between loans funded at origination and draws from committed facilities, the modeling team:

- Searched for funded amounts with a corresponding unfunded amount categorized under the same facility number in any month of the historical time series
- Created a list of those facilities with both a funded amount and at least one unfunded amount
- Treated all funded exposures associated with the facilities on this list as draws from committed facilities
- Treated all funded exposures whose facility numbers were not on this list as closed-end loans

All remaining facilities with no corresponding unfunded amount were assumed to be loans funded at origination. This identification strategy was discussed with the Basel and Capital Adequacy group that prepared the reports used based on CRDW data.

As described in Section 3 on the methodology, the modeling period ends in March 2015, so the April and May 2015 data were not used when constructing the development data time series for the loan segments.

At the time of model development, due to the setup of the aggregation logic, facilities that never had any draws were excluded from total unfunded commitments. The modeling team recommends that for future model redevelopment, these facilities should be included in calculation of unfunded commitments. Historically, these unfunded commitments have been relatively immaterial, and in many instances there are no such facilities in a given month and segment. However, in the future, there may be cases where these exposures do become material.

4.2.3. Data cleansing

Data cleansing was necessary to ensure that exposures were appropriately classified, as unexpected monthly changes were observed for some segments. The modeling team moved certain exposures to the appropriate segments based on fields other than the Regulatory Group and the Asset Description field, as the exposures were incorrectly placed according to these two fields alone as compared to business expectations for balances.

The issues were identified based on two types of analysis:

- By graphing and visually identifying jumps and spikes that represented discrepancies and unexpected movements, such as outlier months
- By comparing historical balances between CRDW and the accounting data system MAQ.

The modeling team conducted data cleansing for the following three categories of exposures: Securities financing and margin loans (Section 4.2.3.1), legacy Mellon balances (Section 4.2.3.2), and Wealth Management Bank exposures (Section 4.2.3.3).

4.2.3.1. Securities Financing and Margin Loans

The segmentation developed in Section 3.1.3 defines the margin loans from Pershing as an individual segment, separate from the margin loans made as part of the Securities Financing Portfolio which are included in the segment named Securities Financing Portfolio.

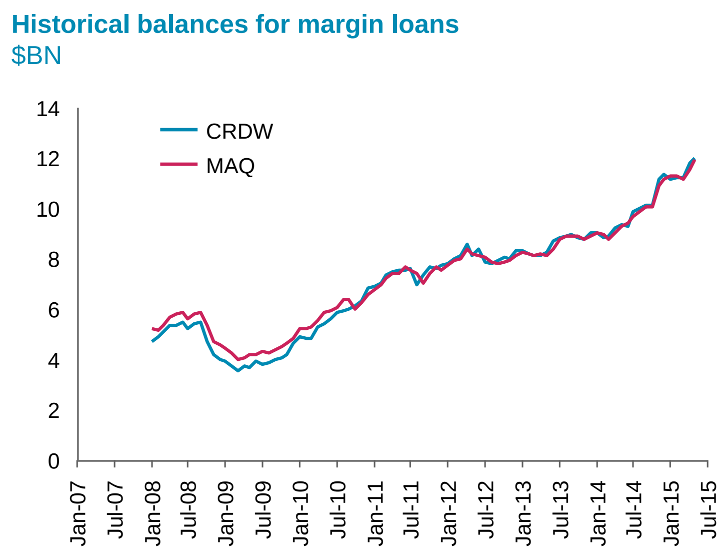
After the introduction of the Securities Financing portfolio in April 2011, its margin loan balances were defined as “Margin Loans” in the Regulatory Group field in CRDW. As a result, based on the Regulatory Group field alone, the margin loans from Pershing and those from the Securities Financing Portfolio are indistinguishable from one another. Moreover, all margin loans, even those made by Pershing, are classified as “Margin loans from Securities Financing” in the Asset Description column following the introduction of Securities Financing in April 2011.

To obtain the necessary segmentation, the modeling team used the Legal Entity field to identify the Pershing margin loans. All exposures that had “Margin Loans” in the Regulatory Group field and “Pershing” in the Legal Entity field were identified as Pershing margin loans (which constitute the margin loan segment as defined in Section 3.1.3). The Legal Entity field is populated starting in June 2012.

This logic successfully separated the Pershing and Securities Financing margin loans from June 2012 onwards. From April 2011 until June 2012, the “Facility Purpose Description” field was used to identify margin loans that are part of the Securities Financing Portfolio Segment. The exposures with the entry “Margin Securities Financing \ B-D Term” were allocated to the Securities Financing Portfolio balance.

These reclassifications reconciled differences in balances between CRDW segments and equivalent product-based segments in the MAQ accounting system, as seen in Figure 23.

Figure 23: MAQ vs. CRDW balances for margin loans



4.2.3.2. Legacy Mellon balances

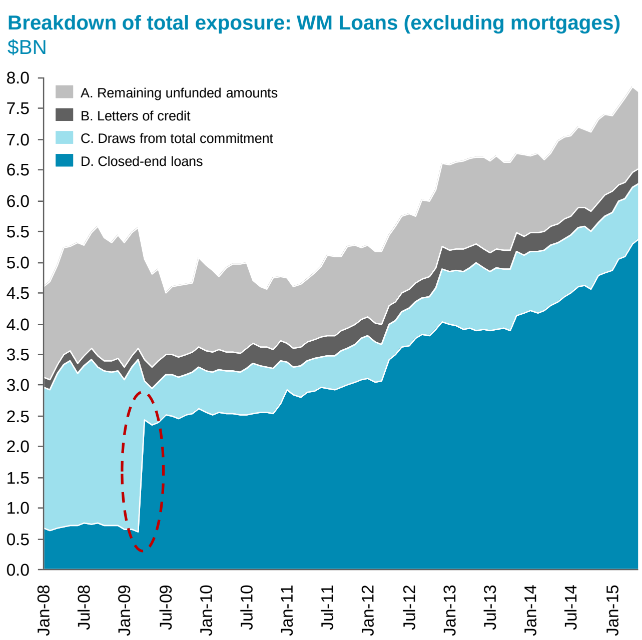
The introduction of legacy Mellon Bank balances into BNY Mellon's systems in 2008 and 2009 resulted in several shifts in the exposure balances. In particular, certain legacy Mellon balances were removed from BNY Mellon's balance sheet due to the sales of Mellon 1st Business Bank (M1BB) in June 2008 and Mellon United National Bank (MUNB) in January 2010. The modeling team excluded these balances consistently from all historical balances. They were identified as exposures that had the values "MUNB customer", "M1BB customer", "M1BB", or "MUNB" in the Customer Name field. The modeling team removed these from the time series entirely so that they did not inflate balances in earlier months.

The modeling team discovered additional Mellon balances causing large spikes in the historical balance data in May 2009. These were identified using the "Facility Number" field; facility IDs in the form of "00000XXXXXX-XXXXX" and "00000XXXXXX-X" were reviewed with the business and accordingly removed as these represented additional Mellon balances that had been sold off.

4.2.3.3. Wealth Management

The Wealth Management segment contained a marked jump in the total volume of balances classified as closed-end loans and a corresponding decline in those classified as draws from facilities in April 2009 compared to preceding months, as seen in Figure 24 below.

Figure 24: Breakdown of total exposure for WM loans (excluding mortgages)



The issue was discussed with the Wealth Management business and it was determined that several former Mellon facilities were reclassified from “committed” to “advisory” as part of the newly merged bank’s de-risking program. This switch was accompanied with several changes in the data. Prior to April 2009, a collection of Mellon exposures were aggregated into a single exposure line and, accordingly, a single facility number. Starting with April 2009, these exposures then split into multiple exposures in the data going forward. The modeling team attempted to reclassify the data appropriately between new origination loans and draws from facilities for the data before April 2009 but could not successfully remedy all discrepancies. As a result, an indicator variable was used for the Wealth Management loan segments for April 2009. This is explained in more detail in Section 3.5.

4.2.3.4. Tri-party repos

The tri-party committed facilities that BNY Mellon engaged in beginning in April 2015 result in a sharp increase in Financial Institution unfunded commitments. These exposures did not fall into the historical data time series when developing loans models, as March 2015 was the last month used as part of the dependent variable time series. Nevertheless, it was determined that in future model runs with updated time series balance data, these commitments should be excluded and treated as a separate qualitative component since they do not exist in the model development data, and also because they have a known anticipated runoff schedule.

The tri-party repo exposures can be identified in the dependent variable data through the following process:

- First filtering on the “Regulatory Group” field for “Financial Institution”
- Next filtering on on the “Asset Desc” field for “Unfunded Commitment”
- Finally removing the unfunded exposures according to the customers and amounts of the exposures based on the following file:

WIP CCAR
Projections for 2017-

There are not expected to be any funded exposures associated with these facilities, as they are intended for intraday usage and carry punitive charges for overnight draws.

4.2.4. Data limitations

The CRDW data limitations are summarized in the following section.

The historical data in CRDW for loans and unfunded commitments had missing values in certain fields in the earlier months of the time series. The segmentation scheme, using the Regulatory Group and Asset Description fields as discussed in Section 3.1.3, was based on two fields that were reliably populated for the entire historical series. A product field was not available in CRDW, although loan products can be identified using the general ledger code field. This would have been possible for recent months; however the field was not reliably populated across the historical time series.

Because the modeling team could not segment by product, certain loan products were not possible to model as individual segments. Specifically, the Trade Financing loans, which are identifiable in the MAQ system using a combination of product and line of business, could not be identified in CRDW: Trade Financing exposures could be identified in recent months in CRDW, but the Facility Description field used to classify them is not reliably populated over the entire historical series. The majority of Trade Financing loans are included in the Financial Institutions segment.

4.2.5. Process for sourcing data

The ongoing maintenance plan for the balance sheet forecasting models requires regular performance monitoring, re-estimation and re-development of the models. As a result, loan balance and rates data will have to be sourced in the appropriate segmentation on a continuous basis going forward.

Loan balance data is collected and stored into a MS Access database. To update this database through the most recent period, the ALM team cleanses monthly CRDW files provided by Risk and then loads the aggregated data into the MS Access database to build the data repository. The following steps were implemented to cleanse the data:

1. Fields that are not used for CCAR modelling and do not map into the MS Access database are removed
2. Tri-party repo transactions are removed from the dataset. (See Section 4.2.3.4 for details regarding the decision to exclude tri-party repo transactions.) Tri-party repo transactions can be identified either through facility number or by filtering the CRDW dataset by the “Ast Cat Code” field for value “UCOM” and the “Coll Class Code” field for value “405”. Multiple validation steps are conducted to ensure that the correct entries have been excluded:
    1. ALMIS database queried for tri-party repo transactions within the relevant time period
    2. Liquidity team provides historical month-end tri-party repo transaction data
3. Transaction-level data contained in the CRDW files are aggregated to the segment-level by running SQL queries on the MS Access database:
    1. The table containing unfunded balances is updated to capture any new facility IDs with unfunded balances
    2. Unfunded balances are matched to transaction-level data based on facility ID in order to reclassify transactions as closed-end loans vs. draws from unfunded commitments
    3. Transactions without a match to an unfunded balance are classified as closed-end loans; transactions with a match are classified as draws from committed facilities
4. Aggregate balances are validated against MAQ and ALMIS data:

1. MAQ is queried to validate monthly funded balance totals in the dataset
2. ALMIS is queried to validate monthly unfunded balances totals and letters of credit totals in the dataset.

The process described above was implemented during a dry-run that the ALM team performed after the model development. During the dry-run, three months of data were checked against development data and were found to be fully consistent with the loan segmentation as used by the balance sheet forecasting models.

Modifications were made to QRM to mimic the loan balance models. QRM is the system that executes the balance sheet forecast during CCAR exercises. A SQL query was used to map QRM categories to CRDW segments based on product type, line of business, GL number, LE number, SIC code, and PPNR ID fields.

Rates data is sourced through MAQ. The ALM team has built Excel templates to match the segment definition of each rate model and linked them to MAQ. Templates are programmed to systemically retrieve actuals each month by refreshing the links to MAQ Management Accounting's reporting application. Results from the templates are loaded into a database monthly to build the data repository.

4.3. Loan rates data

4.3.1. Description of data used

Monthly data for loan balances and interest income were provided to the modeling team by the Corporate Treasury group for the period from January 2008 until April 2015. The data was split by loan products and further sub-divided by lines of business. This included lines of business that do not have current loan balances. To obtain time series for rates, monthly interest income data was divided by monthly balances to produce monthly rates, which were then annualized by multiplying by the actual number of days in the applicable year and then dividing by the actual number of days in the applicable month.

4.3.2. Description of data source

The data is extracted from MAQ, see Section 4.1.1 for a description of MAQ.

4.3.3. Data cleansing

The loan rate data series were assessed for potential data issues at the product level, in line with the agreed loan rate segmentation. Certain segments showed significant volatility in the historical rate time series but these were deemed to either be expected (given the nature of the underlying loans) or uncorrectable. The modeling team and Working Group made the decision not to change the underlying data for modeling.

4.3.4. Data limitations

Data limitations prevented a loan rate approach that could have resulted in higher quality forecasts for some segments. There were two primary limitations in forecasting the rates for loans.

4.3.4.1. Blended rates

As discussed under Section 3.5 on Methodology, blended rates were used for modeling. Ideally, the forecasting approach for loan rates would distinguish between the rates of existing loans and rates of newly originated loans. Such a split is desirable as it is expected to result in higher accuracy of the rates forecast. The reason is that the rates of the existing loan books are known, they are defined by the contractual terms of the existing loans. The new origination rates would be estimated based on variables including interest rates and credit spreads.

In order to use such a rate forecasting approach, the new origination balances would have to be forecasted separately from the balances of the existing loans. Additionally, the rates of newly originated loans have to be available historically. For most segments, the modeling team was not able to obtain balance data of newly originated loans or rates for new originations.

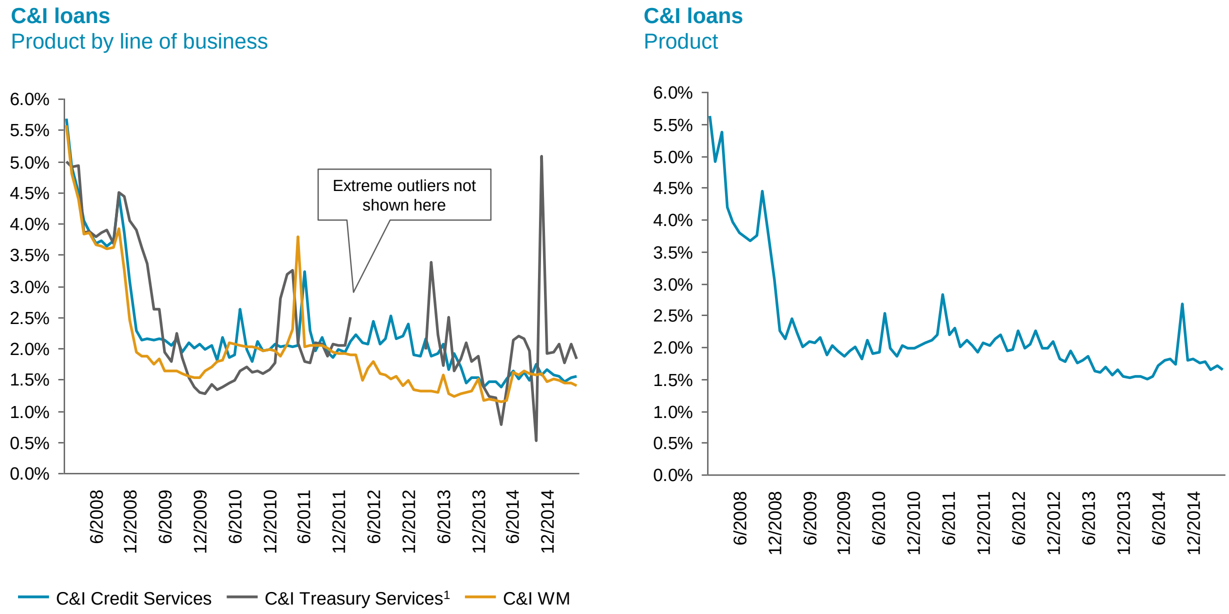
As a result, the loan rates are modeled as “blended rates”, that is, rates that apply to both new and existing volumes. These blended rates are weighted averages of rates determined for loans issued under different rate and spread environments. As a result, rate models are expected to be stronger for segments where volumes were originated under more homogeneous rate and spread environments, e.g. loans types with very short durations like margin loans.

For Wealth Management mortgages, the line of business sourced data for newly originated mortgages and their rates, which would enable forecasts for these quantities using the preferred loan rate forecasting approach described above. This improvement to the modeling approach can be applied either as a challenger model, or as a future enhancement to the current model.

4.3.4.2. Data limitations

Another data limitation in the loan rate data is the high volatility the rates exhibit due to accounting adjustments which hinders the movements due to macro factors. For certain lines of business, accounting adjustments in MAQ caused large spikes in the data. At the aggregate product level, the historical time series are less volatile and the modeling team used the data without further adjustments. Figure 25 below shows the rates data at the line of business level and the product level for the C&I loans segment.

Figure 25: C&I loan rates at the product by line of business and product level



4.4. Investment portfolio data

Two sets of data were received for BNY Mellon's Investment Portfolio: securities holdings data (as of May 31, 2015) and security purchase plans (monthly, with most recent for April 2015). These were both used to better understand the position and management of the portfolio for development of a qualitative forecast approach.

4.4.1. Securities holdings data

During the development of the qualitative framework for the Investment Portfolio, securities holdings data from four separate sources was used: the central booking system ITR, as well as three additional source feeds – IVT, VIE, and XLS. All four feed into QRM, with ITR representing the vast majority of balances (>99%). Data for the Investment Portfolio is split between these sources; as a result, in order to achieve a full overview of the Investment Portfolio, the four sources had to be merged into a single aggregate file. The fields in these files were identical and could therefore be consolidated into a single data set representing the entire Investment Portfolio.

The data provided was at the security-level with each row representing a unique CUSIP. Further information contained in the data included the following fields:

- Currency
- Asset type
- Maturity
- Designation of Available for Sale (AFS) vs. Held to Maturity (HTM)

This data represented the current portfolio as of 5/31/2015. When developing the qualitative forecast approach, portfolio size and composition were evaluated using the ITR, IVT, VIE and XLS data. In particular, the amount of AFS USD securities – along with the breakdown of asset classes between Treasuries, Agencies, and others – was the basis for assessing the viability of potential asset sales plans, as further detailed in Section 9.3 on the Investment Portfolio forecasting approach. The average balance of securities maturing per quarter was used to determine the amount of liquidity that could be sourced through the Investment Portfolio for deposit runoff scenarios.

4.4.2. Purchase plans

In addition to securities holdings data, BNY Mellon purchase plans were used to understand the planned changes in the Investment Portfolio. Internal portfolio purchase plans are split by asset type, index, benchmark yield, investment yield, and target growth, with planned investment purchase amounts by month for the subsequent 12-24 months. BNY Mellon provided purchase plans from November 2014 through April 2015. More recent purchase plans can contain revisions to earlier purchase plans.

Current securities holdings at the start of the forecast, including both portfolio size and composition, are the primary data input into the qualitative framework for forecasting Investment Portfolio size and composition. Additional data and information that need to be collected for the execution of the forecasting approach are discussed in Section 9.3 on the Investment Portfolio.

4.5. Other balance sheet item balance and rate data

Other balance sheet segments consist of the remainder of BNY Mellon's assets and liabilities, excluding deposits, loans, and the Investment Portfolio. All historical balance and interest income/expense data were retrieved as monthly average actuals from January 2008 to March 2015 from MAQ. To obtain time series for rates, monthly interest income/expense data was divided by monthly balances to produce monthly rates, which were then annualized by multiplying by the actual number of days in the applicable year and then dividing by the actual number of days in the applicable month.

In order to ensure that all account balances attributed to a segment were incorporated in the historical series, all balance data retrieved from MAQ was reconciled against a snapshot of BNY Mellon's balance sheet from the April 30, 2015, BNY Mellon Planning Tree. Similarly, rate data was retrieved by replicating the same segments as the balance data.

Additionally, discussions with the respective BNY Mellon business groups provided further insight into the historical balances and rates of these segments, and an additional layer of support for the historical data reviewed.

The rates segments for Pershing Reverse Repos and Trading liabilities Global Markets displayed unreasonable values – such as large negative values – for specific portions of the time series and were therefore removed from the development data for the model-based forecasts. This is further documented under the individual segment forecasts in Section 11.

For two other balance sheet items, Variable Interest Entity Assets and Variable Interest Entity Liabilities, historical changes in accounting treatment severely distorted the historical time series and prevented the application of the statistical modeling approach. Originally part of the Non-

Interest Earning Assets (excluding Goodwill and Intangibles) and Non-Interest Bearing Liabilities segments respectively, the modeling team decided to separate these two components out. Their balances are forecasted separately by the BNY Mellon Risk group.

A summary of final segmentation, data limitations, and solutions to address data limitations are listed in Table 24 and Table 25.

Table 24: Other balance sheet balances and rates (assets)

Segment – Other balance sheet (Assets)	**Data limitation (balances)**	**Data limitation (rates)**	**Solutions for data limitations**
Central bank deposits: Fed deposits	N/A	N/A	N/A
Central bank deposits: Foreign Central Bank deposits	N/A	N/A	N/A
Placements: Nostro	N/A	No development data available to modeling team	Direct usage of a Moody's forecast rate
Placements: Pershing	N/A	No development data available to modeling team	Direct usage of a Moody's forecast rate
Placements: Treasury	N/A	No development data available to modeling team	Direct usage of a Moody's forecast rate
Fed funds sold and rev repos: Reverse repos (Non-Pershing)	N/A	N/A	N/A
Fed funds sold and rev repos: Securities Borrowing & Reverse repos (Pershing)	N/A	Some early rates were negative	Affected rates removed from rate regression and model re-assessed with shorter time series
Securities financing: ABCP, SF loans, Reverse repo	Limited time series	Limited time series	Developed statistical model on limited time series; scrutiny during management review and challenge process will be required
Trading assets: Global Markets	N/A	N/A	N/A
Trading assets: Capital Markets	N/A	N/A	N/A
Non-interest earning assets (excl Goodwill, Intangibles)	VIE assets subjected to changes in accounting treatment	N/A	VIE balance will be forecast separately by the BNY Mellon Risk group
Non-interest earning assets: Goodwill	N/A	N/A	N/A
Non-interest earning assets: Intangibles	N/A	N/A	N/A

Table 25: Other balance sheet balances and rates (liabilities)

Segment – Other balance sheet (Liabilities)	Data limitation (balances)	Data limitation (rates)	Solutions for data limitations
Trading liabilities: Global Markets	N/A	Some early rates had negative signs	Affected rates removed from rate regression and model re-assessed with shorter time series
Trading liabilities: Capital Markets	N/A	N/A	N/A
Short-term borrowings: BD customer payables	N/A	N/A	N/A
Short-term borrowings: Fed funds, Repos (Treasury)	N/A	N/A	N/A
Short-term borrowings: Repos (Pershing)	N/A	N/A	N/A
Short-term borrowings: Commercial Paper	N/A	N/A	N/A
Short-term borrowings: Other borrowed funds	N/A	Volatile rates data	Historical rates data is very volatile and after attempts of developing a regression model, a data-driven qualitative framework will be used for rates forecasting instead
Long term debt	N/A	Rates available by issuance, rather than as a blended rate across entire segment	Rate forecasting approach will forecast rates for new issuances and keep contractual rates for existing issuances
Non-interest bearing liabilities	VIE liabilities subjected to changes in accounting treatment	N/A	N/A

4.6. Sourcing and preparation of independent variable data

The set of independent variables is described in Section 4. Based on the driver hypotheses that were developed in collaboration with the Working Group and the lines of business, the modeling team identified candidate variables that represent each driver. The set of independent variables is presented in Table 26, before any transformations were applied.

Moody's was generally the preferred source for the macroeconomic variables used when the monthly data was readily available, but alternate sources were used mainly to expedite the sourcing process for the modeling team to be able to promptly test various variables requested by the Working Group. Most of these variables sourced elsewhere are commonly used macroeconomic variables that Moody's likely has data for, but were not part of the data series from Moody's that was immediately available to the modeling team (with actuals extending to March 2015).

Also, for variables in the Fed scenario, the sourcing process consisted of the following steps:

- Assess whether the variable data exists in the monthly Moody's database that the modeling team had access to, and compare the data against the historical data published by the Fed together with the CCAR supervisory scenarios
- If the data could not be found or the data did not match, alternate sources were assessed, and the source that more closely aligned to the Fed's historical values were used

The sources of independent variables tested are listed in Table 26.

Table 26: Sources of tested independent variables

Independent variable name	Source	Ticker/Data identifier	Rationale for data source, if not Moody's
Real GDP growth	BEA	Table 1.1.1. Percent Change From Preceding Period in Real Gross Domestic Product	Greater consistency with Fed historical data
Nom Disposable Income	BEA	Table 2.1. Personal Income and Its Disposition	Greater consistency with Fed historical data
Eurekahedge NA HF Index	Bloomberg	HFRXNAM	Expedient
Eurekahedge NA FoF Index	Bloomberg	EHFI222 Index	Expedient
MSCI WORLD Index	Bloomberg	EHFI212 Index	Expedient
Ovrnt Repo Rate	Bloomberg	USRG1T ICUS Curncy	Expedient
SONIA	Bloomberg	SONIO/N Index	Expedient
EONIA	Bloomberg	EONIA Index	Expedient
USD/GBP	Bloomberg	USDGBP Curncy	Expedient
KBW Bank Index	Bloomberg	BKX Index	Expedient
Germany 10yr bond	Bloomberg	GDBR10 Index	Expedient
S&P Euro Sov Bond Index	Bloomberg	SPBDEGIY Index	Expedient
FTSE 100 Volatility Index	Bloomberg	IVUKX30 Index	Expedient
Euro Stoxx Volatility Index	Bloomberg	V2X Index	Expedient
BNY Mellon – Peer Group Debt Yield Spread	BNY Mellon Funding and Short Term Investments, Bloomberg	New Issue Indications – 5-Yr Senior Debt, BNY Mellon Corporation and Peer Group Average, Spread-Over-Libor Basis	Series managed internally at BNY Mellon
BNY Mellon – Peer Group Debt Yield Ratio	BNY Mellon Funding and Short Term Investments, Bloomberg	New Issue Indications – 5-Yr Senior Debt, BNY Mellon Corporation and Peer Group Average, Spread-Over-Libor Basis	Series managed internally at BNY Mellon
BNY Mellon AUC	BNY Mellon Fee Income Forecasting team	Assets Under Custody for the Asset Servicing business	Series managed internally at BNY Mellon
1M-3M Treasury Spread	Calculated from other variables	N/A	N/A
Baa to Treasury Spread	Calculated from other variables	N/A	N/A
3M to 5Y T Spread	Calculated from other variables	N/A	N/A

Independent variable name	Source	Ticker/Data identifier	Rationale for data source, if not Moody's
3M to 10Y T Spread	Calculated from other variables	N/A	N/A
T spread with Fed Funds	T-bill rate – Bloomberg Fed funds effective rate – Moody's	G0BA (ML US Treasury Bill Index), FRFED.US (Fed Funds rate)	Expedient
Market Vol	CBOE	VIX Close	Greater consistency with Fed historical data
10 Year US T-Note Volatility Index	CBOE	CBOE/CBOT 10-year US Treasury Note Volatility Index (TYVIX)	Expedient
EU Real GDP	Datastream	EMGDP...D	Moody's actuals only readily available from Q4 2014
HFRX NA Index	Datastream	HFRXNAM	Expedient
Ovrnt LIBOR-1wk OIS spread	Datastream	BBGBPON, OIUSDSW	Expedient
1 week LIBOR 1 week OIS spread	Datastream	BBUSD1W, OIUSDSW	Expedient
1M Treasury rate	Datastream	USTYCON1R	Expedient
Ovrnt LIBOR	Datastream	BBGBPON	Expedient
FTSE 100 Price Index	Datastream	FTSE100(PI)	Expedient
FTSE All Price Index	Datastream	FTALLSH(PI)	Expedient
Euro Stoxx Price Index	Datastream	DJES50I(PI)	Expedient
Fed Funds Target Rate	Datastream	USFDTRG	Expedient
ECB Marginal Lending Rate	Datastream	EUROMLR	Expedient
BoE Clearng Base Rate	Datastream	LCBBASE	Expedient
EUR M1	Datastream	EMM1....B	Expedient
EUR M2	Datastream	EMM2....B	Expedient
EUR M3	Datastream	EMM3....B	Expedient
UK M0	Datastream	UKM0....B	Expedient
Total Bond Issuance (ex MBS, treasuries)	Dealogic	Bond Issuance_Dealogic so	Expedient
ABS Issuance	Dealogic		Expedient
UK debt (ex MBS)	Dealogic		Expedient
UK debt (ex MBS, gov)	Dealogic		Expedient
Total Bond Issuance (ex MBS, gov)	Dealogic		Expedient
EU Outstanding debt (ex gov)	ECB	All maturities, not including "Central government" and "Other government"	Expedient
EU Gross debt issuances (ex gov)	ECB	All maturities, not including "Central government" and "Other government"	Expedient
Mortgage Rate	Federal Home Loan Mortgage Corp	CONVENTIONAL, CONFORMING 30-YEAR FIXED-RATE	Greater consistency with Fed historical data
EU inflation	Haver	EMCPHARMF	Moody's actuals only readily available from Q4 2014
Nominal GDP growth	Moody's	FGDP.US	
Unemp rate	Moody's	FLBR.US	

Independent variable name	Source	Ticker/Data identifier	Rationale for data source, if not Moody’s
Inflation	Moody's	FCPIU.US	
Real Disposable Income	Moody's	FYPCDPI$Q.US	
UK inflation	Moody's	FCPIQ.IGBR	
US M1	Moody's	FM1Q.US	
S&P Vol (30D MAVG)	Moody's	FSPVOL.US	
DJI	Moody's	FDJMIIUSDDWCFTDQ.US	
Corp Debt Outstanding	Moody's	FXZFL104104005Q.US	
Debt Share of Asset Financing	Moody's	FDEBT.US	
Prime rate	Moody's	FRPRIME.US	
3M Treasury	Moody's	FRTB3M.US	
Federal Funds Rate	Moody's	FRFED.US	
1Y Treasury	Moody's	FRGT1Y.US	
2Y Treasury	Moody's	FRGT2Y.US	
3Y Treasury	Moody's	FRGT3Y.US	
5Y Treasury	Moody's	FRGT5Y.US	
7Y Treasury	Moody's	FRGT7Y.US	
10Y Treasury	Moody's	FRGT10Y.US	
20Y Treasury	Moody's	FRGT20Y.US	
30Y Treasury	Moody's	FRGT30Y.US	
Baa Corporate Yield	Moody's	FRBAAC.US	
USD/EUR	Moody's	FTFXI163.US	
HPI	Moody's	FHCLHP1TIQ00.US	
Com Real Estate Price Index	Moody's	FZFL075035503Q.US	
3M EUR Swap	Moody's	EUR003M Index	
5Y EUR Swap	Moody's	EUSA5 Curncy	
10Y EUR Swap	Moody's	EUSA10 Curncy	
3M UK Swap	Moody's	BP0003M Index	
5Y UK Swap	Moody's	BPSW5 Curncy	
10Y UK Swap	Moody's	BPSW10 Curncy	
3M US Swap	Moody's	US0003M Index	
5Y US Swap	Moody's	USSA5 Curncy	
10Y US Swap	Moody's	USSA10 Curncy	
Weighted Avg USD FX rate	Moody's	FTWDBRD.US	
Real estate loans	Moody's	FBBABLLRCBQ.US	
Fed balance sheet	Moody's	FBRBAQ.US	
Bond and Income Mut Fund Cash Flow	Moody's	FICIFBI.US	
Money market fund Cash Flow	Moody's	FICIFMM.US	
Stock Mut Fund Cash Flow	Moody's	FICIFSM.US	
Real Imports	Moody's	FIMG$.US	
Nominal Imports	Moody's	FIMG.US	
Industrial Production	Moody's	FIP.US	

Independent variable name	Source	Ticker/Data identifier	Rationale for data source, if not Moody's
Nominal Exports	Moody's	FTREG.US	
UK Real GDP	Office for National Statistics	The Economist Intelligence Unit, Market Indicators and Forecasts – Quarterly Indicators; GDP (% real change pa)	Moody's actuals only readily available from Q4 2014
1 Month USD LIBOR	SNL		Expedient
3 Month USD LIBOR	SNL		Expedient
6 Month USD LIBOR	SNL		Expedient
12 Month USD LIBOR	SNL		Expedient
1 Month EUR LIBOR	SNL		Expedient
3 Month EUR LIBOR	SNL		Expedient
6 Month EUR LIBOR	SNL		Expedient
12 Month EUR LIBOR	SNL		Expedient
1 Month GBP LIBOR	SNL		Expedient
3 Month GBP LIBOR	SNL		Expedient
6 Month GBP LIBOR	SNL		Expedient
12 Month GBP LIBOR	SNL		Expedient
TED Spread	St Louis Fed	https://research.stlouisfed.org/fred2/series/TEDRATE#	Expedient

All models were developed on monthly data. In cases where the source data was quarterly (e.g. Real GDP growth), the data was converted to a monthly frequency by interpolating between the quarterly observations. Interpolation means that observations at a higher sampling frequency are estimated from a time series realization collected at a lower sampling frequency. For example, estimating monthly observations from data collected at the quarterly sampling frequency is interpolation. The most commonly used functional form of such an interpolation is the cubic spline [FN].[22] The modeling team used the command PROC EXPAND that is part of the Econometrics and Time Series (ETS) module of the SAS software, SAS/ETS. PROC EXPAND applies a cubic spline function and is the only procedure in the SAS System that can interpolate higher sampling frequency observations from lower sampling frequency observations.

Most of the untransformed independent variables are sourced directly from the listed data sources, without any additional preparation steps required beyond possibly the interpolation of quarterly data to monthly data. However, there are three categories of exceptions, where the independent variables require additional preparation steps. The first category includes all variables with a source listed in the table above as "Calculated from other variables", as listed below:

[22] Details on the SAS software and procedure are described in http://support.sas.com/documentation/onlinedoc/ets/132/expand.pdf (accessed September 18, 2015)

- 1-month to 3-month Treasury Spread: calculated as 1-month Treasury rate minus 3-month Treasury rate
- Baa to Treasury Spread: calculated as Moody's Baa Corporate bond yield minus 10-year Treasury rate
- 3-month to 5-year Treasury Spread: calculated as 5-year Treasury rate minus 3-month Treasury rate
- 3-month to 10-year Treasury Spread: calculated as 10-year Treasury rate minus 3-month Treasury rate

Each of these variables is calculated as a difference between two other variables that are themselves part of the independent variable universe.

The second category of variables that require additional preparation steps includes all variables that are calculated from multiple data series, not all of which themselves are part of the independent variable universe. These variables therefore have data sources listed in the table above for each data series that is required to perform the necessary calculation. The variables in this category are as follows:

- Treasury Spread with Fed Funds: calculated as Fed funds effective rate minus Merrill Lynch US Treasury Bill Index
- Overnight LIBOR to 1-week OIS spread: calculated as the overnight LIBOR minus the 1-week OIS rate
- 1-week LIBOR to 1-week OIS spread: calculated as the 1-week LIBOR minus the 1-week OIS rate
- Total Bond Issuance (ex MBS, treasuries): calculated as the sum of the following US bond issuance data series from Dealogic:
  - Asset-Backed Security
  - Corporate Bond – High Yield
  - Corporate Bond – Investment-Grade
  - Covered Bond
  - Medium-Term Note
  - Preferred Share
  - Sovereign, Local Authority
  - Supranational
  - US Agency
- Total Bond Issuance (ex MBS, gov.): calculated as the sum of the following US bond issuance data series from Dealogic:
  - Asset-Backed Security
  - Corporate Bond – High Yield
  - Corporate Bond – Investment-Grade
  - Covered Bond
  - Medium-Term Note
  - Preferred Share
- UK debt (ex MBS): calculated as the sum of the following UK bond issuance data series from Dealogic:
  - Asset-Backed Security
  - Corporate Bond – High Yield
  - Corporate Bond – Investment-Grade
  - Covered Bond
  - Medium-Term Note
  - Money Market
  - Non-US Agency
  - Preferred Share

  - Short-Term Debt
  - Sovereign, Local Authority
  - Supranational
- UK debt (ex MBS, gov): calculated as the sum of the following UK bond issuance data series from Dealogic:
  - Asset-Backed Security
  - Corporate Bond – High Yield
  - Corporate Bond – Investment-Grade
  - Covered Bond
  - Medium-Term Note
  - Money Market
  - Non-US Agency
  - Preferred Share
  - Short-Term Debt

The third category of independent variables that require additional preparation steps are the rates used in the deposit rate models. As discussed in Section 3.5.2.1, each rate variable used for the deposit rate models is split into a rising and falling rate variable. See Section 3.5.2.1 for details on the calculation of these rising and falling rate variables.

Following the preparation of all of the untransformed independent variable time series, combinations of the following transformations and lags were applied to the time series:

- Transformations:
  - None (levels)
  - First difference month-over-month
  - First difference quarter-over-quarter
  - First difference year-over-year
  - Percentage change month-over-month
  - Percentage change quarter-over-quarter
  - Percentage change year-over-year
- Lags:
  - 1 month
  - 2 months
  - 3 months

Not all transformations and/or lags were allowed for all of the variable time series. For example, percentage change transformations were not allowed for variables that were already in the form of percentages (e.g. interest rates, growth rates). The resulting time series were tested for stationarity, and all series that passed stationarity were allowed into the final set of transformed independent variables used for modeling.

4.7. Independent variable forecast methodology

As part of the evaluation of candidate models, the Working Group evaluated the models' forecast performance. This involved visualizing the models' performance and sensitivities under different macroeconomic scenarios.

To demonstrate the models' sensitivities, the modeling team used variable forecasts based on previous year's supervisory scenarios released by the Federal Reserve. Most of the variable forecasts, therefore, were based on the forecast path of the closest proxy variable in the CCAR 2015 supervisory scenarios. Some variables, however, required alternative forecast methods depending on the appropriateness of the variables in the supervisory scenarios to reasonably proxy its forecast and the availability of alternative forecasts.

A summary of the approaches taken to generate the macroeconomic variable forecasts are listed in Table 27. Details on the forecast methodology for each variable are listed in the Appendix.

Table 27: Summary of approaches for generating macroeconomic forecasts

Forecast approach	Description	Examples of applicable variables

Forecast approach	Description	Examples of applicable variables
2015 CCAR Scenario	• Applied differences or percentage changes of an appropriate proxy Fed variable • Made minor manual adjustments for some variables when their forecast path was too extreme compared to historical values and/or key thresholds were breached (e.g. negative interest rates)	• All variables included in the supervisory scenarios released by the Federal Reserve (e.g. DJI, US unemployment rate) • Variables not included in the supervisory scenarios (e.g. 1, 2, 3 year Treasury Rates)
2008 Crisis	• Severely adverse scenario is based on the experience in the 2008 crisis • Baseline scenario is informed by recent historical performance (i.e. flat from current or continuing the recent trend) • Adverse scenario is set as a value between the baseline and severely adverse scenario • The results were checked against forecasts generated using the 2015 CCAR scenario approach to ensure there were no major differences in forecast results	• LIBOR OIS Spread • TED Spread • Euro Stoxx Volatility
Other Forecasts	• Moody's standard scenarios (Baseline, S3 and S4) or Moody's scenarios for BNY Mellon's 2015 mid-year DFAST submission • BNY Mellon's Asset Under Custody forecast from the DFAST submission	• Standard scenarios – Fed Balance Sheet Total Assets size • DFAST – Assets Under Custody

5. Deposit balance

This section covers the balance models for the deposit segments. The segments are grouped by their lines of business. The key limitations of the models are then discussed.

5.1. Asset Servicing deposit balance models

5.1.1. Business overview and segments

Asset Servicing provides global custody and related services to large banks, insurance companies, funds, ETFs, pensions, endowments, foundations, and other entities. A core service offered is holding and processing of cash in connection with servicing securities portfolios, which results in these clients depositing money on BNY Mellon's balance sheet. As of April 30, 2015, the Asset Servicing line of business has deposits totaling roughly $101 BN, making it the largest individual deposit line of business for BNY Mellon.

For ALM management purposes, Asset Servicing deposits are separated into four segments described in Table 28: non-interest bearing USD deposits (AS DDA), interest bearing USD deposits (AS IB), interest bearing Euro deposits (AS/TS EU) and interest bearing British Pound deposits (AS/TS GB). As described earlier in Section 3.1.2, this segmentation was adopted for the purposes of balance sheet forecasting as well, to align the segmentation with those used for other business purposes.

Table 28: Segment description for Asset Servicing

Segments for Asset Servicing

Segments	Size ($ BN)[23]	Description
AS DDA	23.3	Composed entirely of USD denominated non-interest bearing balances in demand deposit accounts.
AS IB	47.5	Contains all interest bearing Asset Servicing deposits denominated in USD currency. The products contained in this segment are Asset Servicing Cash Reserves, Asset Servicing Trust Time, ADRs (American Depository Receipts) and Asset Servicing USD Foreign Deposits. These deposits are managed within the US, except for Asset Servicing USD Foreign Deposits, which are managed off shore, though are denominated in USD and are considered as part of the US Dollar segment for ALM purposes.
AS/TS EU	14.9	The two largest non-USD denominated balances of Asset Servicing deposits are in Euro and British Pound. Both these balances were pooled with the Treasury Services balances in the respective currencies as the Treasury Services balances. The Treasury Services balances did not meet the materiality threshold to be modelled individually and were deemed most similar to the Asset Servicing deposits. The models for these balances are developed in their native currencies, i.e. Euros and GBP in order to ensure that foreign exchange translation to US Dollars did not impact model selection. Both series are available for a shorter time period than other deposit segments: AS/TS EUR starts in July 2008, AS/TS GBP in January 2009.
AS/TS GB	14.8	

5.1.2. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team and the line of business, a list of driver hypotheses were developed and refined over time. Figure 26 illustrates the initial driver

[23] Month-end spot balance from April 30, 2015

hypotheses that were identified through conversations with the lines of business and the ALM team in advance of the modeling process. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables are included in the Appendix.

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Figure 26: Summary of Asset Servicing deposit balance drivers

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit balances increase when general economic health improves	• US/EU/GB GDP growth, unemployment rate
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase as BNYM is perceived as a relative "safe haven"	• Spread of BNYM debt rate to industry peer rate
	Banking system risk	• Deposit balances increase as banking credit risk increases, as BNYM is perceived as a relative "safe haven"	• Overnight Libor, TED Spread, Libor OIS spread
	Monetary base	• Deposit balances increase when the monetary base increases	• US/EU/GB monetary base, CPI inflation rate
	Assets under custody	• Deposit balances increase as AUC increases	• BNYM AUC forecast
	Equity markets	• Deposit balances increase as equity investments become more attractive	• DJI, MSCI Global, KBW Bank Index, FTSE 500, EuroStoxx Index
	Mutual Fund Cash Flow	• Deposits balances increase as stock and bond and income mutual funds increase activity • Deposit balances decrease as Money Market funds are attracting more capital	• Bond and Income MF CF, Money market MF CF, Stock MF CF
	Market volatility/ uncertainty (equity and rates)	• Deposit balances increase as market volatility and uncertainty increases • Deposit balances increase in flight to quality situations	• VIX, Market Volatility Index, Euro Stoxx Vol, FTSE 100 vol (equity) • US T-note volatility (rates)
	Financial stability of US government	• Deposit balances increase when there is a shock decline to the perceived creditworthiness of the US government	• 1-3 month Treasury yield spread
Rates	**Short-term rates**	• Deposit balances decrease as short-term rates increase (absolute or comparative to competitors), as depositors seek other institutions/instruments with higher deposit rates	• Prime Rate, Fed Funds effective rate, 1 & 3 month Treasury rate, SONIA, EONIA, Overnight Repo rate, T-Bill index spread with Fed funds effective rate
	Treasury Yield Spread	• Deposit balances decrease when yield spreads widen as longer term investment yields become more attractive	• 3 month – 5 year and 3 month – 10 year Treasury yield spread

1. Corporate Credit and FX rates were also tested as extra drivers.

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

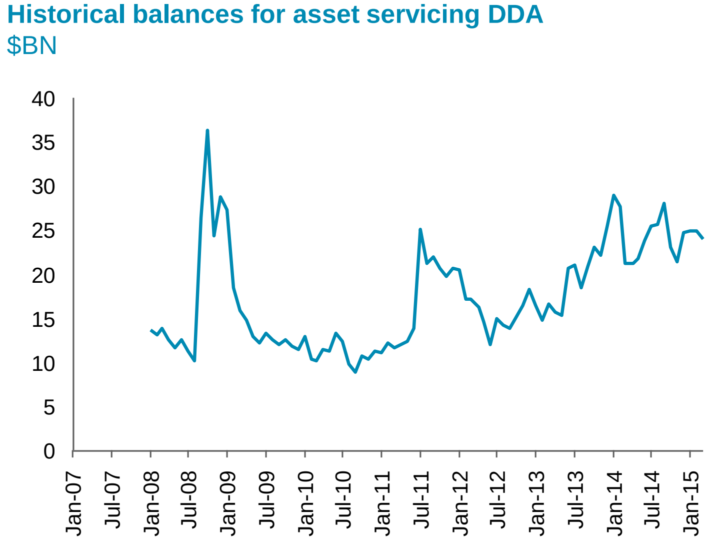
5.1.3. Asset Servicing DDA

5.1.3.1. Deposit balance overview

Over the modeling time period, Asset Servicing Demand Deposit Accounts (Asset Servicing DDA, or AS DDA) balances experienced large, sudden increases in balances in times of economic stress. Most notably during the financial crisis in 2008, deposit balances more than tripled in size as clients were increasingly seeking safer vehicles to store their capital. The sharp increase in balances was shortly followed by a sharp decrease in balances. A similar dynamic was observed in 2011 and 2013, coinciding with the two US debt ceiling crisis. The decrease after the debt ceiling crisis in 2011 was driven by management action which involved engaging clients to draw down their balances. Moreover, management announced to its clients that BNY

Mellon may charge a fee for Asset Servicing deposits, which assisted their efforts to manage down deposit balances.

Figure 27: Historical balances for Asset Servicing DDA



5.1.3.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Asset Servicing DDA segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the AS DDA deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 29.

Table 29: Coefficient estimates for the Asset Servicing DDA model

Asset Servicing DDA (in USD MM)				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
LIBOR_OIS_1wk_DMoM	First difference - MoM	%	3913.140	0.41
OvrNt_Repo_DMoM	First difference - MoM	%	-5155.356	-0.29
SP_Vol_PMoM	Percent change - MoM	Index	42.972	0.26

Intercept	None (level)	$ MM	-15.368	N/A

The model contains the following drivers and variables:

- **Short Term Rates –** overnight repo rate, a measure of the overnight collateralized lending rate
- **Market Volatility (equities)** – S&P 500 volatility index (i.e. the VIX), a common benchmark of conceived market uncertainty in the broad US equity market
- **Banking System Risk** – Libor OIS spread, a measure of banking system risk

The intuition for these variables is as follows:

- The overnight repo rate has a negative coefficient which is consistent with business intuition that deposit balances decrease as short-term rates increase. AS DDA are non-interest bearing deposits, and as such BNY Mellon expects depositors to seek other institutions and instruments with higher yields when rates rise, particularly, off-balance sheet alternatives such as money market funds
- Both the Libor OIS spread and the S&P volatility index have positive coefficients, consistent with the hypothesis – as well as observed behavior during the 2008 financial crisis – that BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in Figure 28.

Figure 28: Candidate models for Asset Servicing DDA

Asset Servicing Demand Deposit Account
Candidate models

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Equity markets		MSCI WORLD Index (% MoM, 1M Lag)	KBW Bank Index (% MoM, 1M Lag)		DJI (% MoM, 1M Lag)
Market volatility/ uncertainty (equity)	S&P Vol (30D MAVG) (% MoM)	S&P Vol (30D MAVG) (% MoM, 1M Lag)	S&P Vol (30D MAVG) (% MoM, 1M Lag)	S&P Vol (30D MAVG) (% MoM)	S&P Vol (30D MAVG) (% MoM)
MF Cash Flow				Stock Mut Fund Cash Flow (Diff YoY)	
Perceived credit risk	1 week LIBOR 1 week OIS spread (Diff MoM)	TED Spread (Diff MoM)	TED Spread (Diff MoM)	TED Spread (Diff MoM)	1 week LIBOR 1 week OIS spread (Diff MoM)
Short-term rates	Ovrnt Repo Rate (Diff MoM)				
Variation in balances explained through estimated first differences	**22%**	**75%**	**75%**	**80%**	**72%**
R-squared (differences)	**47%**	**45%**	**43%**	**43%**	**42%**

Final Model

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.1.3.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.1.3.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Asset Servicing DDA series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 30.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 31.

Table 30: Unit root tests and stationarity tests including a trend variable on balances

AS DDA – Unit root test with trend on balance series

AS DDA – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	5	-3.1	<0.05	Reject unit root
Phillips-Perron	1	-3.3	0.08	Reject unit root
KPSS	5	0.16	0.04	Reject stationarity

Table 31: Unit root tests and stationarity tests including a constant on first differences

AS DDA – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-9.5	<0.01	Reject Unit Root
Phillips-Perron	1	-9.5	<0.01	Reject Unit Root
KPSS	9	0.06	0.81	Fail to Reject Stationarity

Stationarity tests for AS DDA balances yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. This means that there is evidence from the unit tests that the AS DDA balances could be considered trend-stationary. A trend-stationary series can be included in a regression after the time trend is removed. The modeling team considered this estimation strategy for AS DDA. However, it finally decided not to use this version of the model as it was uncertain how long such a trend would persist and if it would persist under different economic scenarios. Moreover, the KPSS test rejected trend-stationarity. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these considerations, the AS DDA deposit balances are modeled on their first differences.

5.1.3.3.2. Historical data review

In addition to checking for stationarity of dependent variables, we also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the AS DDA segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the AS business.

5.1.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%.

Table 32 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the AS DDA model are statistically significant.

Table 32: Statistical significance tests of model and variables for Asset Servicing DDA

Asset Servicing DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	0%	10%	Statistically significant
LIBOR_OIS_1wk_DMoM	3913.140	<1%	10%	Statistically significant
OvrNt_Repo_DMoM	-5155.356	10%	10%	Statistically significant
SP_Vol_PMoM	42.972	4%	10%	Statistically significant
Intercept	-15.368	94%	10%	Statistically not significant

5.1.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

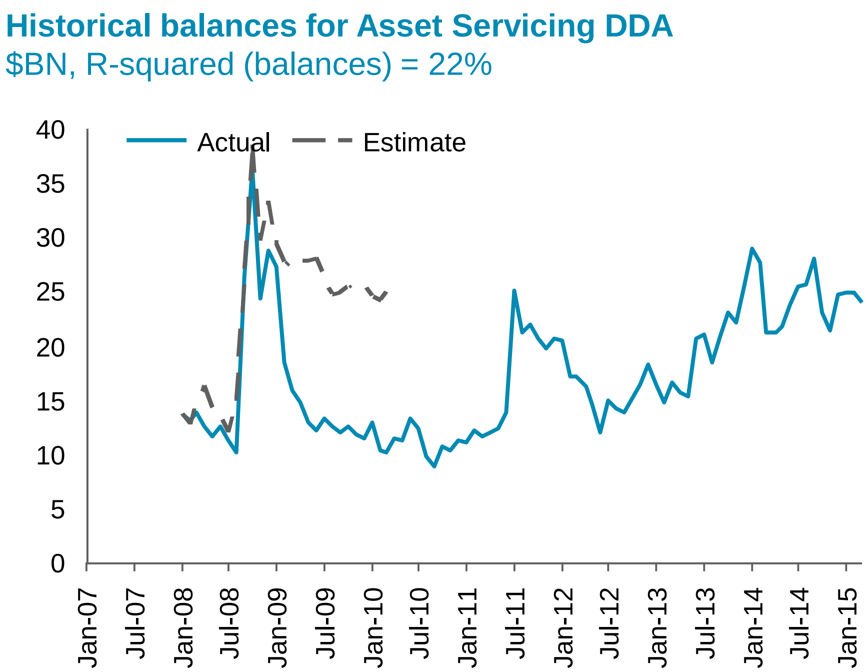
Table 33: Asset Servicing DDA Model Diagnostics

Asset Servicing DDA (in USD MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	47%	-	-
	Adjusted R-squared	45%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.03	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	3%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.33	5	No multicollinearity
Linearity	RESET test	95%	10%	Linear specification appropriate

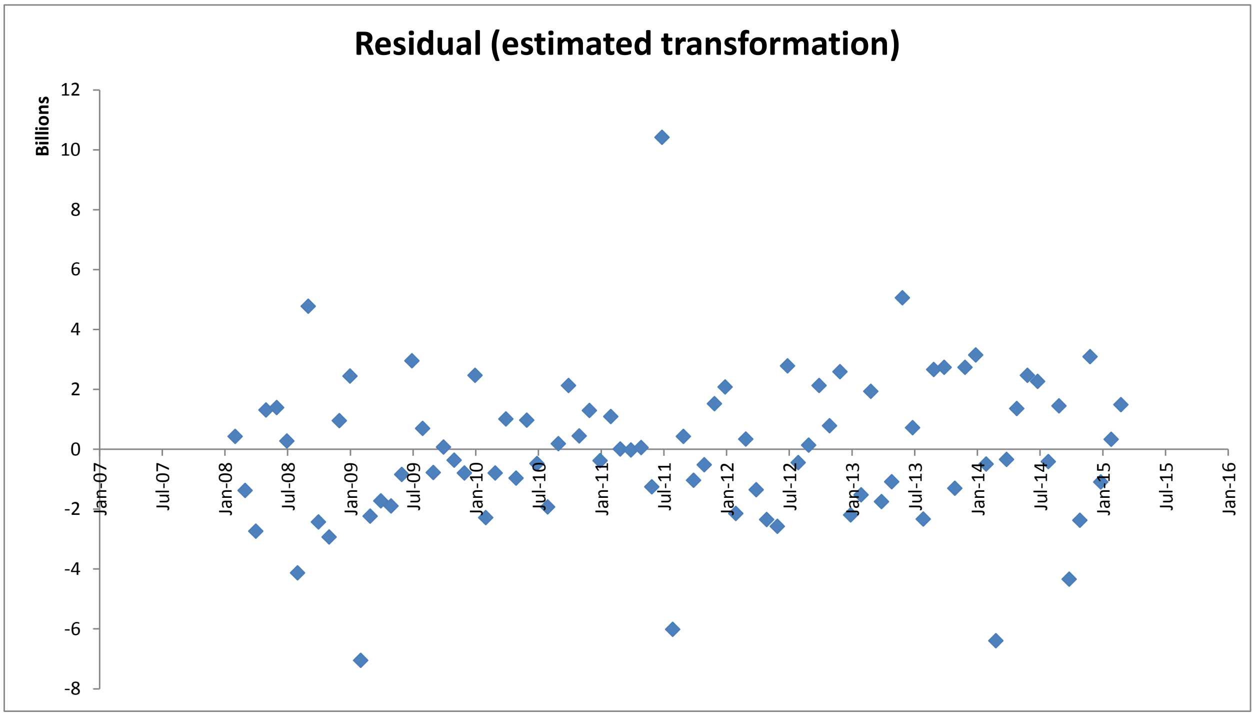
The model fails Heteroskedasticity but passes all other model diagnostic tests that were evaluated, except the Breusch- Godfrey test for serial correlation.

Figure 29: Asset Servicing DDA 9Q In-Sample Prediction



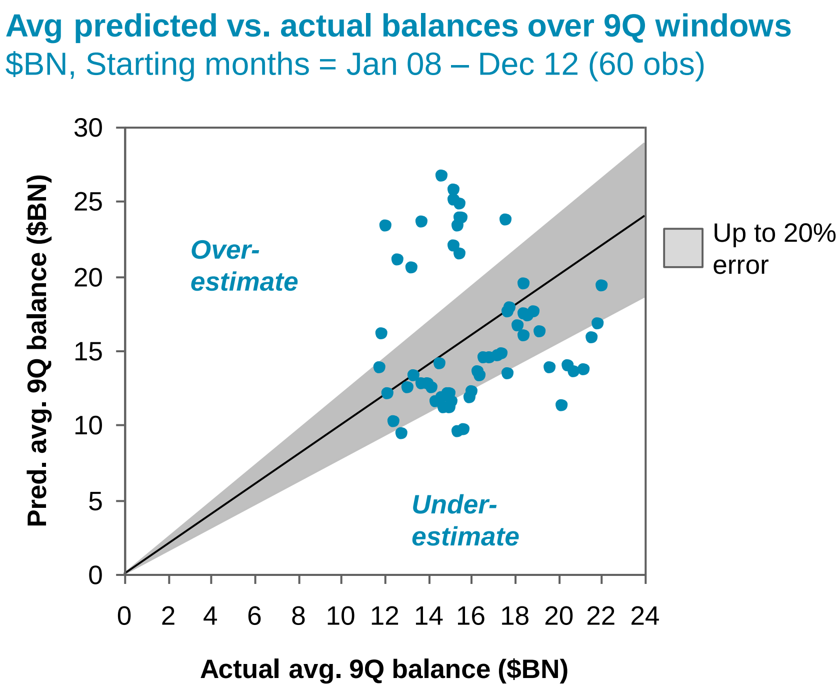
The in-sample back test of the model starting from January 2008 captures the increase in balances, but is only able to partially capture the subsequent fall.

Figure 30: Asset Servicing DDA Residual Plot ($BN)



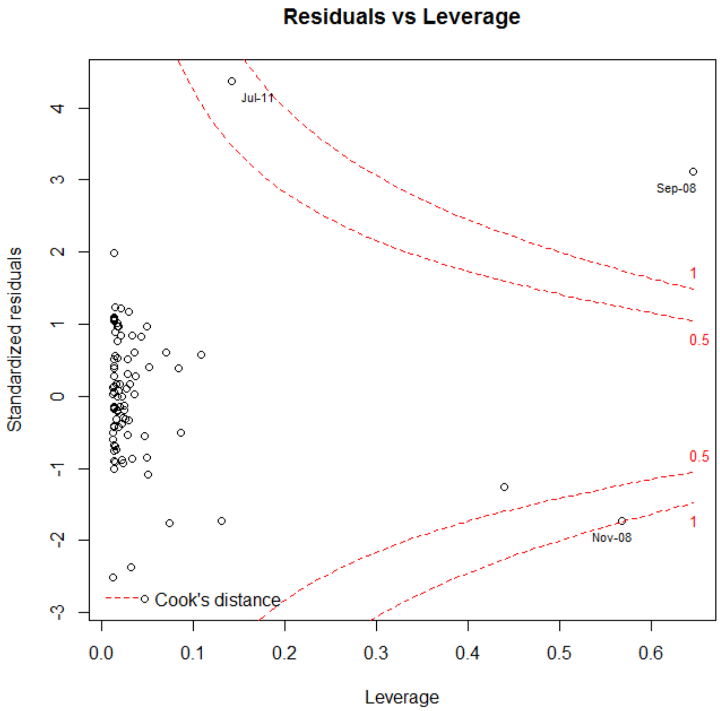
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 31: Asset Servicing DDA Balance Estimation Scatterplot



The points of overestimation on Figure 31 occur around the 2008 financial crisis and the 2011 debt crisis, as the model does not capture the decline in balances following management action to shrink the book. The points of underestimation are around the 2013 debt crisis, as the balance increase due to this idiosyncratic event was not captured by the model.

Figure 32: Influential points in Asset Servicng DDA



For this segment Spetember and November of 2008 are highly influential points. However, this is not surprising as balances increased dramatically due to the financial crisis in these months and does not invalidate the model.

5.1.3.6. Model sensitivity

5.1.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 34. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 34: Sensitivity to changes to independent variables for Asset Servicing DDA

Asset Servicing DDA (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
LIBOR_OIS_1wk_DMoM	First difference - MoM	%	0.41	0.35	1.40
OvrNt_Repo_DMoM	First difference - MoM	%	-0.29	0.31	-0.99

SP_Vol_PMoM	Percent change - MoM	Index	0.26	20.12	0.90
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the AS DDA model, the Libor OIS Spread variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the changes of the Libor OIS Spread results in a 0.35 standard deviation ($1.40 BN) increase in the predicted monthly change of the AS DDA deposits.

5.1.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 35.

Table 35: Statistical sensitivity tests for Asset Servicing DDA

Asset Servicing DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
LIBOR_OIS_1wk_DMoM	3913.140	3907.83	0.73	Statistically insignificant
OvrNt_Repo_DMoM	-5155.356	-4877.18	0.72	Statistically insignificant
SP_Vol_PMoM	42.972	48.21337	0.10	Statistically insignificant
Intercept	-15.368	-135.465	0.23	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.33	Statistically insignificant

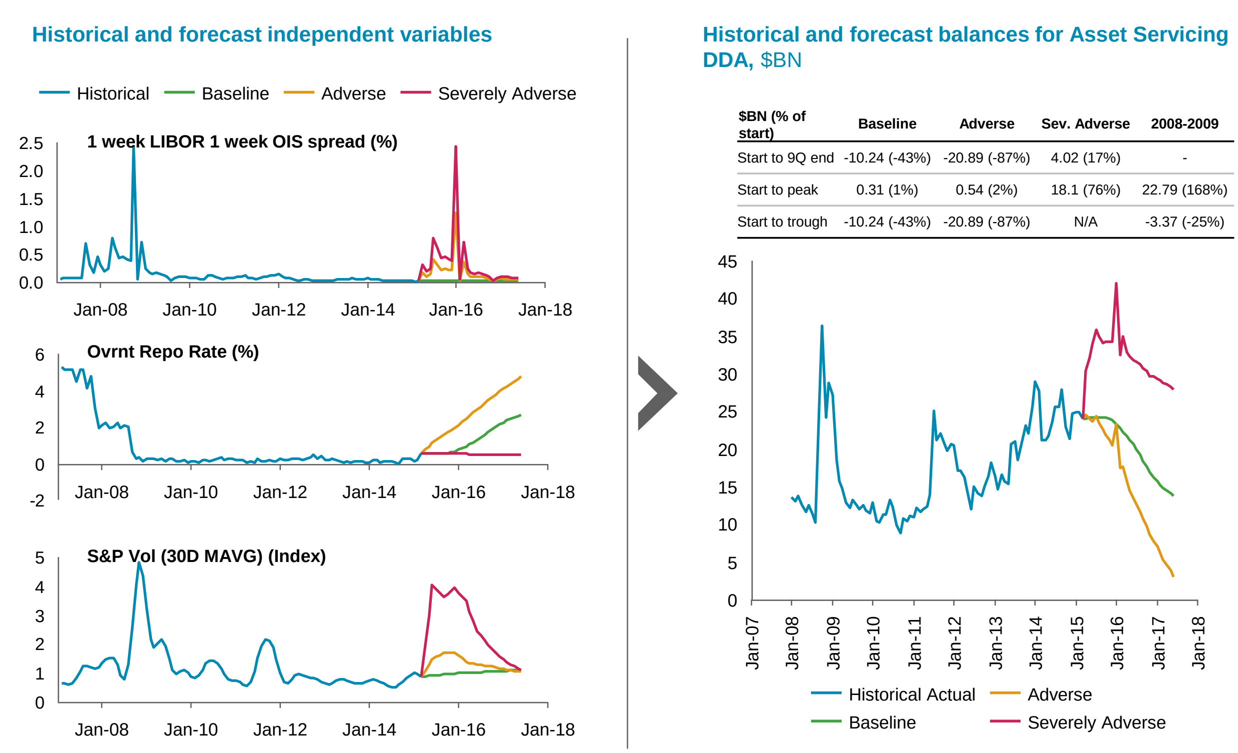
The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.1.3.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 33: Asset Servicing Demand Deposit Account Model Forecast



The Working Group considered the forecast behavior for the selected AS DDA model as reasonable.

The model forecasts are illustrated on Figure 33.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. The line of business suggested that the magnitude of the increase should be monitored closely when the final outputs for submission are generate
- **Interest rate shock (Adverse) scenario:** The model predicts a deposits run-off. This was consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment
- **Baseline scenario:** The baseline scenario has a moderate decline, which is not completely consistent to business intuition that a significant change in balances is not expected

5.1.3.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The AS DDA balances exhibited large and rapid increases and decreases during the modeling period. For instance, BNY Mellon was able to reduce its AS DDA balances following sudden and large balance increases after the 2011 debt ceiling crisis through active client management. Not surprisingly, the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently.

The large potential effect of management action on future balances is a limitation of this model. Historically, BNY Mellon's management actions have had big effects on its balances and might occur again in the future. It is recommended that active client management and other management actions are included in the considerations during the management review and challenge process of this segment.

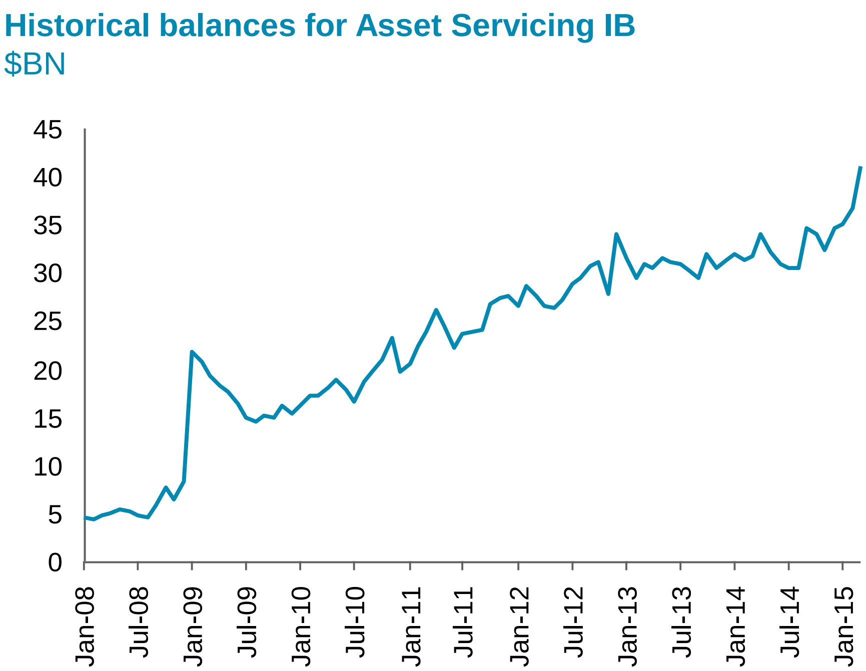
5.1.4. Asset Servicing IB

5.1.4.1. Deposit balance overview

Over the modeling period, Asset Servicing Interest Bearing (Asset Servicing IB, or AS IB) balances have steadily grown over time.

There is, however, a data limitation to this series: the increase in balances on January 2009 is driven mostly by a data limitation. The reason is that the balances for one of the sub-segments, Asset Servicing Foreign Deposits USD, are only available starting in January 2009 even though balances existed prior.

Figure 34: Historical balances for Asset Servicing IB



5.1.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Asset Servicing IB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the AS IB deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 36.

Table 36: Coefficient estimates for selected Asset Servicing IB model

Asset Servicing IB (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
OvrNt_Repo_DMoML1	First difference – MoM	%	-1845.47	-0.16
MSCI__DMoML1	First difference – MoM	Index	5.19	0.15
Intercept	-	$ MM	230.42	N/A
Dummy for Jan 2009		$ MM	12,553.1	N/A

The model contains the following drivers and variables:

- **Short Term Rates** – overnight repo rate, a measure of the overnight collateralized lending rate
- **Equity Markets** – MSCI World Index, a common benchmark of global equity market performance

The intuition of these variables is as follows:

- The overnight repo rate has a negative coefficient which is consistent with business intuition that deposit balances decrease as short-term rates increase. AS IB offers below average yields, BNY Mellon expects depositors to seek other institutions and instruments with higher yields when rates rise, particularly, off-balance sheet alternatives such as money market funds
- The MSCI World Index contains a positive coefficient, which is in line with the intuition that BNY Mellon would expect more deposits when financial markets are performing well and the value of the underlying assets under custody increases

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates. In addition to these variables, a dummy variable was used to address a specific issue identified in the historical data, which is discussed further in Section 5.1.4.3.2.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 35.

Figure 35: Candidate Models for Asset Servicing IB

Asset Servicing Interest Bearing
Candidate models

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
Equity markets	MSCI WORLD Index (Diff MoM, 1M Lag)	MSCI WORLD Index (Diff MoM, 1M Lag)	MSCI WORLD Index (Diff MoM, 1M Lag)	MSCI WORLD Index (Diff MoM, 1M Lag)
General economic health		Unemp rate (Diff MoM, 1M Lag)		
Market volatility/ uncertainty (equity)	Market Vol (Diff QoQ)	Market Vol (Diff QoQ)	S&P Vol (30D MAVG) (Diff QoQ)	
Perceived credit risk	1 week LIBOR 1 week OIS spread (Diff MoM)			
Short-term rates				Ovrnt Repo Rate (Diff MoM, 1M Lag)
Variation in balances explained through estimated first differences	**95%**	**94%**	**95%**	**93%**
R-squared (differences)	**50%**	**50%**	**47%**	**47%**

Final model

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.1.4.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.1.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Asset Servicing IB series is tested to see whether it is a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 37.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 38.

Table 37: Unit root tests and stationarity tests including a trend variable on balances

AS IB – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-2.5	>0.1	Fail to Reject unit root
Phillips-Perron	1	-3.5	0.05	Reject unit root
KPSS	5	0.20	0.02	Reject stationarity

Table 38: Unit root tests and stationarity tests including a constant on first differences

AS IB (in USD MM) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	5	-4.1	<0.01	Reject Unit Root
Phillips-Perron	1	-8.5	<0.01	Reject Unit Root
KPSS	5	0.20	0.27	Fail to Reject Stationarity

Stationarity tests for AS IB on balances yield mixed results: The PP test rejects the unit root, while the ADF test fails to reject the unit root and the KPSS test rejects stationarity. These results suggest the AS IB balances may be non-stationary. In contrast, the difference month over month transform passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Asset Servicing IB deposit balances are modeled as a series of monthly changes in balances.

5.1.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the AS IB segment. However, the regression model for the segment contains a dummy variable for the month of January 2009. The reason is that data for one component in that segment, the Asset Servicing USD Foreign Deposits, only became available starting in January 2009. Although balances for this segment existed prior, they were not captured in the systems used for modeling. The Asset Servicing Foreign Deposits USD sub-segment contained $13 BN of deposits in January 2009. Since the dependent variable is a difference month over month transformation, a single dummy is used to treat this data limitation which consists of a large artificial increase in balances in this month. All candidate models considered for this segment contain this dummy variable. As discussed previously, the data was sourced from MAQ as well as Microstrategy and its accuracy was confirmed with the AS business.

5.1.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 39 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the AS IB model are statistically significant. The intercept is also found to be statistically significant, along with the dummy variable for January 2009..

Table 39: Statistical significance tests of model and variables for Asset Servicing IB

Asset Servicing IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
OvrNt_Repo_DMoML1	-1845.47	2%	10%	Statistically significant
MSCI__DMoML1	5.19	5%	10%	Statistically significant
Intercept	230.42	9%	10%	Statistically significant
Dummy for Jan 2009	12553.1	<1%	10%	Statistically significant

5.1.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)

- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

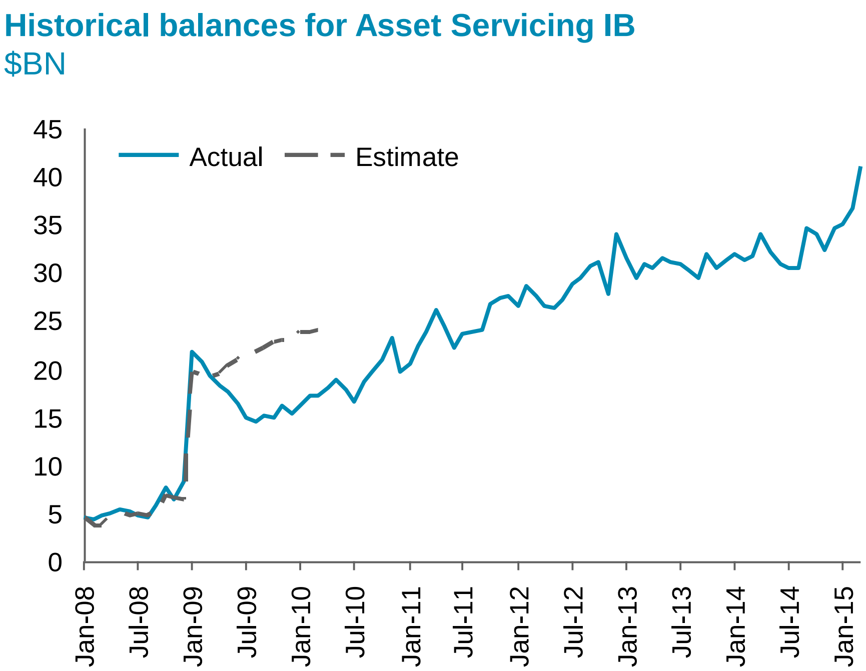
Table 40: Asset Servicing IB Model Diagnostics

Asset Servicing IB (in USD MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	47%	-	-
	Adjusted R-squared	45%	-	-
Heteroskedasticity	Breusch-Pagan test (P-value)	70%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum P-value up to 4 lags)	10%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.18	5	No multicollinearity
Linearity	RESET test	93%	10%	Linear specification appropriate

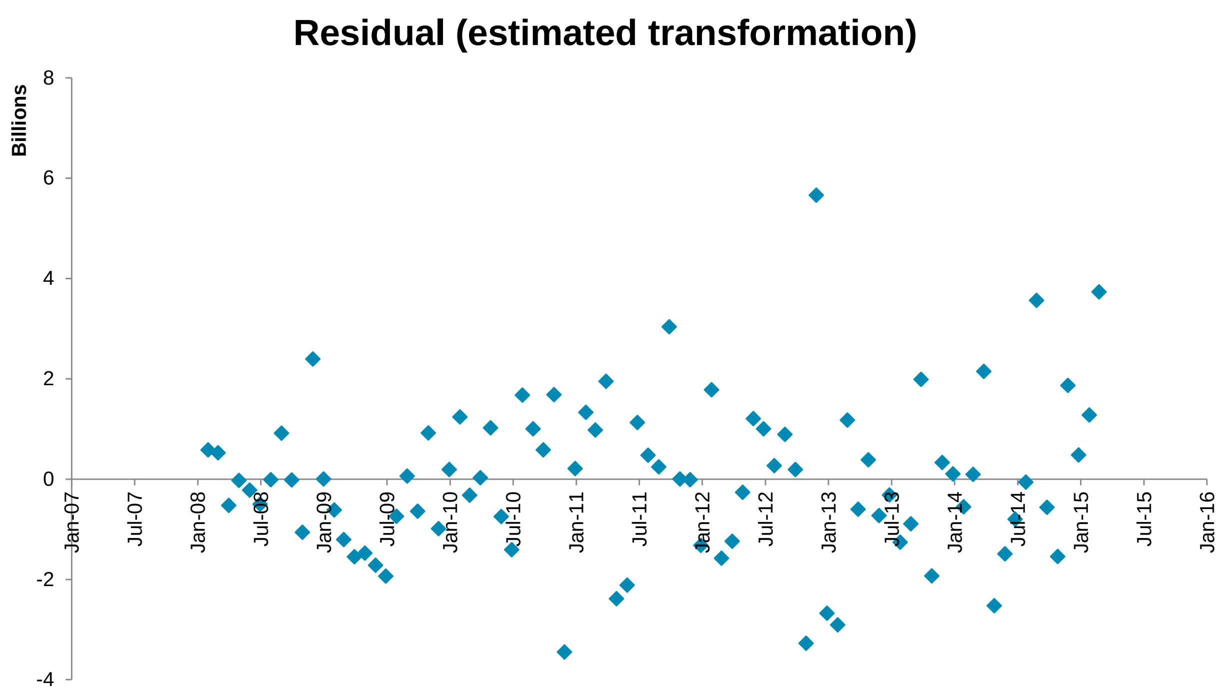
The model passes all model diagnostic tests that were evaluated; serial correlation is treated through the use of the HAC p-value for coefficient estimates.

Figure 36: Asset Servicing IB 9Q In-sample Prediction



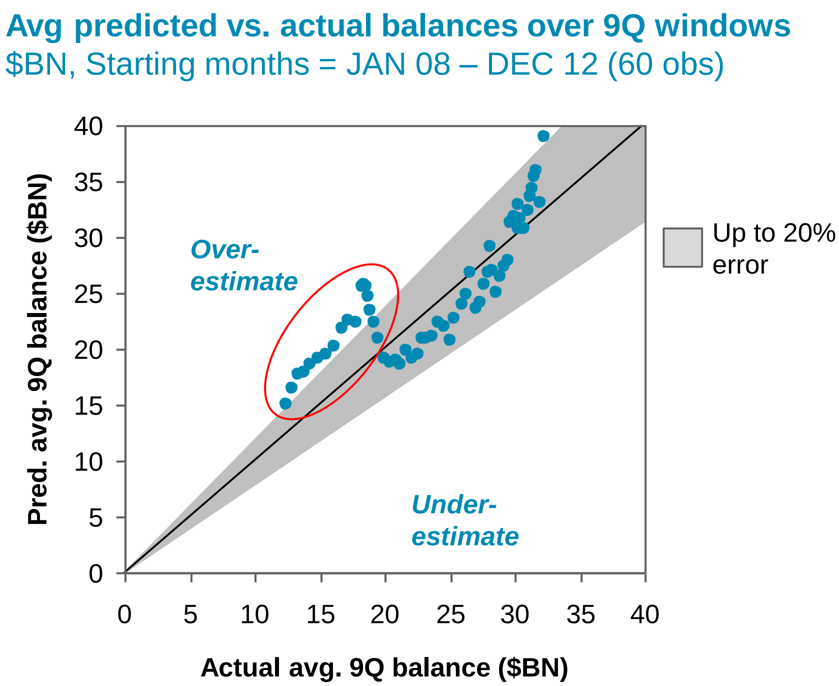
The in-sample back test of the model starting from January 2008 captures the increase in balances, but fails to capture the subsequent fall.

Figure 37: Asset Servicing IB In-sample Prediction ($ BN)



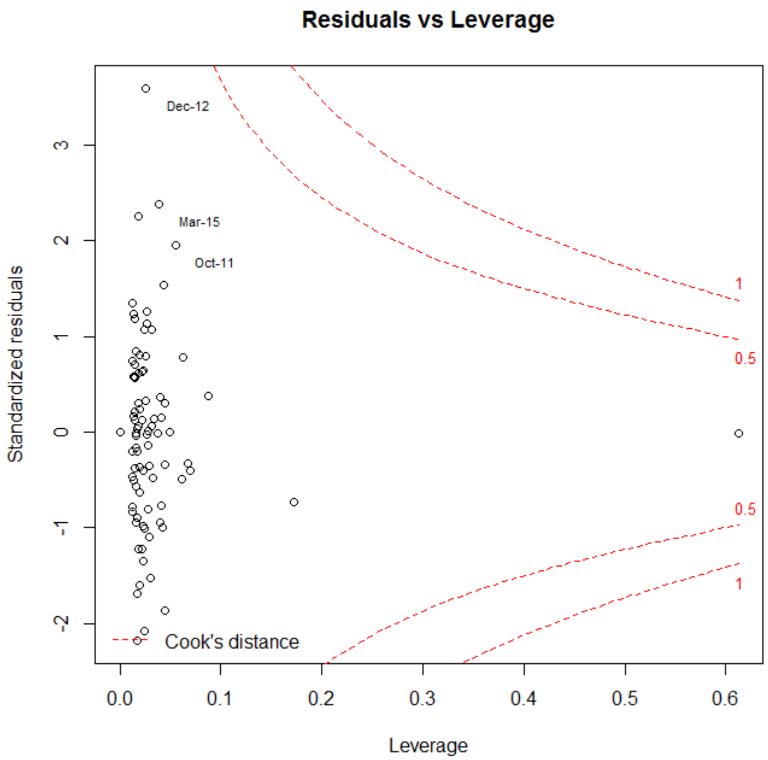
As expected the residuals appear to be randomly distributed around the horizontal axis.

Figure 38: Asset Servicing IB Balance Estimation Scatterplot



The points of overestimation on Figure 38 occur around the 2008 financial crisis, as the model does not capture the decline in balances.

Figure 39: Influential points in Asset Servicing IB



The segment does not contain a high Influential point.

5.1.4.6. Model sensitivity

5.1.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 41. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 41: Sensitivity to changes to independent variables for Asset Servicing IB

Asset Servicing IB (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std dev change in the indep var ($ BN)
OvrNt_Repo_DMoML1	First difference – MoM	%	-0.16	0.19	-0.34
MSCI__DMoML1	First difference – MoM	Index	0.15	62.68	0.32
Intercept	-	$ MM	230.42	N/A	

In the AS IB model, Overnight Repo and MSCI both have standardized coefficients of similar magnitudes with Overnight Repo being slightly larger. A one standard deviation increase in the changes of the Overnight Repo results in a 0.16 standard deviation ($0.34 BN) decrease in the predicted monthly change of the AS IB deposits.

5.1.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 42.

Table 42: Statistical sensitivity tests for Asset Servicing IB

Asset Servicing IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
OvrNt_Repo_DMoML1	-1845.47	-1402.12	0.09	Statistically significant
MSCI__DMoML1	5.19	3.16	0.06	Statistically significant
Intercept	230.42	190.15	0.90	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.11	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.1.4.6.3. Sensitivity to stressed independent variable scenarios

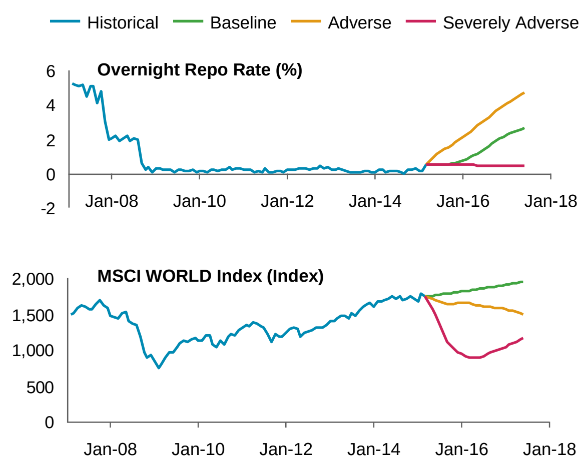
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model’s forecast behavior was tested for different macroeconomic scenarios.

Figure 40: Asset Servicing Interest Bearing Final Model Forecast

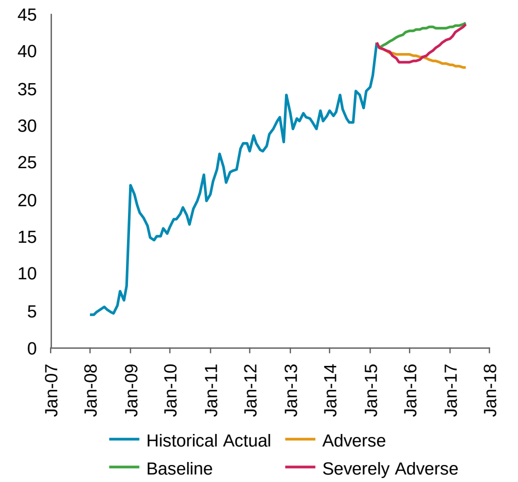
Asset Servicing Interest Bearing: Model 4
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Asset Servicing IB
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	2.62 (6%)	-3.38 (-8%)	2.4 (6%)	-
Start to peak	2.62 (6%)	N/A	2.4 (6%)	17.35 (388%)
Start to trough	-0.66 (-2%)	-3.38 (-8%)	-2.58 (-6%)	-0.06 (-1%)



The Working Group determined that the forecast behavior for the selected Asset Servicing Interest Bearing model requires higher scrutiny during management review.

The model forecasts are illustrated on Figure 40.

- **Severe recession (Severely Adverse) scenario:** The model predicts a slight increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. The line of business suggested that the magnitude of the increase should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts that balances remain flat. This is inconsistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment
- **Baseline scenario:** The baseline scenario has a mild increase, which is consistent to business intuition that a significant change in balances is not expected

5.1.4.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The large potential effect of management action on future balances is a limitation of this model. It is recommended that active client management and other management actions are included in the considerations during the management review and challenge process of this segment.

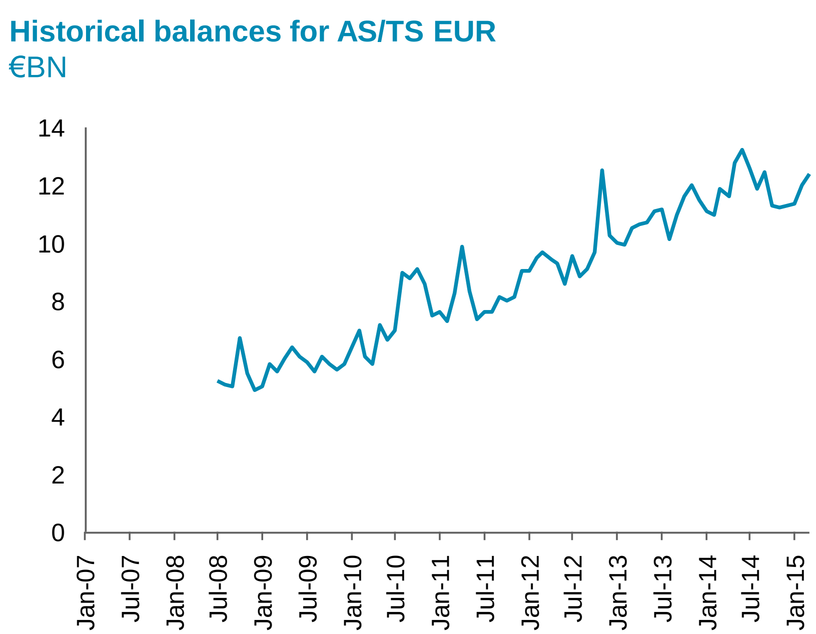
The model also includes a relatively sizable intercept of $230 million. This means that independently of the scenario, the forecast will grow by about $6.2 billion. As a result, the response of the model to a crisis scenario or an interest-hike scenario could be muted. The modeling team recommends that this dynamic be discussed with the lines of business and other stakeholders during the review and challenge process.

5.1.5. Asset Servicing/Treasury Services EU

5.1.5.1. Deposit balance overview

Over the modeling time period, Asset Servicing/Treasury Services EU (AS/TS EU) deposit balances have experienced a steady increase in since 2008.

Figure 41: Historical balances for Asset Servicing/Treasury Services EUR



5.1.5.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Asset Servicing/Treasury Services EU segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the AS/TS EU deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 43.

Table 43: Coefficient estimates for selected Foreign Asset Servicing/Treasury Services Euro model

Foreign Asset Servicing/Treasury Services EUR (in EUR MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Euro_Stoxx_vol_DMoM	First difference – MoM	Index	30.839	0.22
LIBOR_OIS_1wk_DMoM	First difference – MoM	%	376.766	0.18
AUC_DMoML1	First difference – MoM	$ BN	1.108	0.31
Intercept	-	$ MM	-5.752	N/A

The model contains the following drivers and variables:

- **Market Volatility (equities)** – The Euro Stoxx Volatility index, a common benchmark of conceived market uncertainty in the European equity market
- **Banking System Risk** – Libor OIS 1 week spread, a measure of banking system risk
- **Assets under Custody (AUC)** – the balance of assets under custody that are attributed to BNY Mellon's Asset Servicing business

The intuition of these variables is as follows:

- Both the Libor OIS spread and Euro Stoxx Volatility index have positive coefficients, consistent with the hypothesis that BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress
- Assets under Custody has a positive coefficient which is consistent with intuition as well. The more assets under custody at BNY Mellon, the more deposits these assets will generate/require in connection with the cash-related services provided

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 42.

Figure 42: Candidate Models for AS/TS EUR

AS/TS EUR
Candidate models

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Assets under custody	BNY AUC (Diff MoM, 1M Lag)		BNY AUC (Diff MoM, 1M Lag)	BNY AUC (Diff MoM, 1M Lag)	
Corporate credit					Baa Corporate Yield (Diff MoM)
Equity markets		MSCI WORLD Index (Diff MoM, 1M Lag)			
Market volatility/ uncertainty (equity)				Euro Stoxx Volatility Index (Diff MoM)	
Monetary base	EUR M1 (% MoM, 1M Lag)	EUR M1 (% MoM, 1M Lag)			
Perceived credit risk				1wk LIBOR-OIS spread (Diff MoM)	TED Spread (Diff MoM)
Relative creditworthiness of BNYM	BNYM - Peer Group Debt Yield Spread (Diff MoM, 1M Lag)	BNYM - Peer Group Debt Yield Spread (Diff MoM, 1M Lag)	BNYM - Peer Group Debt Yield Spread (Diff MoM, 1M Lag)		
Short-term rates			EONIA (Diff MoM, 1M Lag)		
Variation in balances explained through estimated first differences	**83%**	**70%**	**89%**	**91%**	**90%**
R-squared (differences)	**17%**	**16%**	**15%**	**15%**	**7%**

Final model

Additional drivers tested: MF Cash Flow, Corporate credit, General economic health, Market volatility/ uncertainty (rates), Financial stability of US government, Yield spread, FX rates (to USD)

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.1.5.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.1.5.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Asset Servicing/Treasury Services EU series is tested to see whether it is a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 44.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 45.

Table 44: Unit root tests and stationarity tests including a trend variable on balances

AS/TS Euro – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-4.7	<0.01	Reject unit root
Phillips-Perron	1	-5.6	<0.01	Reject unit root
KPSS	4	0.05	0.58	Fail to Reject stationarity

Table 45: Unit root tests and stationarity tests including a constant on first differences

AS/TS Euro – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-8.2	<0.01	Reject unit root
Phillips-Perron	1	-9.8	<0.01	Reject unit root
KPSS	16	0.17	0.33	Fail to Reject stationarity

Stationarity tests for AS/TS EUR on balances and first differences both suggest that the series may be stationary: The ADF and PP tests reject the unit root and the KPSS test rejects stationarity. Because both the balances and first difference passed stationairity, the modeling team reviewed the segment manually and concluded that the first difference would be more conservative to use. In addition, taking the first difference would be consistent with all other deposits segments.

Based on these results, the AS/TS EUR deposit balances are modeled as a series of monthly changes in balances.

5.1.5.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the AS/TS EU segment. As discussed previously, the data was sourced from Microstrategy and its accuracy was confirmed with the AS business.

The modeling period for this segment starts in July 2008 as Microstrategy data is not available before that month.

5.1.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 46 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the AS/TS EU model are statistically significant.

Table 46: Statistical significance tests of model and variables for Foreign Asset Servicing/Treasury Services Euro

Foreign Asset Servicing/Treasury Services Euro (in EUR MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Euro_Stoxx_vol_DMoM	30.839	10%	10%	Statistically significant
LIBOR_OIS_1wk_DMoM	376.766	<1%	10%	Statistically significant
AUC_DMoML1	1.108	<1%	10%	Statistically significant
Intercept	-5.752	95%	10%	Statistically not significant

5.1.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

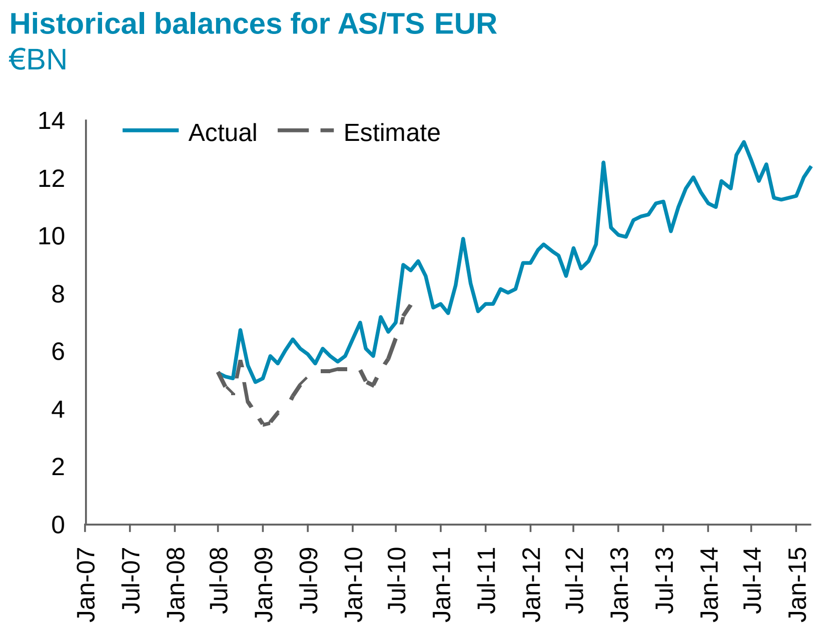
Table 47: Foreign Asset Servicing/Treasury Services Euro Model Diagnostics

Foreign Asset Servicing/Treasury Services Euro (in EUR MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	15%	-	-
	Adjusted R-squared	12%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	65%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	2%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.48	5	No multicollinearity
Linearity	RESET test	32%	10%	Linear specification appropriate

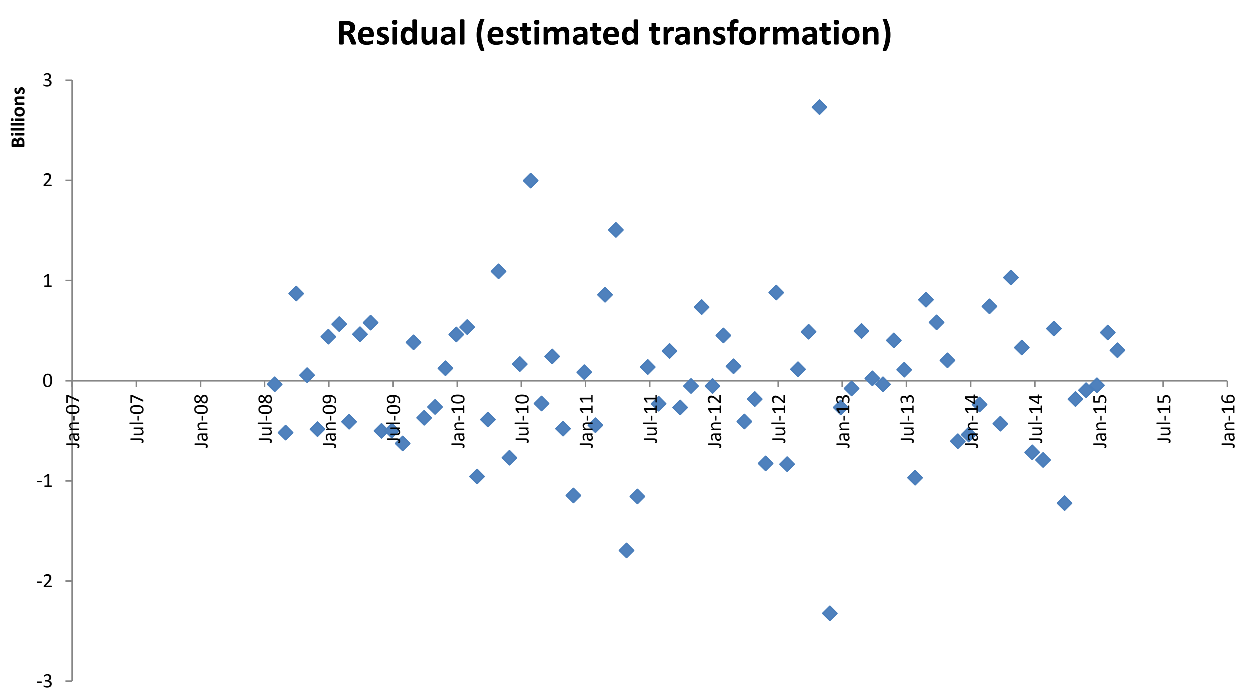
The model passes all model diagnostic tests that were evaluated, except the Breusch- Godfrey test for serial correlation.

Figure 43: Foreign Asset Servicing/Treasury Services Euro 9Q In-sample Prediction



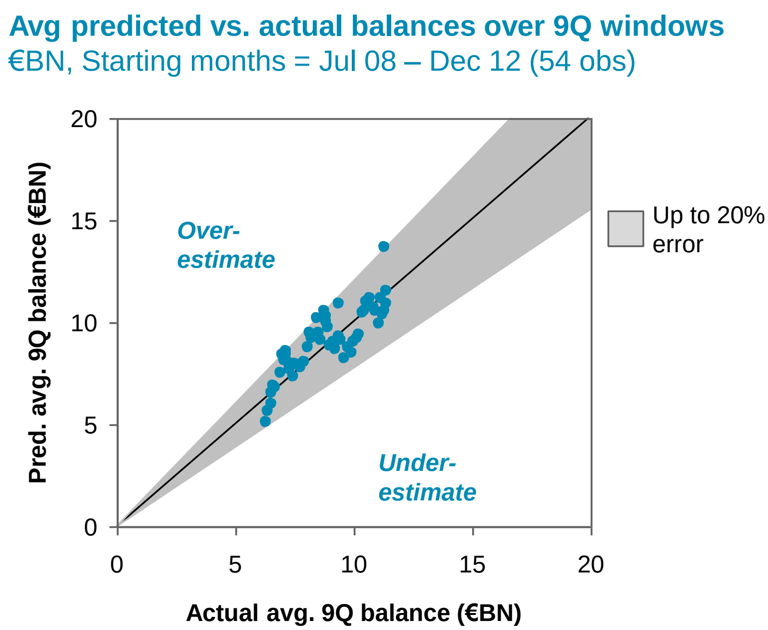
The in-sample back test of the model starting in January 2008 effectively captures the upward trend of the balances but is unable to capture many the numerous small balance fluctuations.

Figure 44: Foreign Asset Servicing/Treasury Services Euro Residual Plot (€BN)



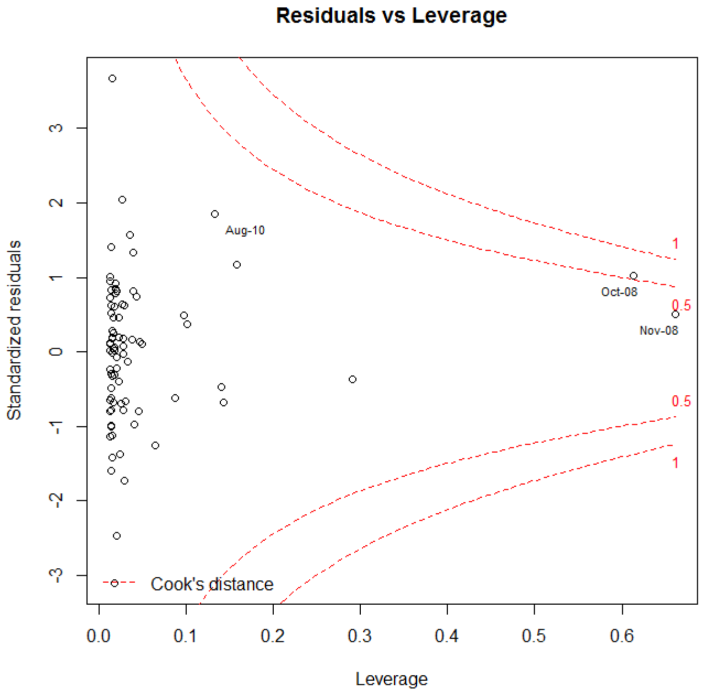
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 45: Foreign Asset Servicing/Treasury Services Euro Balance Estimation Scatterplot



The 9Q estimations of the AS/TS EU balances fall within the 20% error threshold.

Figure 46: Influential points for Foreign Asset Servicing Euro



The segment did not contain an Influential point.

5.1.5.6. Model sensitivity

5.1.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 48. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 48: Foreign Asset Servicing Euro Model Sensitivity

Foreign Asset Servicing EUR (in EUR MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable (€ BN)
Euro_Stoxx_vol_DMoM	First difference – MoM	Index	0.22	5.48	0.17
LIBOR_OIS_1wk_DMoM	First difference – MoM	%	0.18	0.36	0.14
AUC_DMoML1	First difference – MoM	$ BN	0.31	216.62	0.24
Intercept	-	$ MM	N/A	N/A	N/A

In the AS/TS EU model, the Assets under Custody (AUC) variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the changes of AUC results in a 0.31 standard deviation ($0.24 BN) increase in the predicted monthly change of the AS/TS EU deposits.

5.1.5.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 49.

Table 49: Statistical sensitivity tests for AS/TS EUR

Fgn Asset Servicing EUR (in EUR MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
Euro_Stoxx_vol_DMoM	30.839	38.073	0.13	Statistically insignificant
LIBOR_OIS_1wk_DMoM	376.766	330.709	0.34	Statistically insignificant
AUC_DMoML1	1.108	1.057	0.44	Statistically insignificant
Intercept	-5.752	7.979	0.24	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.11	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.1.5.6.3. Sensitivity to stressed independent variable scenarios

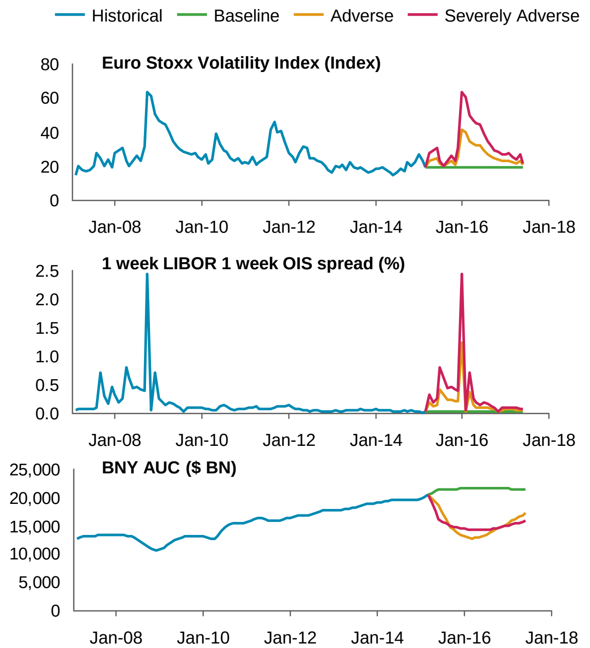
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model’s forecast behavior was tested for different macroeconomic scenarios.

Figure 47: Foreign Asset Servicing/Treasury Services Euro Model Forecast

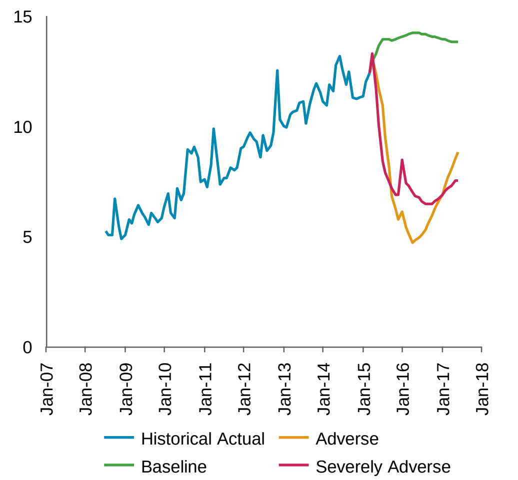
AS/TS EUR: Model 4
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for AS/TS EUR
€BN

€BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	1.44 (12%)	-3.55 (-29%)	-4.88 (-39%)	-
Start to peak	1.83 (15%)	0.71 (6%)	0.89 (7%)	N/A
Start to trough	N/A	-7.69 (-62%)	-5.93 (-48%)	N/A



The Working Group considered the forecast behavior for the selected AS/TS EUR model as requiring higher scrutiny during management review.

The model forecasts are illustrated on Figure 47.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant deposit run-off. In a review of the forecasts with the line of business, this was noted to be directionally inconsistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash, both of which suggest that balances should increase
- **Interest rate shock (Adverse) scenario:** The model predicts a significant deposits run-off. This was consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment. It was noted that the balance runoff in the interest rate shock scenario was should be monitored closely when the final outputs for submission are generated, given the decrease in the forecasted balances is more severe than the decline in AUC as a percentage of the starting level
- **Baseline scenario:** The baseline scenario largely remains flat with a moderate increase in deposits, which is consistent to business intuition that a significant change in balances is not expected

5.1.5.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

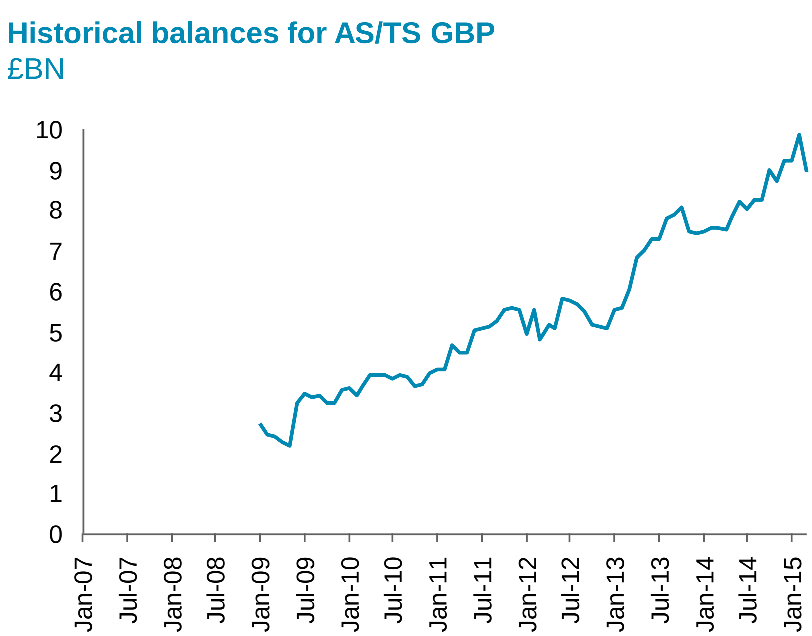
The modeling period for this segment only starts in July 2008. This means, this model is calibrated on a period when interest rates are consistently low. It is recommended that during the management review and challenge process of this segment the lack of higher interest rates during the modeling period is considered and that interest rate effects are considered in a potential management adjustment of the forecast.

5.1.6. Asset Servicing/Treasury Services GBP

5.1.6.1. Deposit balance overview

Over the modeling time period, Asset Servicing/Treasury Services GBP balances have experienced a steady increase in balances since 2008 growing from GBP 3 BN to nearly GBP 10 BN.

Figure 48: Historical balances for Asset Servicing/Treasury Services GB



5.1.6.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Asset Servicing/Treasury Services EU segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the AS/TS EU deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 50.

Table 50: Coefficient estimates for selected Foreign Asset Servicing/Treasury Services GB model

Foreign Asset Servicing/Treasury Services GB (in GBP MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
DJI_PMoML1	Percent change – MoM	Index	32.439	0.28
FTSE_100_vol_PQoQ	Percent change – QoQ	Index	5.295	0.42
OvrNt_Repo_DQoQ	First difference – QoQ	%	-890.871	-0.29
Intercept	-	$ MM	52.905	N/A

The model contains the following drivers and variables:

- **Equity Markets** – Dow Jones Industrial Average, a US equity market index
- **Market Volatility (equities)** – FTSE 100 volatility index, a common benchmark of conceived market uncertainty in the UK equity market
- **Short Term Rates –** Overnight Repo Rate, a measure of the overnight collateralized lending rate

The intuition of these variables is as follows:

- The Dow Jones Index has a positive coefficient, which is in line with the intuition that BNY Mellon would expect more deposits when financial markets are performing well and the value of the underlying assets under custody increases
- The FTSE 100 volatility index has a positive coefficient, consistent with the hypothesis that BNY Mellon is perceived as a relative safe haven and would receive deposits during times of market distress
- The Overnight Repo Rate has a negative coefficient which is consistent with business intuition that deposit balances decrease as short-term rates increase. BNY Mellon expects depositors to seek other institutions and instruments with higher yields when rates rise, particularly, off-balance sheet alternatives such as money market funds

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 49.

Figure 49: Candidate Models for AS/TS GB

AS/TS GBP
Candidate models

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
Equity markets	DJI (% MoM, 1M Lag)			MSCI WORLD Index (Diff QoQ)
Market volatility/ uncertainty (equity)	FTSE 100 Volatility Index (% QoQ)	S&P Vol (30D MAVG) (% MoM, 1M Lag)	S&P Vol (30D MAVG) (% MoM)	FTSE 100 Volatility Index (% QoQ)
Market volatility/ uncertainty (rates)			10 Year US T-Note Volatility (Diff MoM, 1M Lag)	
MF Cash Flow		Stock Mut Fund Cash Flow (Diff QoQ)		
Relative creditworthiness of BNYM				BNYM - Peer Group Debt Yield Ratio (Diff MoM)
Short-term rates	Ovrnt Repo Rate (Diff QoQ)	Ovrnt Repo Rate (Diff QoQ)	Ovrnt Repo Rate (Diff QoQ)	
Variation in balances explained through estimated first differences	**96%**	**97%**	**97%**	**97%**
R-squared (differences)	**19%**	**19%**	**19%**	**16%**

Final model

Additional drivers tested: Assets under custody, Corporate credit, Monetary base, General economic health, Perceived credit risk, Financial stability of US government, Yield spread, FX rates (to USD)

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.1.6.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.1.6.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Asset Servicing/Treasury Services GB series is tested to see whether it is a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 51.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 52.

Table 51: Unit root tests and stationarity tests including a trend variable on balances

AS/TS GB – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-1.9	>0.1	Fail to Reject unit root
Phillips-Perron	1	-2.8	0.18	Fail to Reject unit root
KPSS	4	0.10	0.15	Fail to Reject stationarity

Table 52: Unit root tests and stationarity tests including a constant on first differences

Foreign AS/TS GB (in GBP MM) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	5	-4.9	<0.01	Reject unit root
Phillips-Perron	1	-8.7	<0.01	Reject unit root
KPSS	0	0.05	0.88	Fail to Reject stationarity

Stationarity tests for AS/TS GB on balances yield mixed results: The PP and ADF test fail to reject the unit root while the KPSS test fails to reject stationarity. These results suggest the AS/TS GB balances may be non-stationary. In contrast, the difference month over month transform passes all three tests for stationarity.

Based on these results, the AS/TS GB deposit balances are modeled as a series of monthly changes in balances.

5.1.6.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the AS/TS GB segment. As discussed previously, the data was sourced from Microstrategy and its accuracy was confirmed with the AS business.

The modeling period for this segment starts in January 2009 as Microstrategy data is not available before that month.

5.1.6.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 53 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the AS/TS GB model are statistically significant.

Table 53: Statistical significance tests of model and variables for Foreign Asset Servicing/Treasury Services GB

Foreign Asset Servicing/Treasury Services GB (in GBP MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
DJI_PMoML1	32.439	1%	10%	Statistically significant
FTSE_100_vol_PQoQ	5.295	<1%	10%	Statistically significant
OvrNt_Repo_DQoQ	-890.871	1%	10%	Statistically significant
Intercept	52.905	20%	10%	Statistically not significant

5.1.6.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

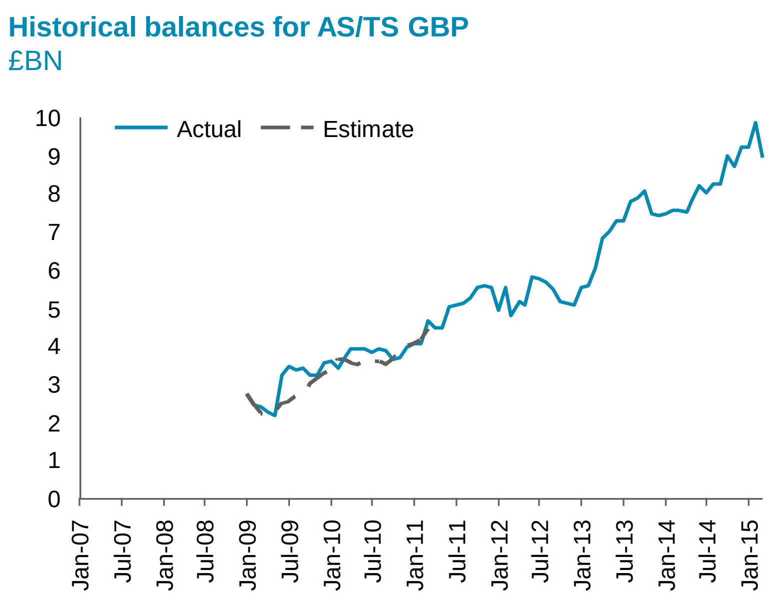
Table 54: Foreign Asset Servicing/Treasury Services GB Model Diagnostics

Foreign Asset Servicing/Treasury Services GB (in GBP MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	19%	-	-
	Adjusted R-squared	16%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	6%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	2%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.72	5	No multicollinearity
Linearity	RESET test	10%	10%	Linear specification inappropriate

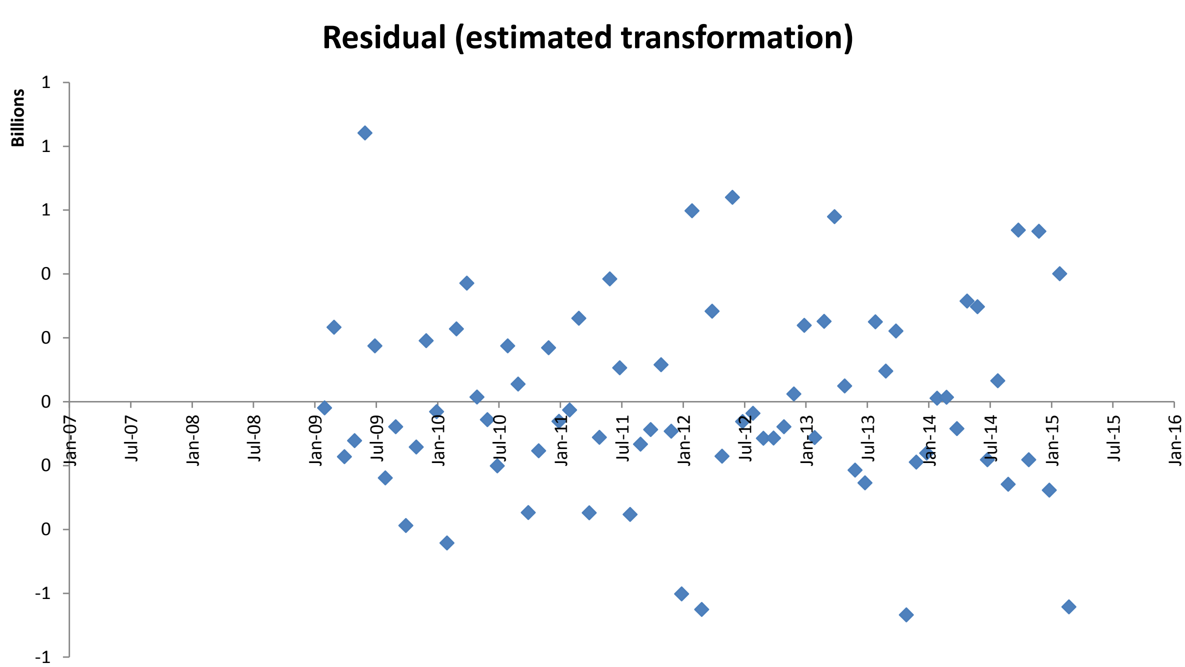
The AS/TS GB model exhibits serial correlation on its residuals. Also, the RESET test for linearity results in a test result that is marginally below the 10% threshold (by 0.3%), but given the scarcity of candidate models to select for this segment, this was tolerated on an exception basis.

Figure 50: Foreign Asset Servicing/Treasury Services GB 9Q In-sample Prediction



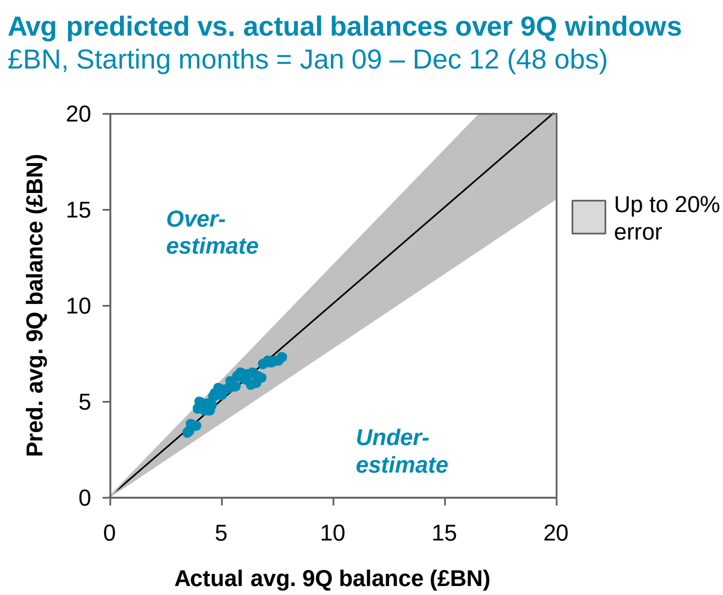
The in-sample back test of the model starting from January 2008 closely follows the trend of the actual historical balances.

Figure 51: Foreign Asset Servicing/Treasury Services GB Residual Plot (£ BN)



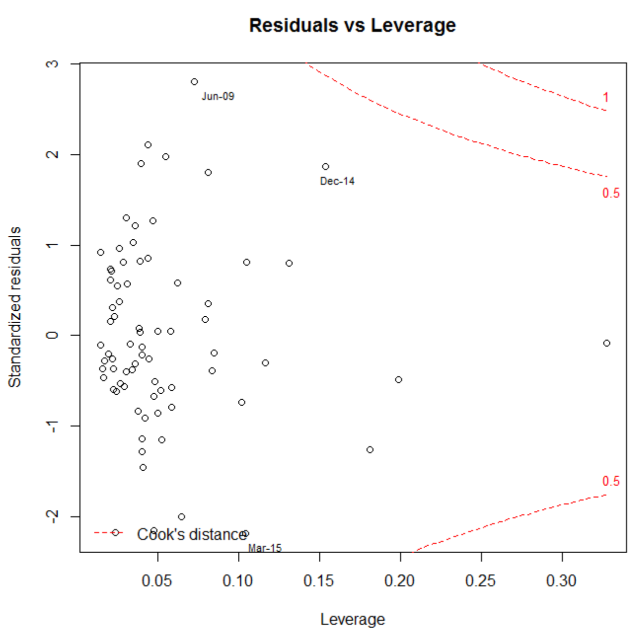
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 52: Foreign Asset Servicing/Treasury Services GB Balance Estimation Scatterplot



All the 9Q estimations of the AS/TS GB balances fall within the 20% error threshold.

Figure 53: Influential points for Foreign Asset Servicing GBP



The segment did not contain any highly influential points.

5.1.6.6. Model sensitivity

5.1.6.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 55. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 55: Foreign Asset Servicing/Treasury Services GB Model Sensitivity

Fgn Asset Servicing/Treasury Services GBP (in GBP MM) – model sensitivity					
Independent variable	**Transformation**	**Unit**	**Standardized coefficient**	**Std. dev of independent variable**	**Change in deposit balances resulting from 1 std. dev change in the independent variable (£ BN)**
DJI_PMoML1	Percent change – MoM	Index	0.28	2.89	0.09
FTSE_100_vol_PQoQ	Percent change – QoQ	Index	0.42	26.58	0.14
OvrNt_Repo_DQoQ	First difference – QoQ	%	-0.29	0.11	-0.10
Intercept	-	$ MM	N/A	N/A	N/A

In the selected AS/TS GB model, the FTSE volatility variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the quarterly changes of the FTSE volatility results in a 0.42 standard deviation ($0.14 BN) increase in the predicted monthly change of the AS/TS GB deposits.

5.1.6.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 56.

Table 56: Statistical sensitivity tests for AS/TS GB

Fgn Asset Servicing GB (in GBP MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
DJI_PMoML1	32.439	20.260	0.17	Statistically insignificant
FTSE_100_vol_PQoQ	5.295	3.409	0.06	Statistically significant
OvrNt_Repo_DQoQ	-890.871	-1038.948	0.46	Statistically insignificant
Intercept	52.905	55.129	0.21	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.22	Statistically insignificant

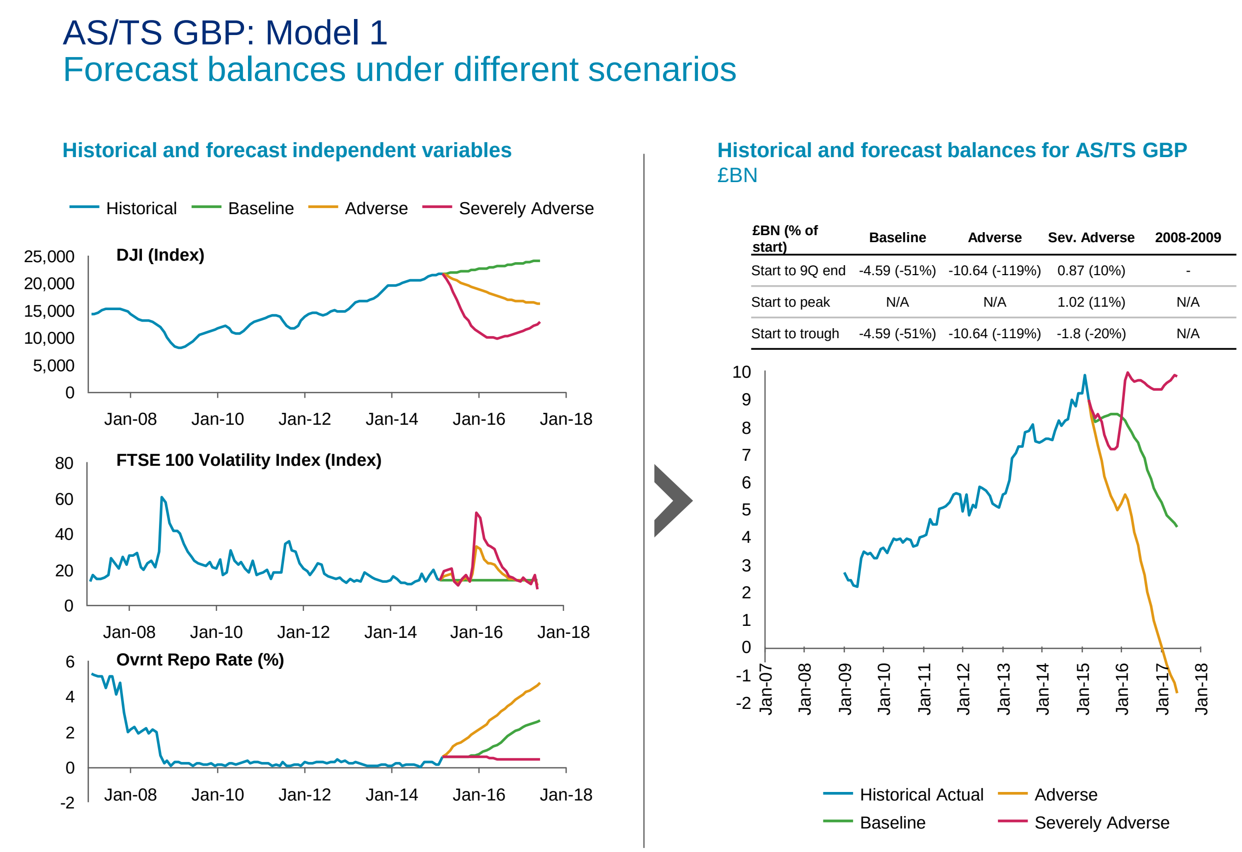
The coefficients of the shortened variables are statistically insignificant with the exception of the FTSE 100 volatility variable. The coefficients of the shortened variables are, however, jointly insignificant, which suggests the model exhibits reasonable stability when removing observations from the development data.

5.1.6.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 54: Foreign Asset Servicing/Treasury Services GB Model Forecast



£BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-4.59 (-51%)	-10.64 (-119%)	0.87 (10%)	-
Start to peak	N/A	N/A	1.02 (11%)	N/A
Start to trough	-4.59 (-51%)	-10.64 (-119%)	-1.8 (-20%)	N/A

The Working Group determined that the forecast behavior for the selected AS/TS GB model requires higher scrutiny during management review.

The model forecasts are illustrated on Figure 54.

- **Severe recession (Severely Adverse) scenario:** The model predicts an initial decline in balances followed by a slight increase in deposits. In a review of the forecasts with the line of business, this was noted that the later increase in balances is directionally consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. The line of business suggested that the magnitude of the increase should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts a significant deposits run-off to the point that balances fall below zero. A decline in balances is in line with business intuition, but the magnitude of the decline needs to be reviewed closely when the final outputs for submission are generated, as there would be a floor to balances even in extreme rate environments as long as there are assets under custody, as there will be operational deposit needs associated with the assets
- **Baseline scenario:** The baseline scenario exhibits a significant decline in balances, which is not consistent to business intuition as a significant change in balances is not expected. The forecast needs to be reviewed closely when the final outputs for submission are generated

5.1.6.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The modeling period for this segment only starts in January 2009. This means this model is calibrated on a period when interest rates are consistently near zero. As a result, this model is overly sensitive to interest rates. It is recommended that during the management review and challenge process of this segment the lack of higher interest rates during the modeling period is considered and that interest rate effects are considered in a potential management adjustment of the forecast.

Also, given the scarcity of intuitive models that could be found, a model that fails the RESET test for model specification was selected. The threshold for determining model misspecification, however, was only breached by 0.3%. Given this result, the model and its RESET test results should be monitored in future recalibrations. If the RESET test result diverges further away from the threshold, an alternate model may need to be selected.

5.2. Corporate Trust deposit balance models

5.2.1. Business overview and segments

Corporate Trust provides its clients with infrastructure, technology and processing services throughout the lifecycle of debt transactions. Services offered include asset and portfolio administration, custody and safekeeping, loan administration and structured finance. Deposit balances are influenced by the underlying dynamics of the debt transactions, which include project financing, municipal, asset-backed/mortgage-backed securities and collateral debt obligations. The clients of this business include financial institutions, corporations, insurers, government and not-for-profit organizations.

As of April 30, 2015, the Corporate Trust line of business has deposits amounting to $54.7 BN, making it the second largest individual deposit line of business for BNY Mellon.

For ALM management purposes, Corporate Trust deposits are separated into four segments, as described in Table 57: non-interest bearing USD deposits (CT DDA), interest bearing USD deposits (CT IB), interest bearing Euro deposits (CT EU) and interest bearing British Pound deposits (CT GB). Unlike Asset Servicing segments, the Corporate Trust segments are entirely composed of deposits from Corporate Trust and do not include deposits from other lines of businesses. As described earlier in Section 3.1.2, this segmentation was adopted for the purposes of balance sheet forecasting as well, to align the segmentation with those used for other business purposes.

Table 57: Segment description for Corporate Trust

Segments for Corporate Trust		
Segment	**Size ($ BN)[24]**	**Description**
CT DDA	25.6	Composed entirely of USD denominated non-interest bearing balances in demand deposit accounts.
CT IB	15.9	Contains all interest bearing Corporate Trust deposits denominated in USD currency. The products contained in this segment are Corporate Trust Cash Reserves and Corporate Trust USD Foreign Deposits. While the former is managed within the US, the latter is managed off-shore.
CT EU	10.5	The two largest non-USD denominated balances of Corporate Trust deposits are in Euro and British Pound. The models for these balances are developed in their native currencies, i.e. Euros and GBP. Both series are available starting in January 2009.
CT GB	2.7	

5.2.2. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team and the line of business, a list of driver hypotheses were developed and refined over time. Figure 55 illustrates the initial driver hypotheses that were identified through conversations with the lines of business and the ALM team in advance of the modeling process. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

[24] Month-end spot balances from April 30, 2015

Figure 55: Summary of Corporate Trust deposit balance drivers

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit balances increase when general economic health improves	• US/EU/GB GDP growth, unemployment rate
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase if other corporate trustees get downgraded, as BNYM will inherit some of these balances • Deposit balances increase if BNYM is perceived as a safer trustee than competitors	• Spread of BNYM debt rate to industry peer rate
	Banking system risk	• Deposit balances increase as banking credit risk increases, as BNYM is perceived as a relative "safe haven"	• Overnight Libor, TED Spread, Libor OIS spread
	Equity markets	• Deposit balances may increase as corporate clients are performing well and equity market is improving	• DJI, MSCI Global, KBW Bank Index, FTSE index, EuroStoxx Index
	Market volatility/ uncertainty (equity and rates)	• Deposit balances may decrease as fewer issuances are made in a volatile economy • Deposit balances may increase as the risk of holding non-cash financial instruments increases	• VIX, Market Volatility Index, Euro Stoxx Vol, FTSE 100 vol (equity) • US T-note volatility (rates)
	Debt issuances	• Deposit balances increase as total debt issuances increase	• US/EU/GB bond issuances, ABS issuances and outstanding debt
Rates	**Long-term rates and corporate credit rates**	• Deposit balances increase as long-term rates fall and refinancing activity increases	• Treasury yields, bund yields, US/UK/Eurozone swaps, corporate bond yields
	Treasury Yield Spread	• Deposit balances decrease when yield spreads widen as longer term investment yields become more attractive	• 3 month – 5 year and 3 month – 10 year Treasury yield spread

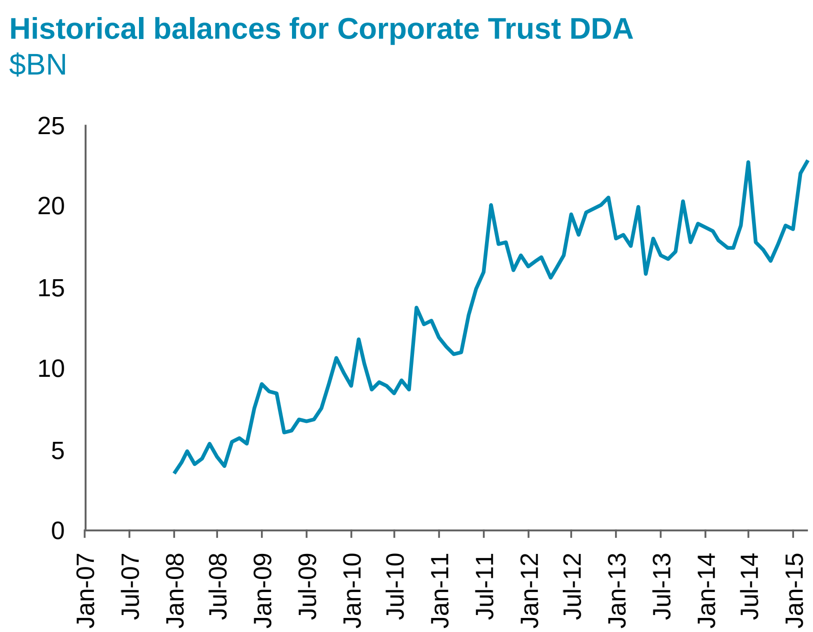
The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

5.2.3. Corporate Trust DDA

5.2.3.1. Deposit balance overview

Over the modeling time period, Corporate Trust Demand Deposit Accounts (Corporate Trust DDA, or CT DDA) balances have experienced a steady growth trend with some volatility. Notably, there was a sharp increase of balances in the first half of 2011, which can be largely attributed to the US debt ceiling crisis.

Figure 56: Historical balances for Corporate Trust DDA



5.2.3.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Corporate Trust DDA segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the CT DDA deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 58.

Table 58: Coefficient estimates for selected Corporate Trust DDA model

Corporate Trust DDA (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Market_Vol_PMoML1	Percent change – MoM	Index	-16.950	-0.28
Tot_bond_exMBSgov_PMoML1	Percent change – MoM	$ MM	4.914	0.16
Treasury5y_DMoM	First difference – MoM	%	-3528.414	-0.31

Corporate Trust DDA (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Intercept	-	$ MM	150.279	N/A

The model contains the following drivers and variables:

- **Market volatility (equities)** – Maximum of close-day value of the S&P 500 volatility index, a common benchmark of conceived market uncertainty in the broad US equity market
- **Debt issuances** – Total bond issuance excluding mortgage backed securities and government-issued bonds, a proxy for corporate bonds issuances in the US
- **Long-term rates** – Treasury 5-year yield, a long-term US interest rate

The intuition of these variables is as follows:

- Unlike other deposit segment balances, CT deposit balances are negatively correlated with market volatility index because corporations are less likely to issue debt under volatile market environment, and therefore, balances at BNY Mellon would decrease
- The total bond issuance variable has a positive coefficient, which is consistent with business intuition that deposit balances increase as total bond issuances, and therefore issuances that BNY Mellon is a trustee for, increases
- The Treasury 5-year yield has a negative coefficient, which is consistent with business intuition that deposit balances decrease as long-term rates increase. Higher long term rates would decrease debt issuances and refinancing, which would result in lower deposit balances

The Corporate Trust models result in scenario forecasts that behave quite differently from other lines of business, such as Asset Servicing. The modeling team had several discussions around the drivers used for these segments, in particular, around the sign of equity indices and market volatility measures as well as the appropriate interest rates. While the deposit balances of many other lines of business tend to be positively correlated with equity indices, the Corporate Trust line of business felt that a negative coefficient would be more appropriate. Corporate Trust deposits are mainly driven by the number of issuances that BNY Mellon obtains trusteeship for. The line of business argued that falling equity prices would reduce the relative cost of capital raised through equity and therefore reduce the number of corporate debt issuances the bank can compete for. Accordingly, as high market volatility would disrupt the debt issuance market a negative sign on market volatility was accepted upon discussions with the lines of business. It was brought to the line of business's attention that such a model would not show a flight-to-safety effect and they confirmed that they did not believe there would be a pronounced flight-to-safety effect based on their business model. Finally, because long-term interest rates are an important factor in corporate decisions to issue debt, long-term interest rates were consistently preferred over short-term interest rates. In contrast to the balances in the Asset Servicing line of business, the Corporate Trust deposits balances are not the result of individual client decisions that might factor in short-term changes in the yield on the deposits, but rather the result of the cash requirements of the deals in trusteeship at BNY Mellon. The modeling team therefore believes that the CT DDA model is aligned with the fundamental drivers of its balances as it uses the information provided by the subject matter experts. In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 57.

Figure 57: Candidate Models for Corporate Trust Demand Deposit Account

Corporate Trust Demand Deposit Account
Candidate models

	Candidate models		
Drivers Considered	**1**	**2**	**3**
Debt issuances		Total Bond Issuance (ex MBS, gov) (% MoM, 1M Lag)	
Equity markets	KBW Bank Index (% MoM)		MSCI WORLD Index (Diff QoQ)
Long-term rates	5Y Treasury (Diff MoM)	5Y Treasury (Diff MoM)	
Market volatility/ uncertainty (equity)	Market Vol (% MoM, 1M Lag)	Market Vol (% MoM, 1M Lag)	Market Vol (% MoM, 1M Lag)
Variation in balances explained through estimated first differences	**93%**	**93%**	**85%**
R-squared (differences)	**19%**	**18%**	**11%**

Final model

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model as well as sensitivity tests are described in the following sections.

5.2.3.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.2.3.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Corporate Trust DDA series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 59.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 60.

Table 59: Unit root tests and stationarity tests including a trend variable on balances

Corporate Trust DDA – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	8	-1.1	>0.10	Fail to reject unit root
Phillips-Perron	1	-3.7	0.03	Reject unit root
KPSS	5	0.24	<0.01	Reject stationarity

Table 60: Unit root tests and stationarity tests including a constant on first differences

Corporate Trust DDA – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-12	<0.01	Reject unit root
Phillips-Perron	1	-12	<0.01	Reject unit root
KPSS	2	0.03	0.97	Fail to reject stationarity

Stationarity tests for CT DDA balances yield mixed results: The PP test rejects the unit root, while the ADF test fails to reject the unit root and the KPSS test rejects stationarity. These results suggest that the CT DDA balances may not be stationary. In contrast, the monthly first difference series passes all three tests for unit root and stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the CT DDA deposit balances are modeled on their first differences.

5.2.3.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the CT DDA segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the CT business.

5.2.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 61 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the CT DDA model are statistically significant.

Table 61: Statistical significance tests of model and variables for Corporate Trust DDA

Corporate Trust DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market_Vol_PMoML1	-16.950	<1%	10%	Statistically significant
Tot_bond_exMBSgov_PMoML1	4.914	3%	10%	Statistically significant
Treasury5y_DMoM	-3528.414	<1%	10%	Statistically significant
Intercept	150.279	38%	10%	Statistically not significant

5.2.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

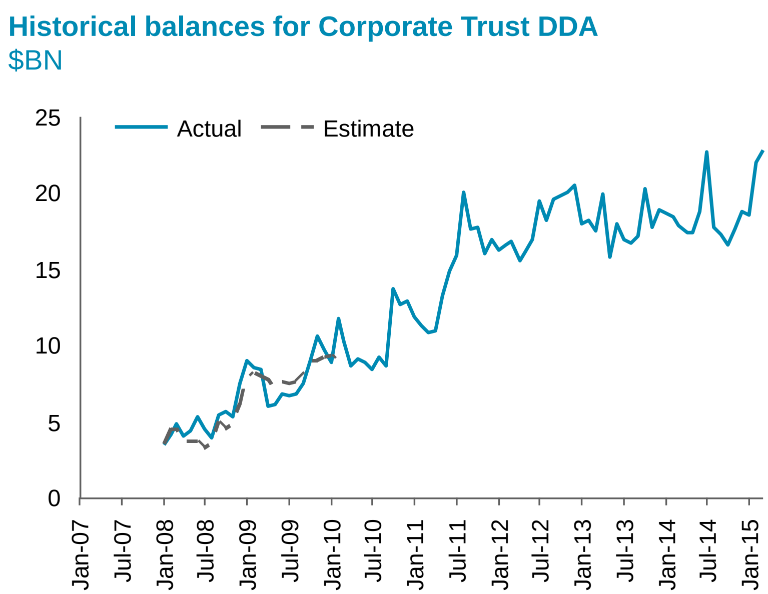
Table 62: Corporate Trust DDA Model Diagnostics

Corporate Trust DDA – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	18%	-	-
	Adjusted R-squared	15%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.99	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.27	5	No multicollinearity
Linearity	RESET test	42%	10%	Linear specification appropriate

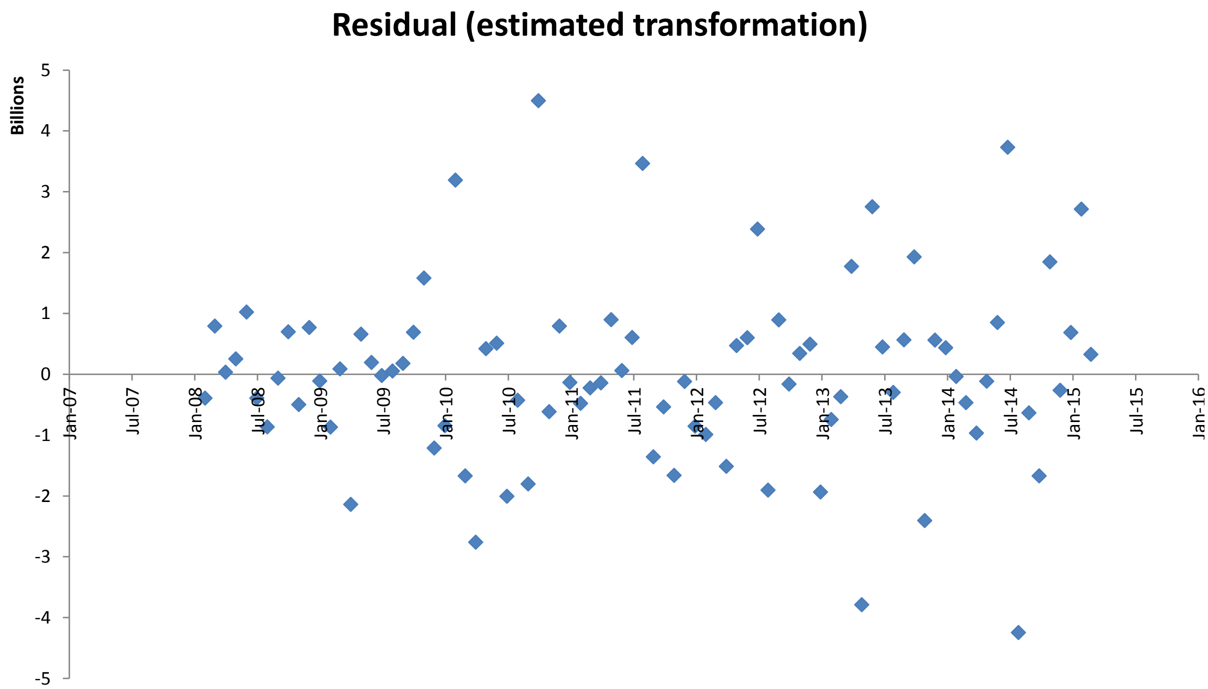
The model passes all model diagnostic tests that were evaluated, except the Breusch-Godfrey test for serial correlation.

Figure 58: Corporate Trust DDA In-sample Prediction



The in-sample back test of the model starting from January 2008 follows the balance fairly closely during the first 9 quarters.

Figure 59: Corporate Trust DDA Residual Plot ($ BN)



As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 60: Corporate Trust DDA Balance Estimation Scatterplot

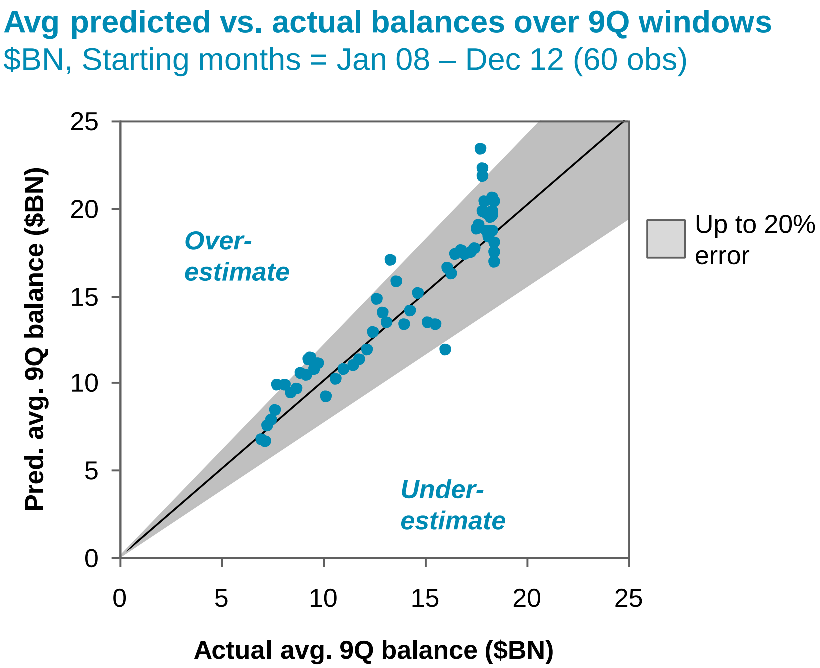
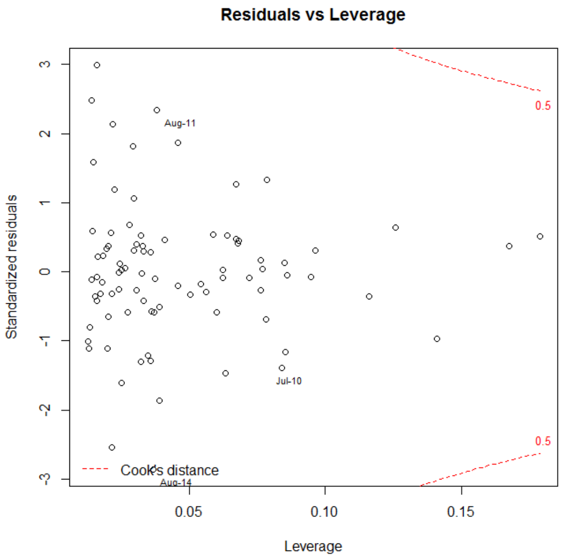


Figure 60 shows that average 9Q predictions are generally in line with the actual balances.

Figure 61: Influential points in Corporate Trust DDA



This segment has no highly influential points.

5.2.3.6. Model sensitivity

5.2.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 63. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 63: Sensitivity to changes to independent variables for Corporate Trust DDA

Corporate Trust DDA (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independen t variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Market_Vol_PMoML1	Percent change – MoM	Index	-0.28	27.15	-0.46
Tot_bond_exMBSgov_ PMoML1	Percent change – MoM	$ MM	0.16	52.12	0.26
Treasury5y_DMoM	First difference – MoM	%	-0.31	0.14	-0.51
Intercept	-	$ MM	N/A	N/A	N/A

In the CT DDA model, the Treasury 5-year yield variable has the standardized coefficient with the largest magnitude. The modeling team found that a one standard deviation increase in the changes of the Treasury 5-year yield results in a 0.31 standard deviation ($0.51 BN) decrease in the predicted monthly change of the CT DDA deposits.

5.2.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown on Figure 67.

Table 64: Statistical sensitivity tests for Corporate Trust DDA

Corporate Trust DDA (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Market_Vol_PMoML1	-16.950	-13.892	0.55	Statistically insignificant
Tot_bond_exMBSgov_PMoML1	4.914	3.155	0.37	Statistically insignificant
Treasury5y_DMoM	-3528.414	-3592.570	0.50	Statistically insignificant
Intercept	150.279	102.095	0.61	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.63	Statistically insignificant

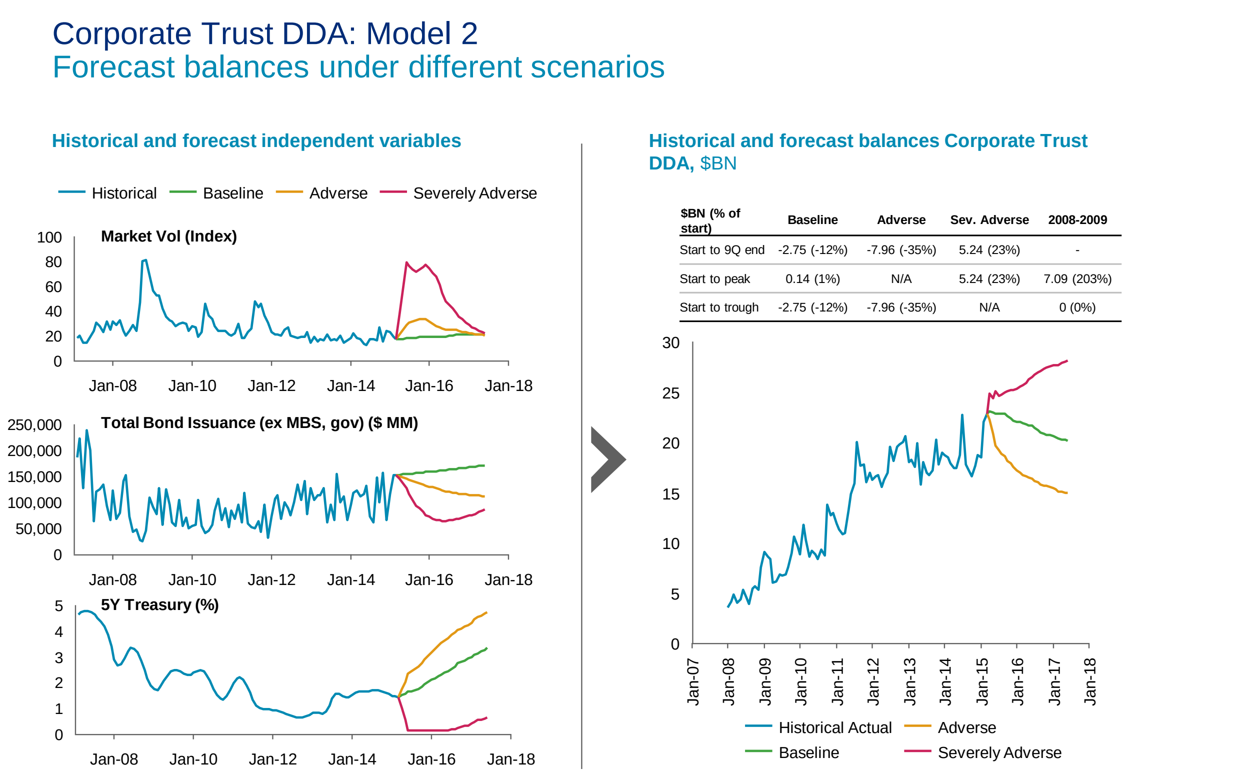
The coefficients of the shortened variables are statistically insignificant individually and collectively. This suggests the model maintains stability when removing observations from the development data.

5.2.3.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 62: Corporate Trust Demand Deposit Account Final Model Forecast



The Working Group considered the forecast behavior for the selected CT DDA model as reasonable.

Figure 62 illustrates the forecast behavior of the selected model.

- **Severe recession (Severely Adverse) scenario**: The model predicts an increase in deposits. Except for the first month in the forecasting period, the 5-year Treasury yield contributes to the forecast positively, while the total bond issuance and market volatility variables contribute negatively. Moreover, the intercept contributes positively every month. Cumulatively, after the fourth month, the contribution of the Treasury yield and the intercept consistently outweigh the negative contributions of total bond issuance and market volatility which leads to an increasing CT DDA forecast over the forecasting period. The Treasury yield on average accounts for 42% of the monthly net increases. Intuitively, this result is supported by business intuition which suggests that when treasury yields fall, long-term debt becomes more attractive to raise, which allows for growth in the Corporate Trust business.
- **Interest rate shock (Adverse) scenario**: The model predicts a deposits run-off. This was consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment
- **Baseline scenario**: The baseline scenario largely remains flat with a mild decline, which is consistent to business intuition that a significant change in balances is not expected

5.2.3.7. Model limitations

The limitations to the Corporate Trust DDA segment are discussed in Section 4.1.5.

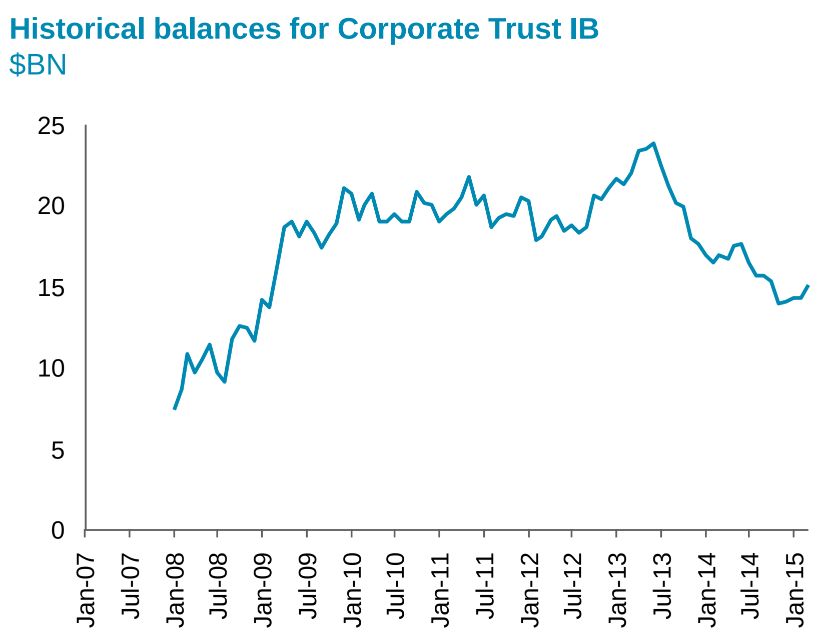
The CT DDA balances exhibited considerable rapid increases and decreases during the modeling period. For instance, there was a steep increase in CT DDA balance in 2011 in response to the US debt ceiling crisis, a political event. Not surprisingly, the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently.

5.2.4. Corporate Trust IB

5.2.4.1. Deposit balance overview

Over the modeling time period, Corporate Trust Interest Bearing (Corporate Trust IB, or CT IB) balances have experienced steep balance growth periods in times of economic stress. Most notably, during the financial crisis starting in 2008, deposit balances more than doubled in size as clients were increasingly seeking safer investments for their capital. The balances remain relatively flat in the following years, until the balances again notably increase during the 2013 US debit ceiling crisis. Balance levels have been declining since the crisis.

Figure 63: Historical balances of Corporate Trust IB



5.2.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the CT IB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the CT IB deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 65.

Table 65: Coefficient estimates for selected Corporate Trust IB model

Corporate Trust IB (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Market_Vol_DMoML1	First difference – MoM	Index	-27.588	-0.19
Treasury5y_DQoQ	First difference – QoQ	%	-559.477	-0.21
Intercept	-	$ MM	50.829	N/A

The model contains the following drivers and variables:

- **Market volatility (equities)** – The maximum close-of-day value of S&P 500 volatility index (i.e. the VIX), a common benchmark of conceived market uncertainty in the broad US equity market
- **Long-term rates** – Treasury 5-year yield, a long-term US interest rate

The intuition of these variables is as follows:

- Unlike other deposit segment balances, CT deposit balances are negatively correlated with market volatility index because corporations are less likely to issue debt under volatile market environment, and therefore, would decrease their balances with BNY Mellon
- The Treasury 5-year yield contains a negative coefficient, which is consistent with business intuition that deposit balances decrease as long-term interest rates increase. Higher long term rates would decrease debt issuances and refinancing, which would result in higher deposit balances

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 64.

Figure 64: Candidate models for Corporate Trust IB

Corporate Trust Interest Bearing
Candidate models

	Candidate models					
Drivers Considered	**1**	**2**	**3**	**4**	**5**	**6**
Debt issuances	ABS Issuance (% MoM, 1M Lag)	ABS Issuance (% MoM, 1M Lag)		ABS Issuance (% QoQ)		
Long-term rates		1Y Treasury (Diff QoQ)	2Y Treasury (Diff QoQ)	1Y Treasury (Diff MoM)	2Y Treasury (Diff QoQ)	5Y Treasury (Diff QoQ)
Market volatility/ uncertainty (equity)			Market Vol (% MoM, 1M Lag)		Market Vol (Diff MoM, 1M Lag)	Market Vol (Diff MoM, 1M Lag)
Monetary base	Fed balance sheet (% MoM)					
Banking system risk	TED Spread (Diff QoQ)					
Relative creditworthiness of BNYM		BNYM - Peer Group Debt Yield Spread (Diff QoQ)	BNYM - Peer Group Debt Yield Spread (Diff QoQ)			
Variation in balances explained through estimated first differences	**68%**	**59%**	**70%**	**77%**	**53%**	**31%**
R-squared (differences)	**19%**	**18%**	**17%**	**12%**	**9%**	**6%**

Final model

The Working Group had initially selected Model 5. During the line of business review, feedback was provided that the 2-year Treasury yield variable was not intuitive. It was indicated that the maturity was too short to capture the rate that BNY Mellon's clients would consider in their decision to issue debt or refinance debt, as the maturity the debt instruments that BNY Mellon is a trustee for is typically longer. Therefore, the final model, which contains a 5-year Treasury rate as a variable instead of the 2-year rate, was selected instead. The Working Group reviewed and commented favorably on the change.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.2.4.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.2.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Corporate Trust IB series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 66.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 67.

The log differences of the balances are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 68.

Table 66: Unit root tests and stationarity tests including a trend variable on balance

Corporate Trust IB – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-0.6	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.1	0.54	Fail to reject unit root
KPSS	5	0.3	<0.01	Reject stationarity

Table 67: Unit root tests and stationarity tests including a constant on first differences

Corporate Trust IB – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-4.7	<0.01	Reject unit root
Phillips-Perron	1	-9.1	<0.01	Reject unit root
KPSS	3	0.55	0.03	Reject stationarity

Table 68: Unit root tests and stationarity tests including a constant on log differences

Corporate Trust IB – Single mean unit root test on log difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-4.9	<0.01	Reject unit root
Phillips-Perron	1	-9.4	<0.01	Reject unit root
KPSS	4	0.68	0.01	Reject stationarity

The modeling team reviewed the balance, first difference transformation, and log transformation to determine the appropriate transformation. The CT interest-bearing balances do not pass any stationarity tests, and therefore, could not be concluded as stationary. Both the monthly first difference series and log series pass two out of the three tests for stationarity: The ADF test and PP test reject the unit root, but the KPSS test rejects stationarity. Given the conflicting results, the modeling team reviewed both series manually, and confirmed that there were no visual indications of nonstationarity for the monthly first difference series. The first difference series was selected as it provides a simpler model and allows for consistency with the other segments.

Based on these results and observations, the CT IB deposit balances are modeled on their first differences.

5.2.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the CT IB segment. As discussed previously, the data was sourced from MAQ and Microstrategy, both of whose accuracy have been confirmed with the CT business.

5.2.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 69 reports the results of the significance tests.

All of the coefficient estimates in the CT IB model are statistically significant.

Table 69: Statistical significance tests of model and variables for Corporate Trust IB

Corporate Trust IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	8%	10%	Statistically significant
Market_Vol_DMoML1	-27.588	9%	10%	Statistically significant
Treasury5y_DQoQ	-559.477	6%	10%	Statistically significant
Intercept	50.829	67%	10%	Statistically not significant

5.2.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

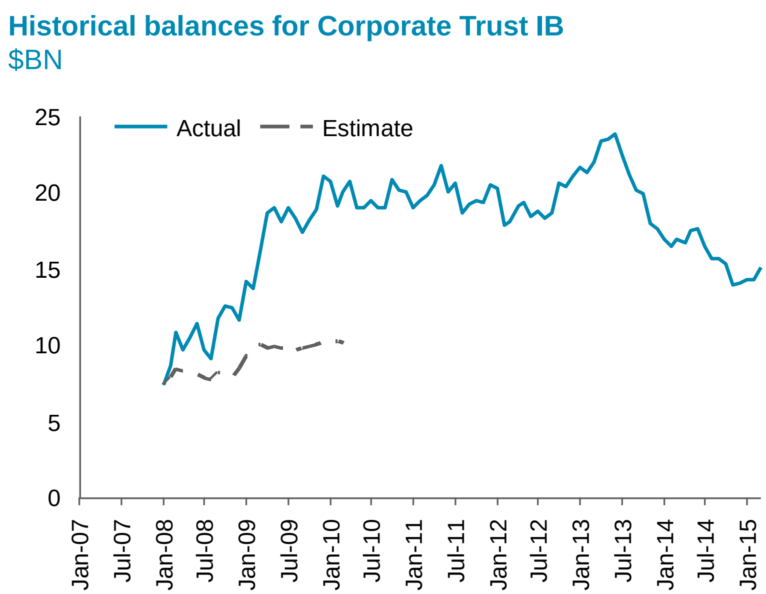
Table 70: Corporate Trust IB Model Diagnostics

Corporate Trust IB – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	6%	-	-
	Adjusted R-squared	4%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.23	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	61%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.08	5	No multicollinearity
Linearity	RESET test	82%	10%	Linear specification appropriate

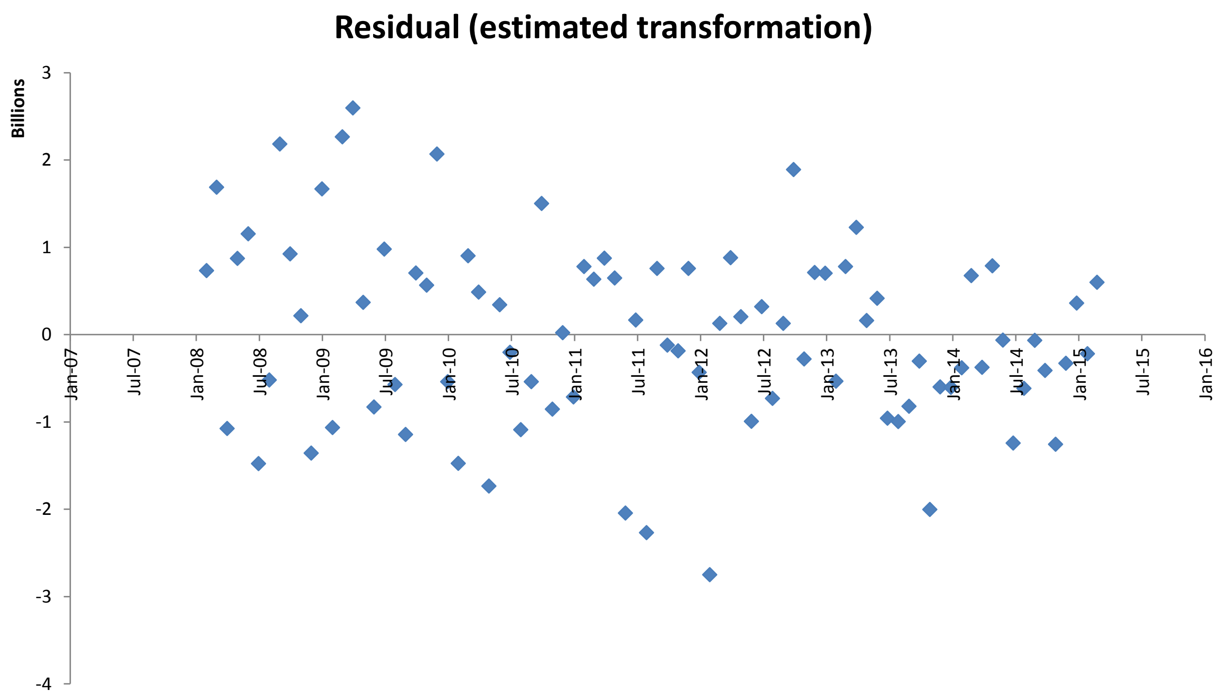
The model passes all model diagnostic tests that were evaluated.

Figure 65: Corporate Trust IB In-sample Prediction



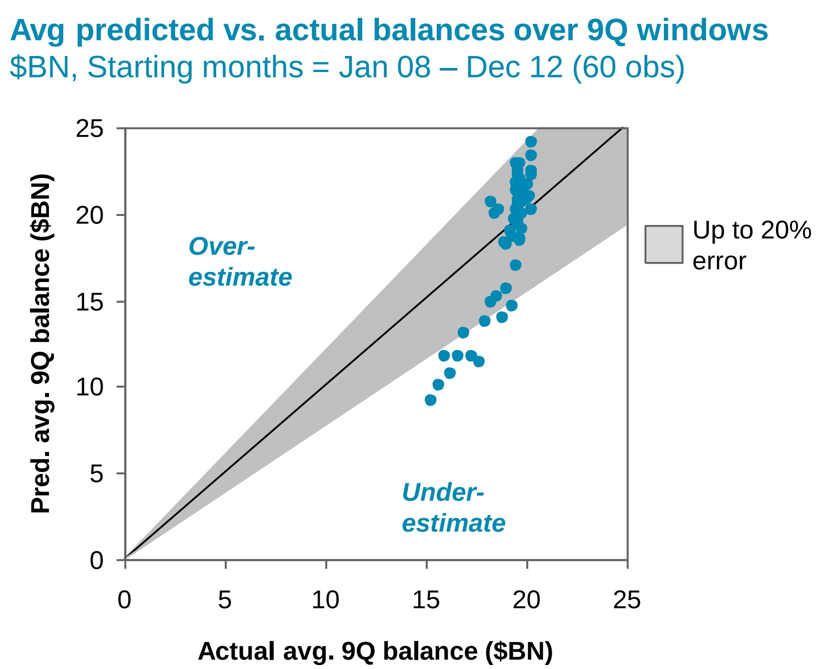
The in-sample back test of the model starting from January 2008 underestimates the CT IB balances.

Figure 66: Corporate Trust IB In-sample Prediction ($ BN)



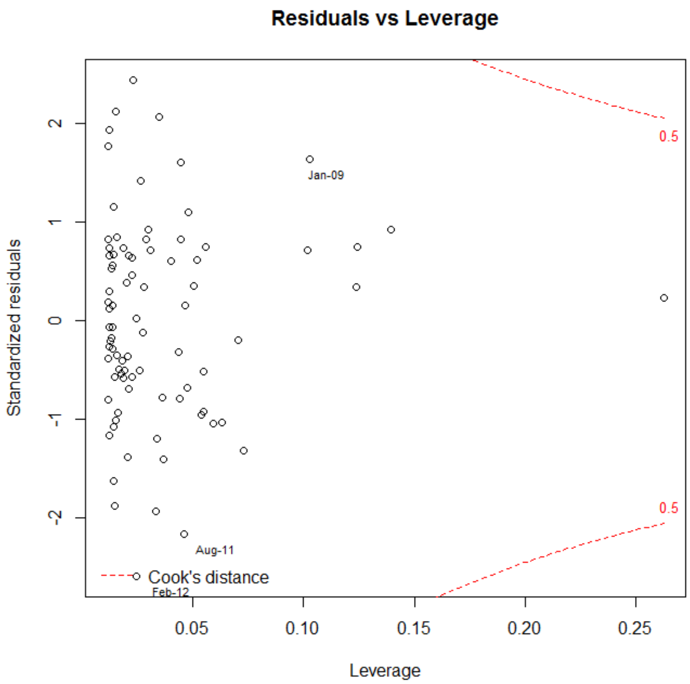
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 67: Corporate Trust IB Balance Estimation Scatterplot



The points of underestimation in Figure 67 could be attributed to the 2008 financial crisis, when the balance increase due to an unusually high surge of client demand was not captured by the model. Most of the predictions are generally in line with the actual balances of Corporate Trust IB.

Figure 68: Corporate Trust IB



This segment had no highly influential points.

5.2.4.6. Model sensitivity

5.2.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 71. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 71: Sensitivity to changes to independent variables for Corporate Trust IB

Corporate Trust IB (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Market_Vol_DMoML1	First difference – MoM	Index	-0.19	7.42	-0.20
Treasury5y_DQoQ	First difference – QoQ	%	-0.21	0.41	-0.23

Intercept	-	$ MM	N/A	N/A	N/A

In the CT IB model, the Treasury 5-year yield variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the quarterly changes of the Treasury 5-year yield results in a 0.21 standard deviation ($0.23 BN) decrease in the predicted monthly change of the CT IB deposits.

5.2.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 72.

Table 72: Statistical sensitivity tests for Corporate Trust IB

Corporate Trust IB (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Market_Vol_DMoML1	-27.588	-20.182	0.45	Statistically insignificant
Treasury5y_DQoQ	-559.477	-347.740	0.50	Statistically insignificant
Intercept	50.829	191.112	0.15	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.31	Statistically insignificant

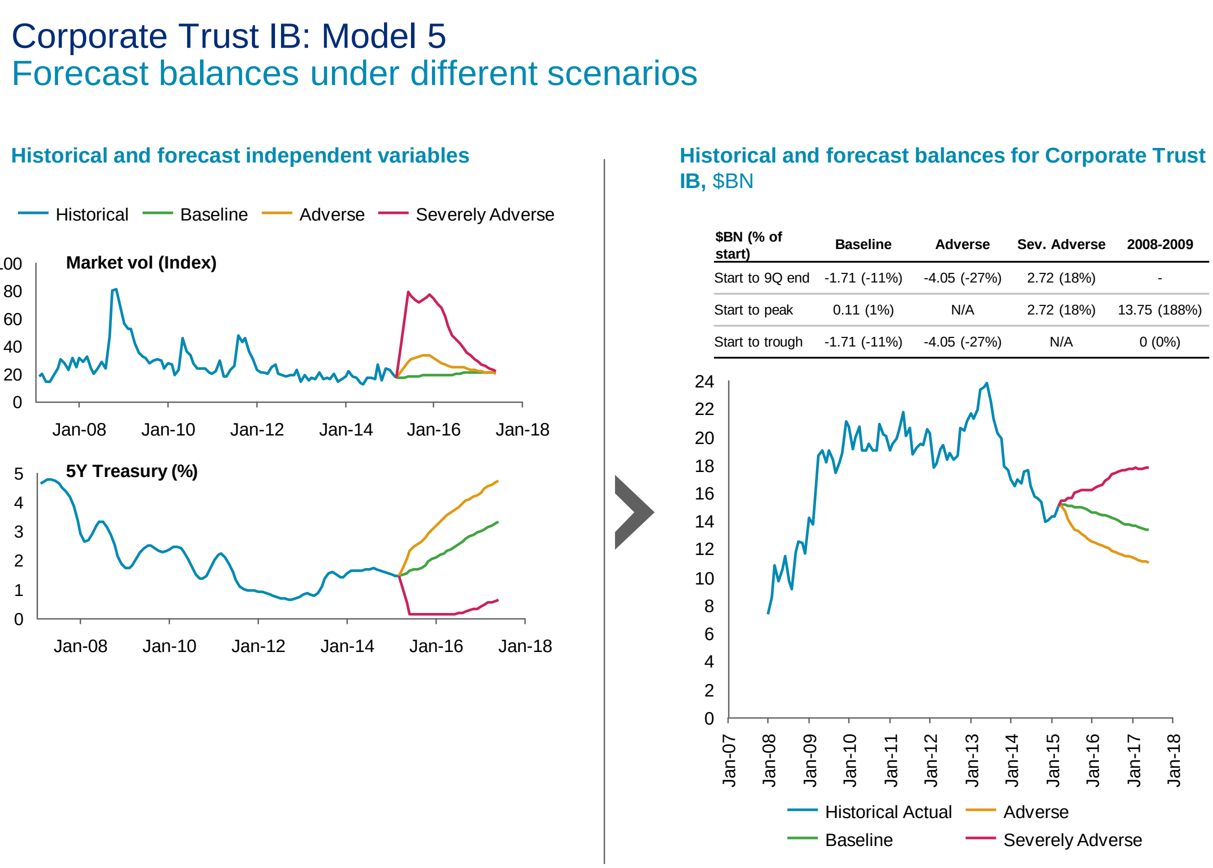
The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data.

5.2.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 69: Corporate Trust Interest Bearing Final Model Forecast



The Working Group determined that the forecast behavior for the selected Corporate Trust Interest Bearing model as reasonable.

The model forecasts are illustrated on Figure 69.

- **Severe recession (Severely Adverse) scenario**: The balances show a modest increase, as clients display a "flight to safety" behavior towards their BNY Mellon accounts
- **Interest rate shock (Adverse) scenario:** The balances experience a modest decrease. This is driven in part by the substitution effect by the 5-year Treasury yield: the higher the long-term Treasury rate, the less likely corporations would be willing to refinance their debt, hence drive down the Corporate Trust deposits
- **Baseline scenario**: The baseline scenario largely remains flat with a mild decline, which is consistent to business intuition that a significant change in balances is not expected

5.2.4.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

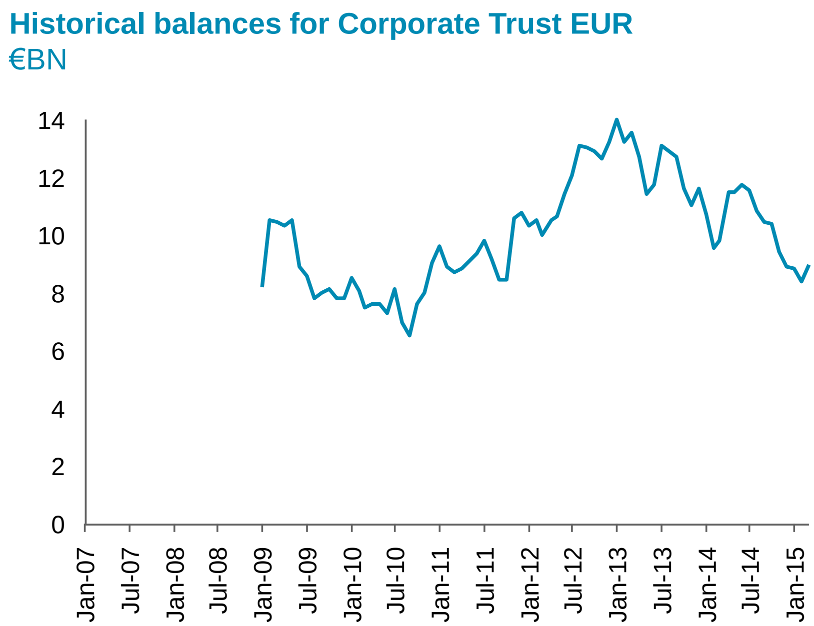
The CT IB balances exhibited considerable, rapid increases during the modeling period. For instance, CT IB balances increased almost two-fold during the financial crisis. In addition, the balances once again grew rapidly in 2013 as a response to the US debt ceiling crisis. The modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently. While it is not expected that the model would predict a political event such as the debt ceiling crisis, the under-prediction of the balances during the 2008 and 2009 global financial crisis needs to be considered during the management review and challenge process.

5.2.5. Corporate Trust EU

5.2.5.1. Deposit balance overview

Over the modeling time period, Corporate Trust EU (CT EU) balances have experienced a varied trend. In the beginning of 2009, balances experienced a sharp increased, followed by a decline of equal magnitude mid-2009. Balances then experienced growth from mid-2009 to 2013, but balances have followed a downward trend more recently.

Figure 70: Historical balances for Corporate Trust EU



5.2.5.2. Model summary

A statistically sound model that is consistent with business intuition was found for the CT EU segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the CT EU deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 73.

Table 73: Coefficient estimates for selected Corporate Trust EU model

Fgn Corporate Trust EU (in EUR MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
ABS Issuance	Percent change – QoQ	€MM /% chg	1.42	0.30
EU Inflation	Difference YoY	€MM /% chg	96.43	0.26

Intercept	-	€ MM	-32.79	N/A

The model contains the following drivers and variables:

- **Debt Issuances** –ABS Issuance caputres the size of the US asset-backed securities issuance market, a proxy for size of the market in Europe
- **Monetary Base**–EU inflation is a proxy for monetary expansion.

The intuition of these variables is as follows:

- The more debt issuances there are, the more business BNY Mellon is expected to have in their Corporate Trust business. The line of business has indicated that the asset-backed securities market is one of the most important markets for the European Corporate Trust business

With higher inflation, more debt issuances are expected in the economy as the monetary supply expands. In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 71.

The working group initially had decided to use model 3, however this modelwas rejected by model risk management, in further ocnverstaion with the lines of business it was decided to use model #4 as a replacement.

Figure 71: Candidate models for Corporate Trust EU

Corporate Trust EUR
Candidate models

Drivers Considered	Candidate models 1	2	3	4	5
Debt issuances				ABS Issuance (% QoQ)	
Equity markets	DJI (% MoM, 1M Lag)	DJI (% MoM, 1M Lag)	MSCI WORLD Index (% QoQ)		
Market volatility/ uncertainty (equity)	Market Vol (% QoQ)	Euro Stoxx Volatility Index (% QoQ)	Euro Stoxx Volatility Index (% QoQ)		S&P Vol (30D MAVG) (Diff QoQ)
Monetary base	EU inflation (Diff YoY)			EU inflation (Diff YoY)	EU inflation (Diff YoY)
Variation in balances explained through estimated first differences	36%	7%	38%	13%	10%
R-squared (differences)	24%	18%	11%	11%	10%
Comments	• Includes EU variable	• Includes EU variable • MSCI in model #3 preferred over DJI	• Includes EU variable	• Includes EU variable	• Includes EU variable

Final Model

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.2.5.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.2.5.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The CT EU series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 74.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 75.

Table 74: Unit root tests and stationarity tests including a trend variable on balance

Corporate Trust EU – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-1.3	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.8	0.71	Fail to reject unit root
KPSS	5	0.18	0.02	Reject stationarity

Table 75: Unit root tests and stationarity tests including a constant on first differences

Corporate Trust EU – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-6.9	<0.01	Reject unit root
Phillips-Perron	1	-8.3	<0.01	Reject unit root
KPSS	3	0.14	0.42	Fail to reject stationarity

Stationarity tests for CT EU balances do not pass any stationarity tests. These results suggest that the CT EU balances is not stationary. In contrast, the monthly first difference series passes all three tests for stationarity: The ADF and PP tests reject unit root, as well as the KPSS test failing to reject stationarity.

Based on these results, the CT EU deposit balances are modeled on their first differences.

5.2.5.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the CT EU segment. As discussed previously, the data was sourced from Microstrategy and its accuracy was confirmed with the CT business.

The modeling period for this segment starts in January 2009 as Microstrategy data is not available before that month.

5.2.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold

- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 76 reports the results of the significance tests.

All of the coefficient estimates in the CT EU model are statistically significant.

Table 76: Statistical significance tests of model and variables for Corporate Trust EU

Corporate Trust EU (in EUR MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)		2%	10%	Statistically significant
ABS Issuance (% QoQ)	1.42	1%	10%	Statistically significant
EU Inflation (Diff YoY)	96.43	3%	10%	Statistically significant
Intercept	-32.79	71%	10%	Statistically not significant

5.2.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

Table 77: Corporate Trust EU Model Diagnostics

Corporate Trust EU – Model diagnostics

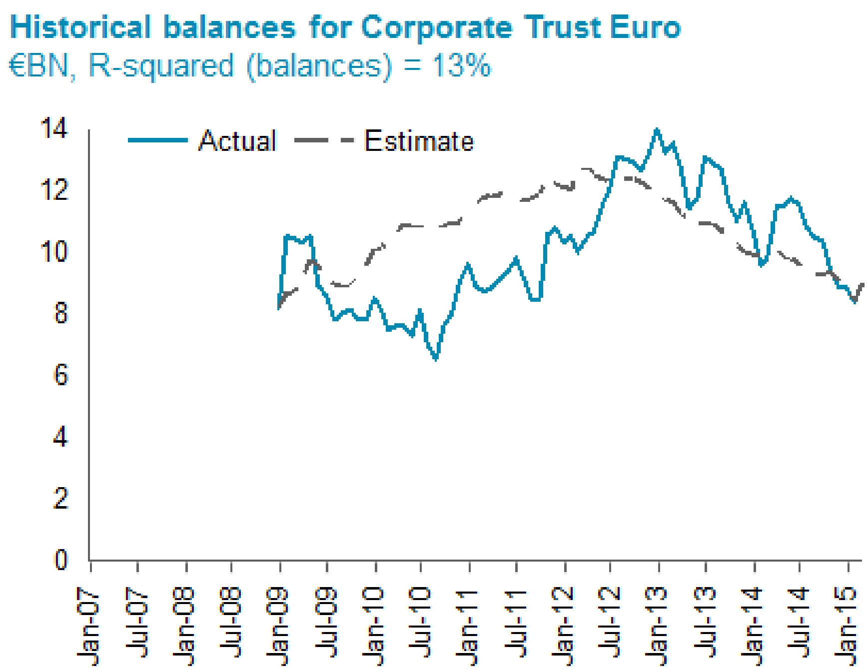
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	10.5%	-	-
	Adjusted R-squared	8%	-	-

Corporate Trust EU – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Heteroskedasticity	Breusch-Pagan test (p-value)	0.03	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	11 %	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.12	5	No multicollinearity
Linearity	RESET test	51 %	10%	Linear specification appropriate

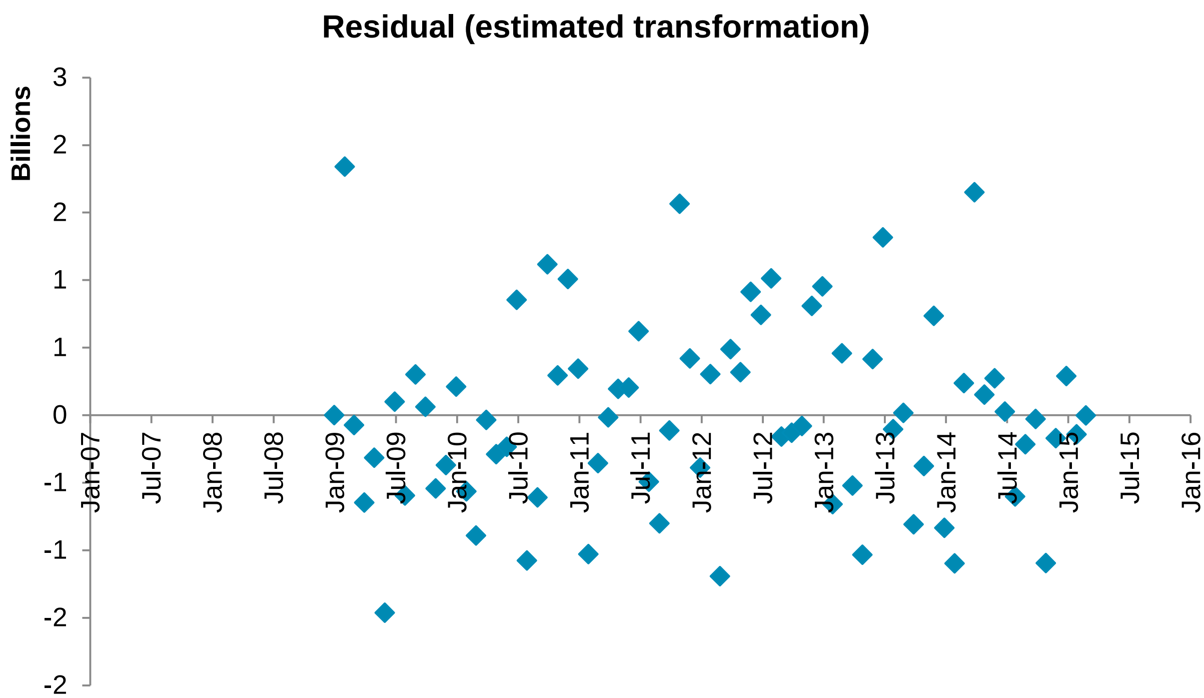
The model passes all model diagnostic tests that were evaluated.

Figure 72: Corporate Trust EU In-sample Prediction



The in-sample back test of the model starting from January 2009 follows the balance closely.

Figure 73: Corporate Trust EU Residual Plot (€ BN)



As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 74: Corporate Trust EU Balance Estimation Scatterplot

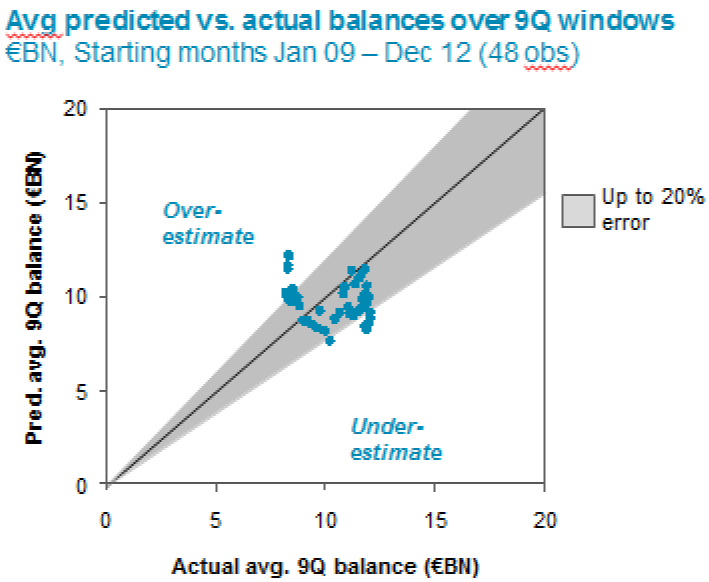
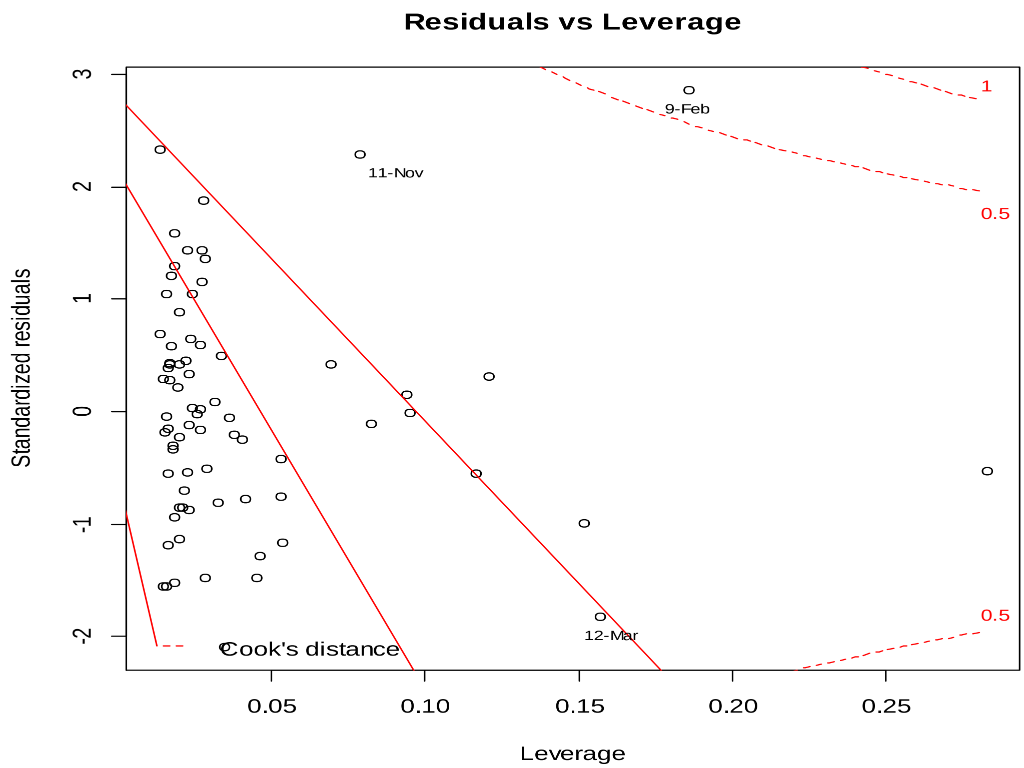


Figure 74 shows that most 9Q average balance predictions are generally in line with actual balances.

Figure 75: Influential points in Corporate Trust EU (scheduled to be updated during regular model maintenance after CCAR 2016)



The segment has no highly influential points with Cook's distance larger than 1.

5.2.5.6. Model sensitivity

5.2.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 78. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 78: Sensitivity to changes to independent variables for Corporate Trust EU

Corporate Trust EU (in EUR MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in

					the independent variable (€ BN)
ABS_issuance_PQoQ	Percent change – QoQ	€MM /% chg	0.30	155.98	0.22
Euro_inf_DYoY	First Difference - YoY	€MM /% chg	0.26	2.12	0.20
Intercept	-	€MM	0.00	N/A	N/A

In the CT EU model, the MSCI World Index variable has the standardized coefficient with the largest magnitude. The modeling team found that a one standard deviation increase in the quarterly changes of the MSCI World Index results in a 0.39 standard deviation (€0.29 BN) decrease in the predicted monthly change of the CT EU deposits.

5.2.5.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 79.

Table 79: Statistical sensitivity tests for Corporate Trust EU

Corporate Trust EU (in EUR MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
ABS_issuance_PQoQ	1.42	1.07	0.95	Statistically insignificant
Euro_inf_DYoY	96.43	46.73	0.11	Statistically insignificant
Intercept	-32.79	32.26	0.78	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.38	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data.

5.2.5.6.3. Sensitivity to stressed independent variable scenarios

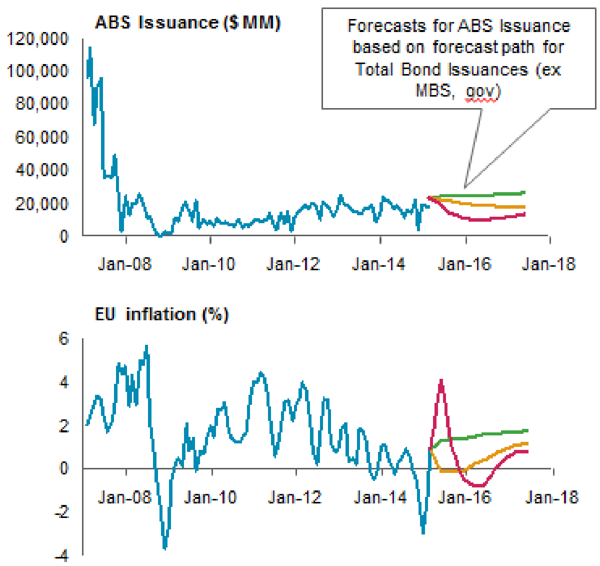
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model’s forecast behavior was tested for different macroeconomic scenarios.

Figure 76: Corporate Trust EU Model Forecast

Corporate Trust Euro: Alternative Model 1
Forecast balances under different CCAR scenarios

Historical and forecast independent variables



Historical and forecast balances for Corporate Trust Euro
€BN

€BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	1.38 (15%)	0.35 (4%)	-0.37 (-4%)	-
Start to peak	1.51 (17%)	0.35 (4%)	1.15 (13%)	N/A
Start to trough	N/A	-0.57 (-6%)	-1.09 (-12%)	N/A

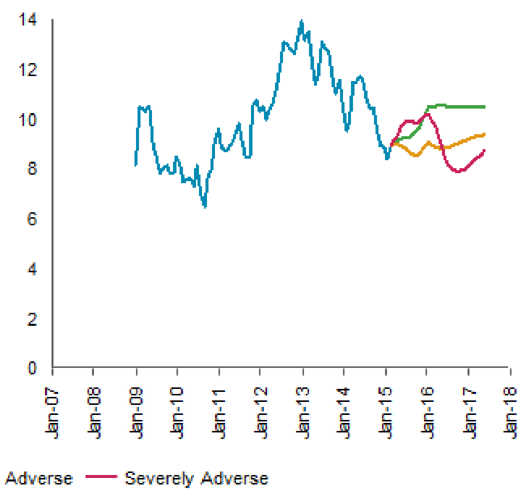
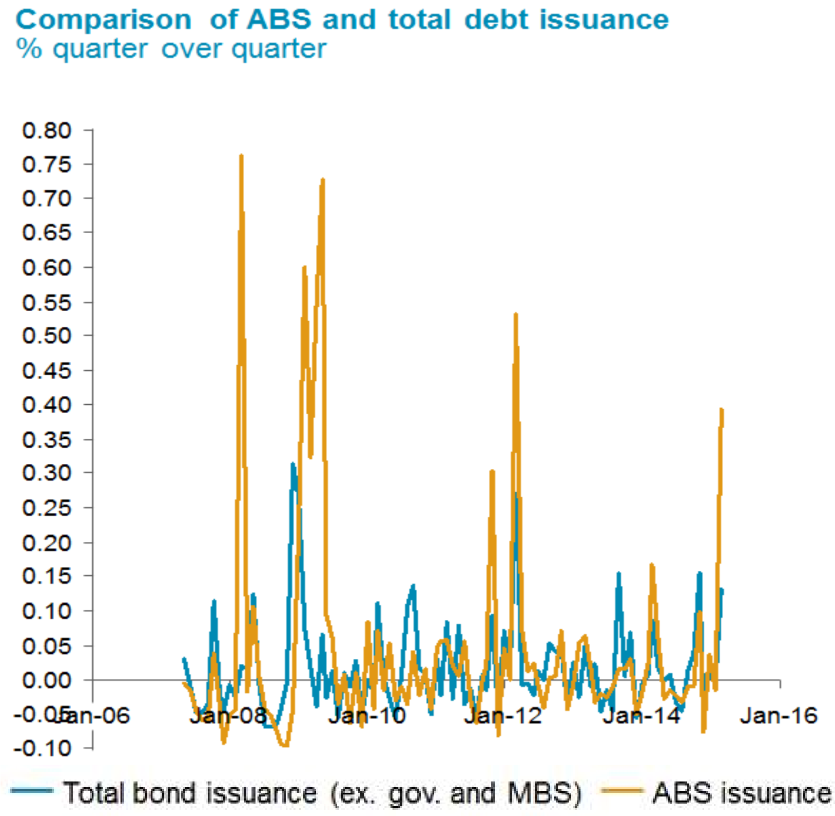


Figure 76 illustrates the forecast behavior of the selected model

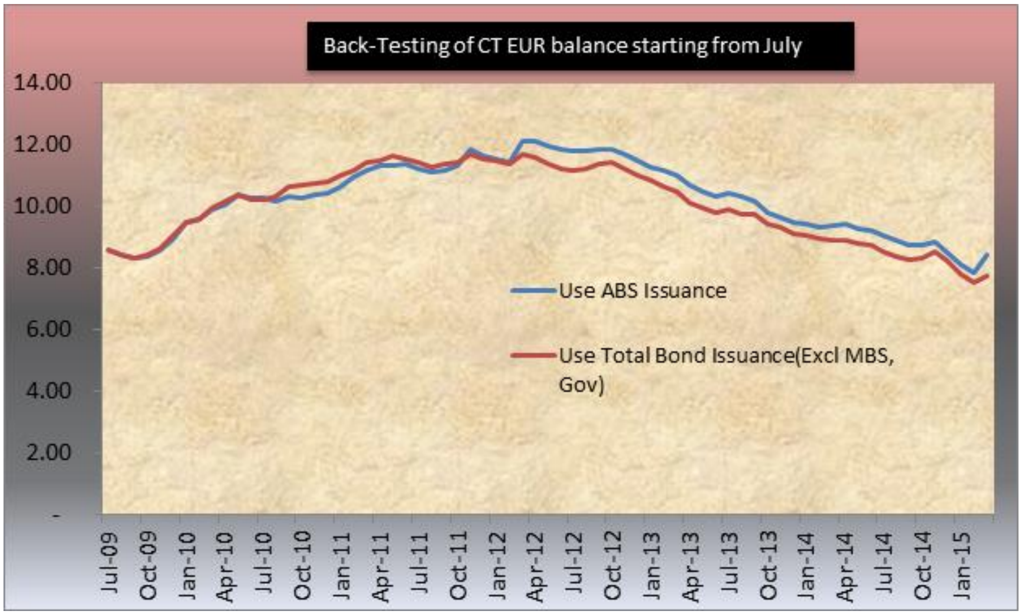
- **Severe recession (Severely Adverse) scenario**: The balances experience a slight increase initially but drop off as the crisis worsens
- **Interest rate shock (Adverse) scenario:** The balances remain at the current level with small fluctuations as macroeconomic factors remain steady
- **Baseline scenario**: The baseline scenario displays an increase in balances as the issuance markets grow in a steady economy.

The projection above is using CCAR 2015 scenarios. For ABS issuance, the proxy variable of Total Bond Issuance (ex MBS, Gov) is used in 2016 CCAR forecasting because ABS issuance forecasts were not available for CCAR 2016 from Moody's. A review of all of the variables that were forecasted by Moody's revealed that the Total Bond Issuances (excl MBS, Gov) as an appropriate proxy, as ABS issuance is the main component of total bond issuance (excl MBS, Gov) and the historical movement of the variables align.

Figure 71 Comparison of ABS and total debt issuance (ex MBS, gov)



Below is the Corporate Trust Euro balance historical back-testing result starting from July 2009. The use of ABS Issuance and Total Bond Issuance (Excl MBS, Gov) do not differentiate much on the balance outputs over 69 months. This supports the proposal that using Total Bond Issuance (Excl MBS, Gov) as a proxy of ABS issuance is appropriate in Corporate Trust Euro balance model.



5.2.5.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

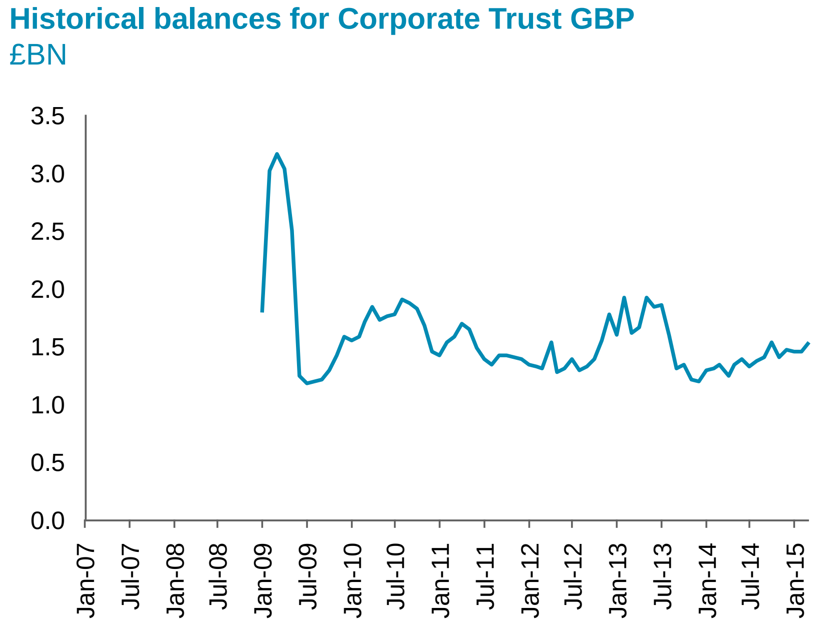
The modeling period for this segment only starts in January 2009. This means this model is calibrated on a period when interest rates are consistently low. It is recommended that during the management review and challenge process of this segment the lack of higher interest rates during the modeling period is considered and that interest rate effects are considered in a potential management adjustment of the forecast.

5.2.6. Corporate Trust GBP

5.2.6.1. Deposit balance overview

Over the modeling time period, Corporate Trust GBP (CT GBP) balances have remained between GBP1 BN and 2 BN. One exception was in the beginning of 2009 following the 2008 financial crisis, when the balances experienced a sharp increase and a subsequent decline of similar magnitude.

Figure 77: Historical balances for Corporate Trust GBP



5.2.6.2. Data issues

The modeling team examined the historical values for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the CT GBP segment. As discussed previously, the data was sourced from Microstrategy and its accuracy was confirmed with the CT business. The modeling period for this segment starts in January 2009 as Microstrategy data is not available before that month.

5.2.6.3. Summary of approach

A simple model was developed in which the CT GBP balance forecast would be tied to the CT Euro forecast. To do so, the historical average proportion of CT GBP to CT Euro balances will be calculated and used to scale down the size and magnitude of the CT Euro segment forecasts such that they are appropriate for the smaller CT GBP segment.

5.2.6.3.1. Approach

The simple model links the forecasts for the CT GBP deposits to the forecasts for the CT Euro deposits. The line of business considers the CT GBP segment to have similar deposit dynamics as the CT Euro segment and felt comfortable linking the two forecasts.

The creation of the CT GBP forecasts is a two-step process. The goal is to apply the CT Euro forecasts in a magnitude that is appropriate for the CT GBP segment.

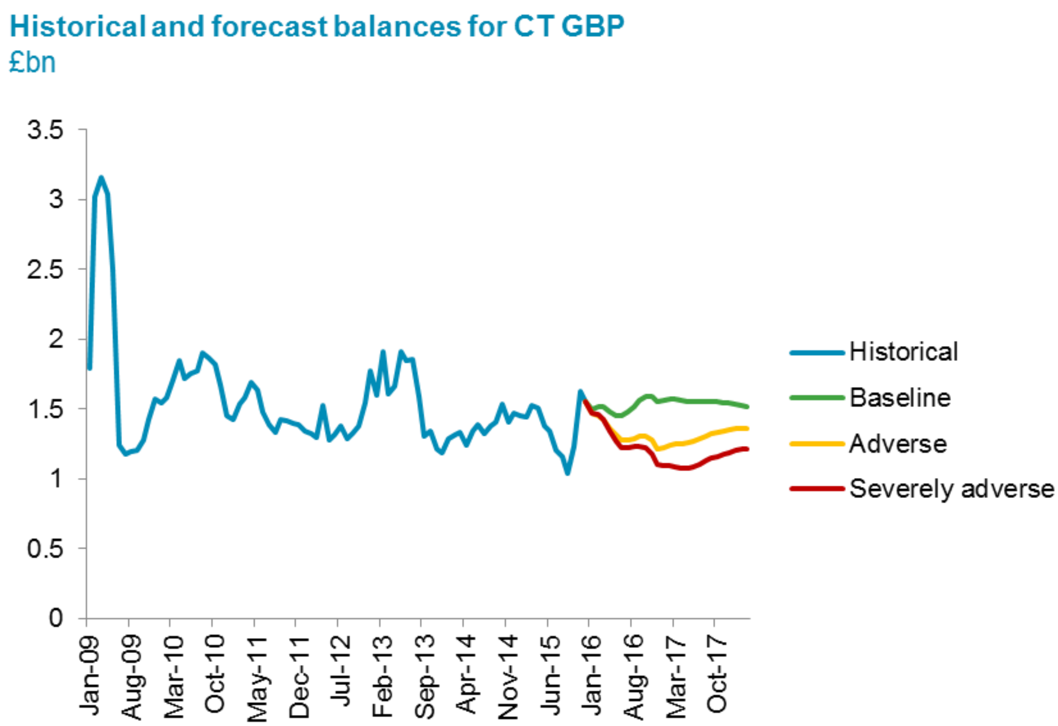
First, to create the proper magnitude, a scaling factor needs to be determined. The scaling factor is calculated as the proportion of CT GBP balances to CT Euro balances over the most recent three months.

$$Scaling\ factor = \frac{Sum\ of\ last\ 3\ month\ balances\ for\ CT\ GBP}{Sum\ of\ last\ 3\ month\ balances\ for\ CT\ Euro}$$

Next, this scaling factor is applied to each month of the CT Euro balance forecast to scale it down to an appropriate size for CT GBP.

$$CT\ GBP\ Month\ A\ forecast = \ CT\ Euro\ Month\ A\ forecast * Scaling\ factor$$

Figure 78 Historical and forecast balances for CT GBP



5.2.6.3.2. Previous Statistical approach

A model for CT GBP was developed as part of the Balance and Rate Forecasting Model that the ALM team developed in 2015.

Due to the limited data availability for the foreign currency deposit segments, the CT GBP model had weaknesses. The weakness is as following: The modeling period for this segment only starts in January 2009. This means this model is calibrated on a period when interest rates are consistently near zero. As a result, this model is overly sensitive to interest rates. It was during the management review and challenge process of this segment that the lack of higher interest rates during the modeling period was recognized and interest rate effect was considered to be adjusted in the future.

The Model Validation process resulted in a rejection of the CT GBP model. The Model Validation team assessed the model's output to be counter-intuitive. As a result of this feedback, the model development team presented two alternative candidate models to the IMG Group (the segment's line of business). One of the alternative models contained MSCI World, S&P Volatility and 30-year Treasury yield as variables and the other contained MSCI World, FTSE Volatility, and total bond Issuance as variables.These models were discussed in a meeting with the IMG Group on January 26, 2016, and the IMG group gave feedback that neither model could be supported with business intuition. The IMG group did support linking the forecast path of the CT GBP segment with the CT Euro balances as they considered the two markets to be quite similar, with the English market considered to be less sensitive or reactive. Thus, a simple model was adopted.

5.2.6.4. Model limitations

The CT GBP placement approach has the same limitations, if any, as the CT EUR model.

5.3. Treasury Services deposit balance models

5.3.1. Business overview and segments

The Treasury Services business includes working capital and cash management solutions, trade finance services, international payment services, Global Markets, capital markets and liquidity services. To effectively manage their financial supply chain and working capital, clients maintain liquidity in the form of deposits, investments, and lines of credit with BNY Mellon's Treasury Services. As of April 30, 2015, the Treasury Services line of business had deposits totaling $43.9 BN.

For ALM management purposes, Treasury Services deposits are separated into two segments described in Table 80: interest bearing deposits (TS IB) and non-interest bearing deposits (TS DDA). As described earlier in Section 3.1.2, this segmentation was adopted for the purposes of balance sheet forecasting as well, to align the segmentation with those used for other business purposes. The Treasury Services deposits denominated in Euro and British Pound were pooled with the Asset Services balances in the respective currencies as Treasury Services balances did not meet the materiality criteria. They are considered most similar to the Asset Servicing Deposits and were therefore pooled with the Asset Servicing interest bearing deposits in Euros and British Pound, respectively.

Table 80: Segment description for Treasury Services

Segments for Treasury Services		
Segments	**Size ($ BN)[25]**	**Description**
TS DDA	15.4	Composed entirely of USD denominated non-interest bearing balances in demand deposit accounts.
TS IB	28.5	Contains all interest bearing Treasury Services deposits denominated in USD currency. The sub-segments within it include Late Night Investments (LNI), Checking with Interest (CWI), foreign deposits in USD, Treasury Services MMDAs, Rent Secured deposits, and interest bearing demand deposit accounts (IB DDA).

The models for each of the Treasury Services sub-segments are discussed in sequence in the subsequent sections.

5.3.2. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team and the line of business, a list of driver hypotheses were developed and refined over time. Figure 79 illustrates the initial driver hypotheses that were identified through conversations with the lines of business and the ALM team in advance of the modeling process. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

[25] Month-end spot balances from April 30, 2015

Figure 79: Summary of Treasury Services deposit balance drivers

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit balances increase when general economic health improves	• Real GDP growth, unemployment rate
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase as BNYM is perceived as a relative "safe haven"	• Spread of BNYM debt rate to industry peer rate
	Banking system risk	• Deposit balances increase as banking credit risk increases, as BNYM is perceived as a relative "safe haven"	• Overnight Libor, TED Spread, Libor OIS spread
	Equity markets	• Deposit balances may increase as corporations have increasingly better performance • Deposit balances may decrease as corporations are more likely to reinvest excess cash into their business	• DJI, KBW Bank Index, FTSE, MSCI
	Market volatility/ uncertainty (equity/rates)	• Deposit balances increase as market volatility and uncertainty increases	• VIX (equity) • 10 Year T-Note volatility index (rates)
	Financial stability of US government	• Deposit balances increase when there is a shock decline to the perceived creditworthiness of the US government	• 1-3 month Treasury yield spread
Rates	**Short-term rates**	• Deposit balances decrease as short-term interest rates increase, as spreads with competitors and alternatives widen	• Prime Rate, Fed Funds effective rate, 1 & 3 month Treasury rate, SONIA, EONIA, Overnight Repo rate, T-Bill index spread with Fed funds effective rate
	Corporate credit rates	• Deposit balances may increase as credit risk in the economy increases • Deposit balances may decrease as corporations chase higher yielding products in higher rate environments	• Corporate BAA, BAA to Treasury spread
	Yield spread	• Deposit balances may decrease when yield spreads widen as longer term investment yields become more attractive	• 3 month – 5 year and 3 month – 10 year Treasury yield spread
FX	**FX rates (to USD)**	• Deposit balance increases when the USD appreciates against the GBP and EUR	• USD/EUR rate, USD/GBP rate

1. Mutual fund cash flow, hedge fund indices and long term rates were also tested as extra drivers.

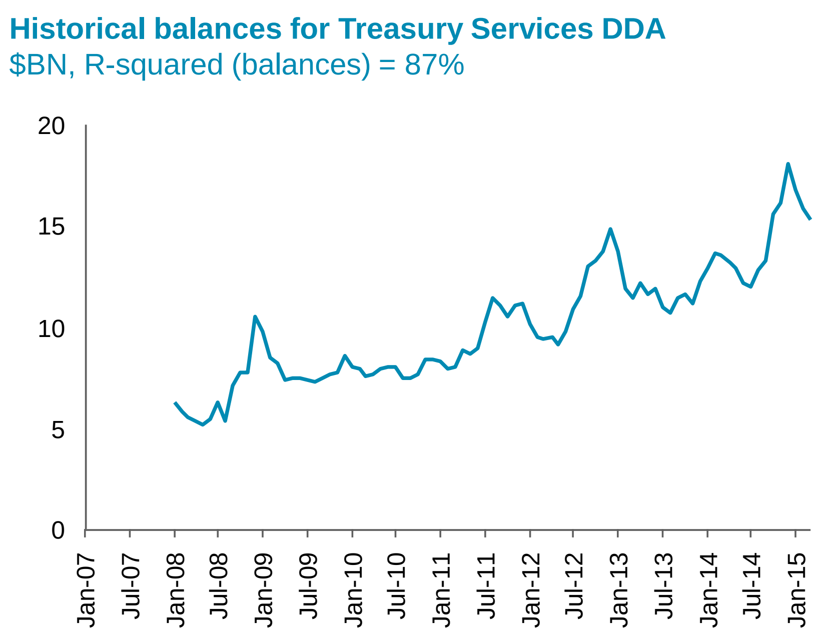
The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

5.3.3. Treasury Services DDA

5.3.3.1. Deposit balance overview

Over the modeling time period, Treasury Services Demand Deposit Account (Treasury Services DDA, or TS DDA) balances have shown a steady upward trend. Most notably balances experienced a large increase during the 2008 financial crisis as clients were increasingly seeking safer investments for their capital. This type of behavior occurred during the debt ceiling crises of 2011 and 2013 as well.

Figure 80: Historical Balances for Treasury Services DDA



5.3.3.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Treasury Services DDA segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the TS DDA deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed on Figure 90.

Table 81: Coefficient estimates for the Treasury Services DDA model

Treasury Services DDA (in USD MM)

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Market_Vol_PMoM	Percent change – MoM	Index	10.146	0.35
Stock_MF_CF_DMoM	First difference – MoM	$ MM	-0.027	-0.18
Intercept	-	$ BN	88.133	N/A

The model contains the following drivers and variables:

- **Market Volatility (equities)** – S&P 500 volatility index (i.e. the VIX), a common benchmark of conceived market uncertainty in the broad US equity market
- **Mutual Fund Cash Flow –** Stock Mutual Fund Cash Flow, a measure of mutual fund activity in the market

The intuition of these variables is as follows:

- Market Volatility has a positive coefficient, consistent with the hypothesis, as well as observed behavior during the 2008 financial crisis, that BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress
- Stock Mutual Fund Cash Flow has a negative coefficient, consistent with the hypothesis that deposit balances decrease as money market funds attract more capital in a substitution effect to deposits

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Alternative models were considered prior to selecting the final model following the model-based approach described in Section 3.3. The shortlisted models for this segment are listed in Figure 81.

Figure 81: Candidate Models for Treasury Services DDA

Treasury Services Demand Deposit Accounts
Candidate models

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Corporate credit				Baa to Treasury Spread (Diff MoM, 1M Lag)	
Equity markets		MSCI WORLD Index (Diff QoQ)			
FX rates (to USD)	USD/GBP (Diff MoM)				
General economic health			Real GDP growth (Level, 1M Lag)		
Mutual Fund Cash Flow					Stock Mut Fund Cash Flow (Diff MoM)
Market volatility/ uncertainty (equity)	Market Vol (Diff QoQ)	Market Vol (% QoQ)	Market Vol (% QoQ)	Market Vol (% MoM)	Market Vol (% MoM)
Banking system risk	1 week LIBOR-OIS spread (Diff MoM, 1M Lag)	1 week LIBOR-OIS spread (Diff MoM, 1M Lag)	1 week LIBOR-OIS spread (Diff MoM, 1M Lag)	1 week LIBOR-OIS spread (Diff MoM, 1M Lag)	
Variation in balances explained through estimated first differences	**87%**	**85%**	**87%**	**85%**	**87%**
R-squared (differences)	**29%**	**28%**	**27%**	**27%**	**18%**

Final model

Additional drivers tested: Relative creditworthiness of BNYM, Hedge fund index, Short-term rates, Market volatility/ uncertainty (rates), Long-term rates, Financial stability of US government, Yield spread

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model as well as sensitivity tests are described in the following sections.

The Working Group had initially selected Model 2. During the line of business review, feedback was provided that the negative coefficient on the Libor-OIS variable was unintuitive, as one would expect the TS deposits to be positively correlated to the Libor OIS spread. Candidate Models 1, 3 and 4 also contained the same variable with a negative coefficient. Therefore, the final model, which does not contain the Libor-OIS spread, was selected instead.

5.3.3.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.3.3.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. All Treasury Services deposit balance segments are tested to see if they are growth variables, as there is a possibility that they could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 82.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 83.

Table 82: Unit root tests and stationarity tests including a trend variable on balances

Treasury Services DDA (in USD MM) – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-4.1	0.01	Reject unit root
Phillips-Perron	1	-3.2	0.09	Reject unit root
KPSS	5	0.09	0.22	Fail to Reject stationarity

Table 83: Unit root tests and stationarity tests including a constant on first differences

Treasury Services DDA (in USD MM) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-8.1	<0.01	Reject unit root
Phillips-Perron	1	-8.1	<0.01	Reject unit root
KPSS	1	0.04	0.95	Fail to Reject stationarity

Stationarity tests for TS DDA balances show that the level passes across all three tests for stationarity. This means that the TS DDA balances can be considered trend-stationary. A trend-stationary series can be included in a regression after the time trend is removed. The modeling team considered this estimation strategy for TS DDA. However, it finally decided not to use this version of the model as it was uncertain how long such a trend would persist and if it would persist under different economic scenarios.

Based on these considerations, the TS DDA deposit balances are modeled on their first differences which are stationary.

5.3.3.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the TS DDA segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the TS business.

5.3.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 84 reports the results of the significance tests.

All of the coefficient estimates in the TS DDA model are statistically significant.

Table 84: Statistical significance tests of model and variables for Treasury Services DDA

Treasury Services DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market_Vol_PMoM	10.146	<1%	10%	Statistically significant
Stock_MF_CF_DMoM	-0.027	7%	10%	Statistically significant
Intercept	88.133	26%	10%	Statistically not significant

5.3.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

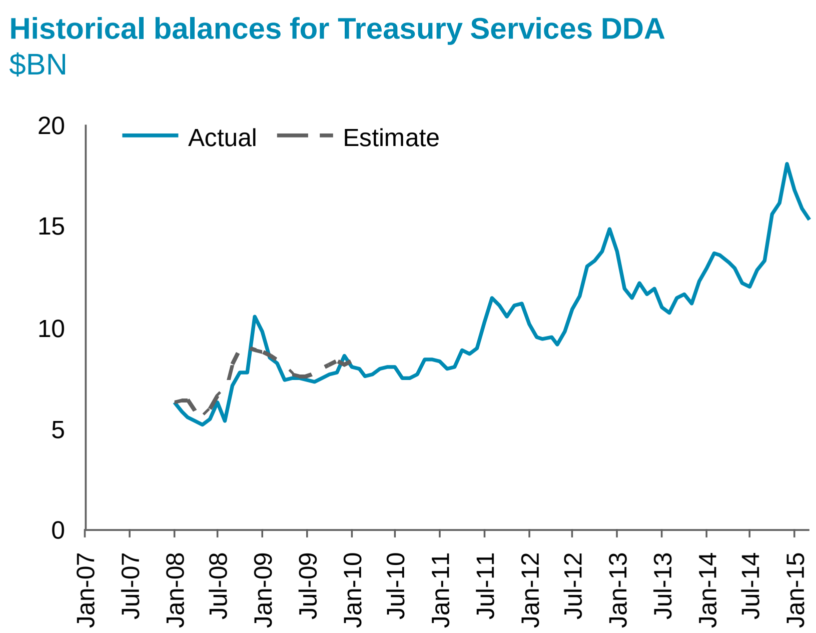
Table 85: Treasury Services DDA Model Diagnostics

Treasury Services DDA (in USD MM) – Model diagnostics

Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	18%	-	-
	Adjusted R-squared	16%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	93%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	14%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.04	5	No multicollinearity
Linearity	RESET test	53%	10%	Linear specification appropriate

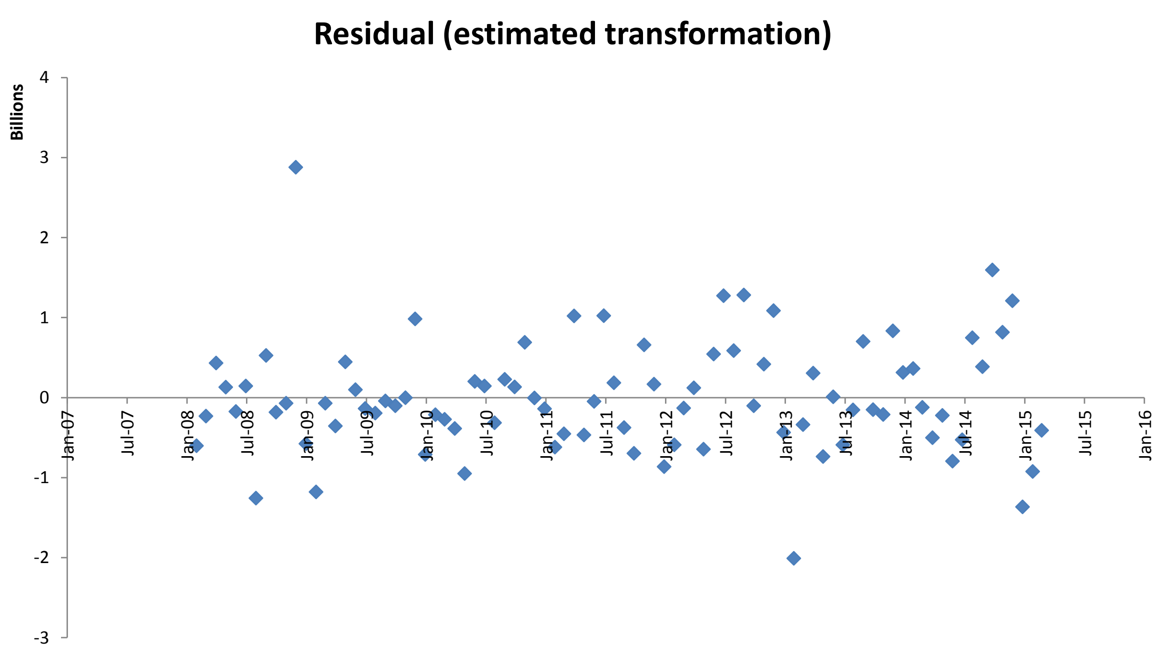
The model passes all model diagnostic tests that were evaluated.

Figure 82: Treasury Services DDA 9Q In-Sample Prediction



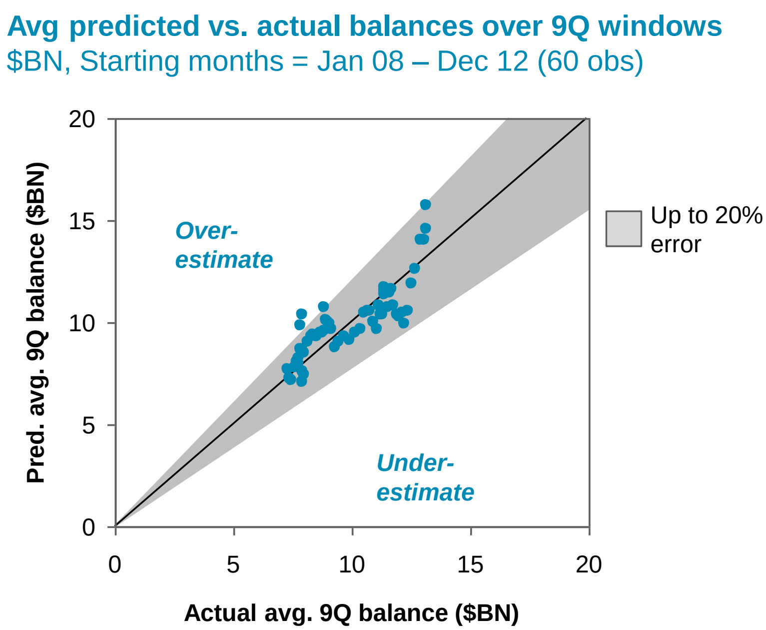
The in-sample back test of the model starting from January 2008 closely follows the trend of the historical balances.

Figure 83: Treasury Services DDA Residual Plot ($ BN)



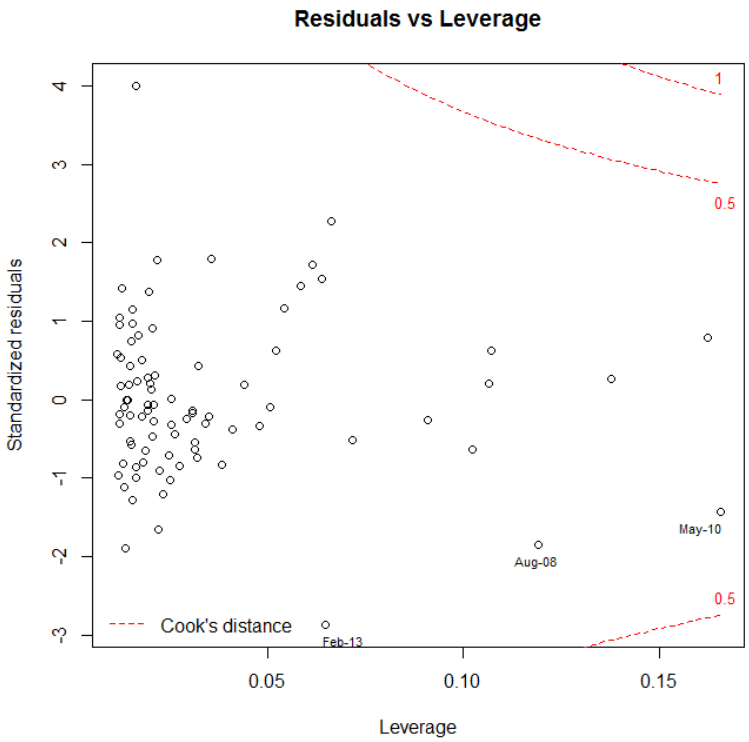
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 84: Treasury Services DDA Balance Estimation Scatterplot



All the average 9Q estimations of the TS DDA balances fall within the 20% error threshold to actuals.

Figure 85: Influential points for Treasury Services DDA



The segment did not have a highly influential point.

5.3.3.6. Model sensitivity

5.3.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 86. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 86: Sensitivity to changes in the independent variable for Treasury Services DDA

Treasury Services DDA (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Market_Vol_PMoM	Percent change – MoM	Index	0.35	27.08	0.27
Stock_MF_CF_DMoM	First difference – MoM	$ MM	-0.18	5461.55	-0.15
Intercept	-	$ MM	N/A	N/A	N/A

In the TS DDA model, the Market Volatility Index (S&P 500) variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the percent changes of the Market Volatility Index results in a 0.35 standard deviation ($0.26 BN) increase in the predicted monthly change of the TS DDA deposits.

5.3.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 87.

Table 87: Statistical sensitivity tests for Treasury Services DDA

Treasury Services DDA (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Market_Vol_PMoM	10.146	6.029	0.01	Statistically significant
Stock_MF_CF_DMoM	-0.027	-0.027	0.58	Statistically insignificant
Intercept	88.133	87.278	0.84	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.07	Statistically significant

The shortened period coefficient for Market Volatility Index and the Chow Test on all shortened period coefficients were statistically significant which suggests the model may not remain stable when removing observations from the development data. This suggests that the higher scrutiny should be applied during the management review and challenge process and that the model should be refreshed once a sufficient number of additional monthly observations is available.

5.3.3.6.3. Sensitivity to stressed independent variable scenarios

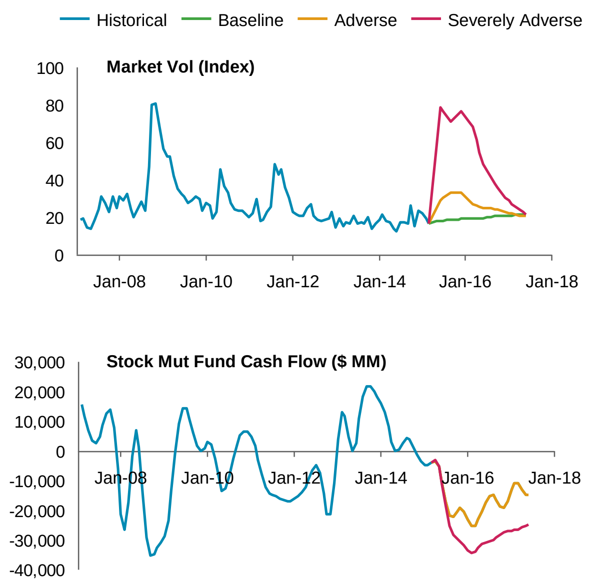
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 86: Treasury Services Demand Deposit Account Model Forecast

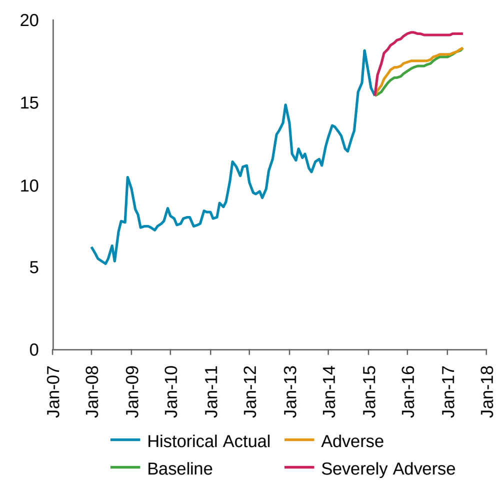
Treasury Services DDA: Model 5
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Treasury Services DDA
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	2.9 (19%)	2.93 (19%)	3.82 (25%)	-
Start to peak	2.9 (19%)	2.93 (19%)	3.87 (25%)	4.25 (68%)
Start to trough	N/A	N/A	N/A	-1.06 (-17%)



The Working Group considered the forecast behavior for the selected TS DDA model as reasonable.

The model forecasts are illustrated on Figure 86.

- **Severe recession (Severely Adverse) scenario:** The model predicts an increase in deposits. This is directionally consistent with the line of business expectations that clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. The magnitude of the increase should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts a slight increase in deposits. This was not consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment and the business suggested the model should be scrutinized when the final outputs for submission are generated
- **Baseline scenario:** The baseline scenario shows a moderate increase in line with historic growth which is consistent to business intuition that a significant change in balances is not expected

5.3.3.7. Model limitations

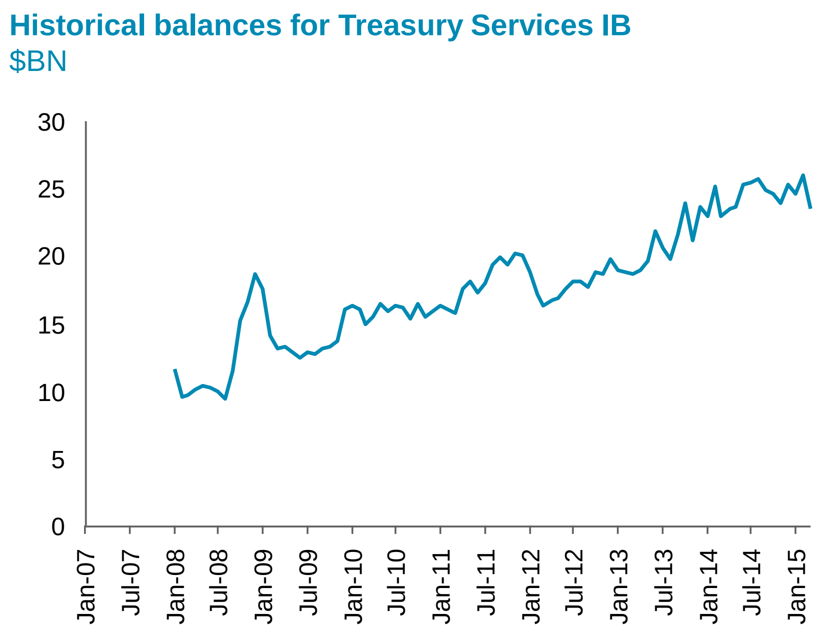
The limitations applicable to all deposit models are discussed in Section 5.9.

5.3.4. Treasury Services IB

5.3.4.1. Deposit balance overview

Over the modeling time period, Treasury Services Interest Bearing (Treasury Services IB, or TS IB) deposits have steadily grown over time. The most notable change in balances occurred during the financial crisis in 2008 where deposit balances nearly doubled in size as clients were increasingly seeking safer investments for their capital.

Figure 87: Historical Balance for Treasury Services IB



5.3.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Treasury Services IB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the TS IB deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 88.

Table 88: Coefficient estimates for the Treasury Services IB model

Treasury Services IB (in USD MM)				
Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Market_Vol_DQoQ	First difference – QoQ	Index	61.555	0.68
MSCI__DQoQ	First difference – QoQ	Index	3.430	0.34
OvrNt_Repo_DMoM	First difference – MoM	%	-1203.141	-0.19
Intercept	-	$ BN	116.264	N/A

The model contains the following drivers and variables:

- **Market Volatility (equities)** – S&P 500 volatility index (i.e. the VIX), a common benchmark of conceived market uncertainty in the broad US equity market
- **Equity Markets** – MSCI World Index, a common benchmark of global equity market performance
- **Short Term Rates –** overnight repo rate, a measure of the overnight collateralized lending rate

The intuition of these variables is as follows:

- Market Volatility contains a positive coefficient, consistent with the hypothesis, as well as observed behavior during the 2008 financial crisis, that BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress
- The MSCI World Index contains a positive coefficient, which is in line with the intuition that BNY Mellon would expect more deposits as the global economy and thus corporations are performing well financially and will require more working capital
- The overnight repo rate has a negative coefficient which is consistent with business intuition that deposit balances decrease as short-term rates increase. TS IB offers below average yields, BNY Mellon expects depositors to seek other institutions and instruments with higher yields when rates rise, particularly, off-balance sheet alternatives such as money market funds

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Figure 88: Candidate Models for Treasury Services IB

Treasury Services Interest Bearing
Candidate models

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
Equity markets	FTSE 100 Price Index (Diff QoQ)	MSCI WORLD Index (Diff QoQ)	MSCI WORLD Index (Diff QoQ)	FTSE 100 Price Index (Diff QoQ)
Market volatility/ uncertainty (equity)	Market Vol (Diff QoQ)	Market Vol (Diff QoQ)	Market Vol (Diff QoQ)	Market Vol (% QoQ)
Banking system risk			1 week LIBOR-OIS spread (Diff MoM)	1 week LIBOR-OIS spread (Diff MoM)
Short-term rates	Ovrnt Repo Rate (Diff MoM)	Ovrnt Repo Rate (Diff MoM)		
Variation in balances explained through estimated first differences	**94%**	**92%**	**88%**	**90%**
R-squared (differences)	**35%**	**34%**	**33%**	**33%**

Final model

Additional drivers tested: Corporate credit, MF Cash Flow, Relative creditworthiness of BNYM, Hedge fund index, General economic health, Market volatility/ uncertainty (rates), Long-term rates, Financial stability of US government, Yield spread, FX rates (to USD)

The Working Group selected the final model from among the short list in Figure 88.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model as well as sensitivity tests are described in the following sections.

5.3.4.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.3.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. All Treasury Services deposit balance segments are tested to see if they are growth variables, as there is a possibility that they could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 89.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 90.

Table 89: Unit root tests and stationarity tests including a trend variable on balances

Treasury Services IB (in USD MM) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	11	-1.7	>0.10	Fail to Reject unit root
Phillips-Perron	1	-3.7	0.02	Reject unit root
KPSS	5	0.09	0.21	Fail to Reject stationarity

Table 90: Unit root tests and stationarity tests including a constant on first differences

Treasury Services IB (in USD MM) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	3	-4.9	<0.01	Reject unit root
Phillips-Perron	1	-9.6	<0.01	Reject unit root
KPSS	0	0.02	0.99	Fail to Reject stationarity

Stationarity tests for TS IB balances show that the level passes the PP and KPSS tests for stationarity. However, the ADF test failed at 10% significance, therefore the modeling team also looks at the first difference in which the series passes all three tests for stationarity. These results strongly suggest that the first difference of the series is stationary.

Based on these results, the TS IB deposit balances are modeled on their first differences.

5.3.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the TS IB segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the TS business.

5.3.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 91 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the TS IB model are statistically significant.

Table 91: Statistical significance tests of model and variables for Treasury Services IB

Treasury Servicing IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market_Vol_DQoQ	61.555	<1%	10%	Statistically significant
MSCI__DQoQ	3.430	<1%	10%	Statistically significant
OvrNt_Repo_DMoM	-1203.141	<1%	10%	Statistically significant
Intercept	116.264	29%	10%	Statistically not significant

5.3.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

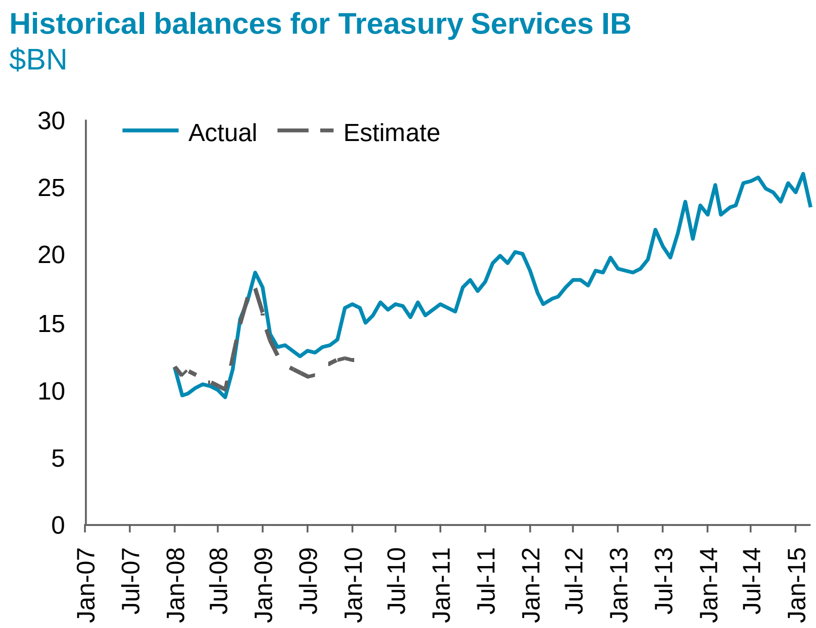
Table 92: Treasury Services IB Model Diagnostics

Treasury Servicing IB (in USD MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	34%	-	-
	Adjusted R-squared	31%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	56%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.86	5	No multicollinearity
Linearity	RESET test	90%	10%	Linear specification appropriate

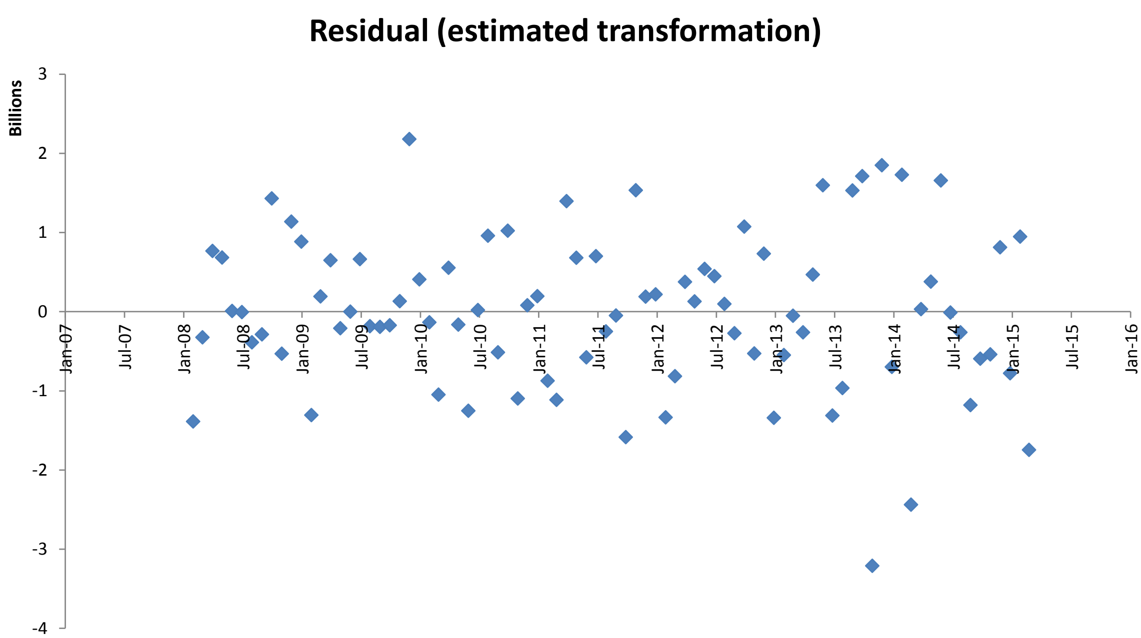
The model passes all model diagnostic tests that were evaluated, except the Breusch-Godfrey test for serial correlation.

Figure 89: Treasury Services IB 9Q In-Sample Prediction



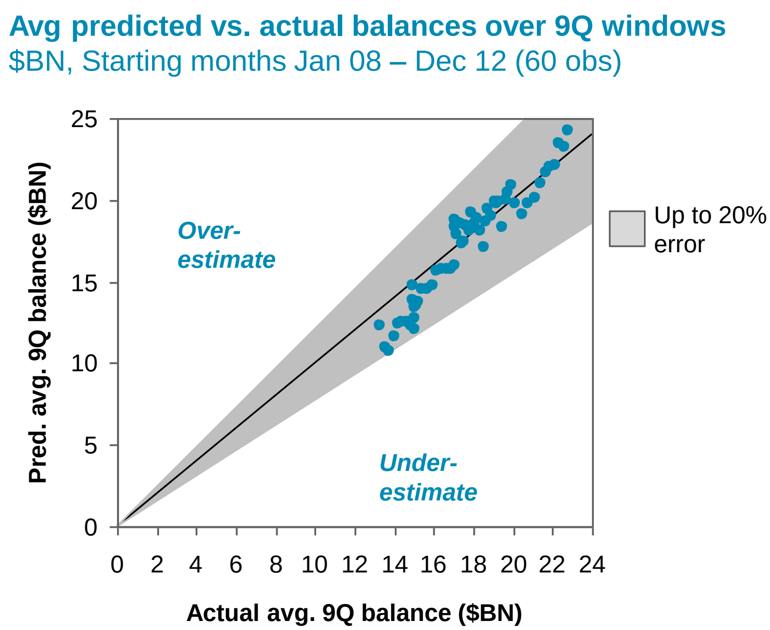
The in-sample back test of the model starting from January 2008 captures the increase and the subsequent fall in balances.

Figure 90: Treasury Services IB Residual Plot ($ BN)



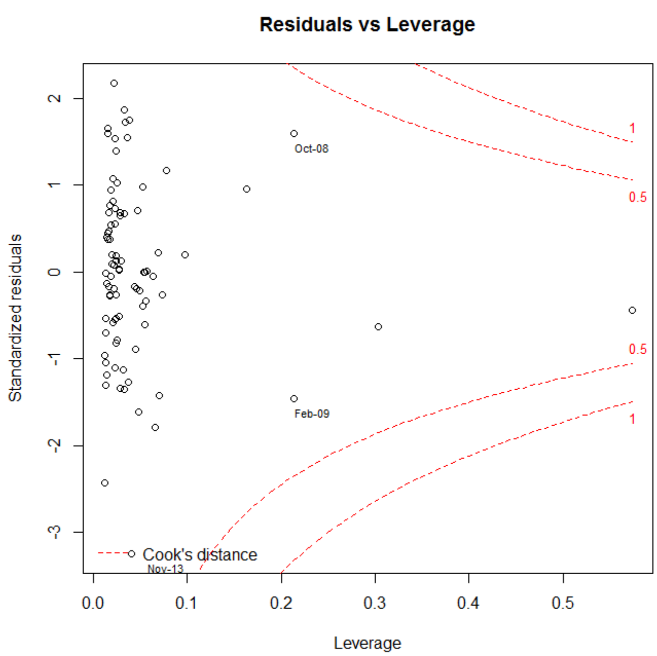
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 91: Treasury Services IB Balance Estimation Scatterplot



All the 9Q estimations of the TS IB balances fall within the 20% error threshold.

Figure 92: Influential points for Treasury Services IB



The segment does not contain any highly influential points.

5.3.4.6. Model sensitivity

5.3.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 93. The standardized coefficient reported describes the standard deviation change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 93: Sensitivity to changes in the independent variable for Treasury Services IB

Treasury Services IB (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Market_Vol_DQoQ	First difference – QoQ	Index	0.68	13.27	0.82
MSCI__DQoQ	First difference – QoQ	Index	0.34	118.91	0.41
OvrNt_Repo_DMoM	First difference – MoM	%	-0.19	0.19	-0.23
Intercept	-	$ MM	N/A	N/A	N/A

In the TS IB model, the Market Volatility Index (S&P 500) variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Market quarterly changes of the Volatility Index results in a 0.68 standard deviation ($0.82 BN) increase in the predicted monthly change of the TS IB deposits.

5.3.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 94.

Table 94: Statistical sensitivity tests for Treasury Services IB

Treasury Services IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
Market_Vol_DQoQ	61.555	54.923	0.12	Statistically insignificant
MSCI__DQoQ	3.430	2.623	0.08	Statistically significant
OvrNt_Repo_DMoM	-1203.141	-1097.711	0.58	Statistically insignificant
Intercept	116.264	131.690	0.03	Statistically significant
Chow-test on all shortened period coefficients	-	-	0.04	Statistically significant

The shortened period coefficient for the MSCI Index, the intercept and the Chow Test on all shortened period coefficients were statistically significant which suggests the model may not remain stable when removing observations from the development data. Given the higher overall sensitivity of the segment, more attention in monitoring this segment is planned.

5.3.4.6.3. Sensitivity to stressed independent variable scenarios

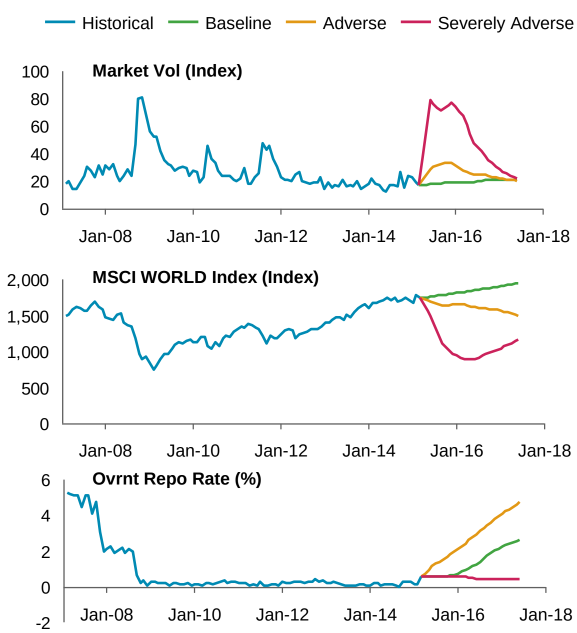
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 93: Treasury Services Interest Bearing Model Forecast

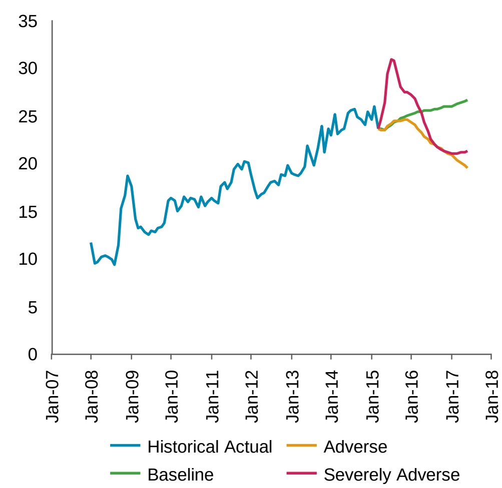
Treasury Services Interest Bearing: Model 2
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Treasury Services IB
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	3.06 (13%)	-4.01 (-17%)	-2.23 (-9%)	-
Start to peak	3.06 (13%)	0.95 (4%)	7.34 (31%)	7.05 (61%)
Start to trough	-0.02 (0%)	-4.01 (-17%)	-2.58 (-11%)	-2.27 (-20%)



The Working Group considered the forecast behavior for the selected TS IB model as reasonable.

The model forecasts are illustrated on Figure 93.

- **Severe recession (Severely Adverse) scenario:** The model predicts an initial increase in deposits followed by a steep decline. In a review of the forecasts with the line of business, it was noted that the fall in deposits was not consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY

Mellon to hold their cash. Discussion with the line of business suggests that the magnitude and direction of the change in balances should be monitored closely when the final outputs for submission are generated

- **Interest rate shock (Adverse) scenario:** The model predicts a decline in deposits. This was consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment
- **Baseline scenario:** The baseline scenario shows a moderate increase in line with historic growth which is consistent to business intuition that a significant change in balances is not expected

5.3.4.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The large potential effect of management action on future balances is a limitation of this model. Historically, BNY Mellon's management actions have had big effects on its balances and might occur again in the future. It is recommended that active client management and other management actions are included in the considerations during the management review and challenge process of this segment.

5.4. Alternative Investment Services/Global Collateral Services deposit balance models

5.4.1. Business overview and segments

BNY Mellon's Alternative Investment Services (AIS) line of business offers fund administration and custody services to hedge funds, fund of hedge funds, and private equity clients worldwide. AIS services clients in many aspects of their transactions such as trade execution, custody, middle offices support, clearance and other cash management, as well as financing services. AIS also provides core accounting and administrative services as well as value added administrative services. These services include portfolio valuation, fund accounting, investor services, tax preparation and independent pricing of certain security types. A core service offered is holding and processing of cash in connection with servicing securities portfolios, which results in these clients depositing money on BNY Mellon's balance

Global Collateral Services (GCS) provides broker-dealers and institutional investors with various services related to collateral management. GCS utilizes BNY Mellon's global capabilities in segregating, allocating, financing and transforming collateral on behalf of clients, including broker-dealer collateral management, securities lending, collateral financing, liquidity and derivatives services teams.

For ALM management purposes, AIS and GCS deposits are combined and then segregated into two segments described in Table 95: non-interest bearing USD deposits (AIS/GCS DDA) and interest-bearing deposits (AIS/GCS IB). As described earlier in Section 3.1.2, this segmentation was adopted for the purposes of balance sheet forecasting as well, to align the segmentation with those used for other business purposes.

Table 95: Segment description for Alternative Investment Services/Global Collateral Services

Segments for AIS/GCS

Segments	Size ($ BN)[26]	Description
AIS/GCS DDA	17.0	Composed entirely of USD denominated non-interest bearing balances in AIS and GCS demand deposit accounts.
AIS/GCS IB	16.5	Contains all interest bearing Alternative Investment Services and Global Collateral Services deposits denominated in USD currency. The products contained in this segment are Alternative Investment Services Cash Reserves, Global Collateral Services Cash Reserves and Global Collateral Services USD Foreign Deposits.

5.4.2. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team and the line of business, a list of driver hypotheses were developed and refined over time. Figure 94 illustrates the initial driver hypotheses that were identified through conversations with the lines of business and the ALM team in advance of the modeling process. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

[26] Month-end spot balances from April 30, 2015

Figure 94: Summary of Alternative Investment Services/Global Collateral Services drivers

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit balances increase when general economic health improves	• US GDP growth, unemployment rate
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase as BNYM is perceived as a relative "safe haven"	• Spread of BNYM debt rate to industry peer rate
	Banking system risk	• Deposit balances increase as banking credit risk increases, as BNYM is perceived as a relative "safe haven"	• Overnight Libor, TED Spread, Libor OIS spread
	Monetary base	• Deposit balances increase when the monetary base increases	• US monetary base, CPI inflation rate
	Assets under custody	• Deposit balances increase as AUC increases	• BNYM AUC forecast
	Equity markets	• Deposit balances increase as equity investments become more attractive	• DJI, MSCI Global, KBW Bank Index
	Hedge fund index	• Deposit balances increase as hedge fund performance improves	• Hedge fund and fund of fund indexes
	Market volatility/ uncertainty (equity and rates)	• Deposit balances increase as market volatility and uncertainty increases • Deposit balances increase in flight to quality situations • Deposit balances increase as AIS clients experience increases in redemptions	• VIX, Market Volatility Index (equity) • US T-note volatility (rates)
	Financial stability of US government	• Deposit balances increase when there is a shock decline to the perceived creditworthiness of the US government	• 1-3 month Treasury yield spread
Rates	**Short-term rates**	• Deposit balances decrease as short-term rates increase (absolute or comparative to competitors), as depositors seek other institutions/instruments with higher deposit rates	• Prime Rate, Fed Funds effective rate, 1 & 3 month Treasury rate, Overnight Repo rate, T-Bill index spread with Fed funds effective rate

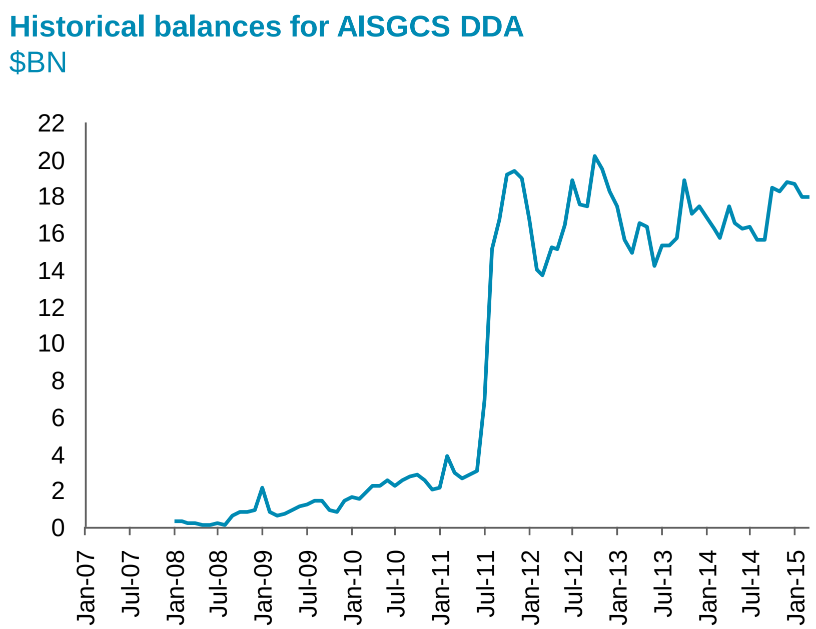
The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

5.4.3. Alternative Investment Services and Global Collateral Services DDA

5.4.3.1. Deposit balance overview

Alternative Investment Services and Global Collateral Services Demand Deposit Account (AIS/GCS DDA) balances have increased as the new business became established. AIS/GCS balances were steadily growing following the inception of the business in 2008. However, during the 2011 debt ceiling crisis the segment experienced a large, sudden increase in balances to $15 BN. This increased balance has remained at BNY Mellon and has been stable up to the present.

Figure 95: Historical balances for Alternative Investment Services and Global Collateral Services DDA



5.4.3.2. Model summary

A statistical model that is partially consistent with business intuition was found for the Alternative Investment Services and Global Collateral Services DDA segment. The model exhibits the following statistical characteristics:

- **Stationarity:** The model is estimated on a month-over-month transformation of the Alternative Investment Services and Global Collateral Services DDA deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are individually statistically significant but fail the joint significance test

- **Diagnostic tests:** The model fails the model specification test described in Section 3.3.3 on Methodology but exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 96.

Table 96: Coefficient estimates for the AIS/GCS DDA model

AIS/GCS DDA (in USD MM)				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
EH_HF_index_DYoY	First difference – YoY	Index	14.519	0.20
Market_Vol_PQoQ	Percent change – QoQ	Index	17.377	0.60
TED_Spread_DQoQ	First difference – QoQ	%	-1075.890	-0.34
Intercept	-	$ MM	-339.709	N/A

The model contains the following drivers and variables:

- **Hedge Fund Index –** Eurekahedge North American Hedge Fund Index, a return index of hedge funds in North America
- **Market Volatility (equities)** – S&P 500 volatility index (i.e. the VIX), a common benchmark of conceived market uncertainty in the broad US equity market
- **Banking System Risk** – TED spread (interest rate spread between the three month US LIBOR rate and three month Treasury Bill rate), a measure of banking system risk

The intuition for these variables is as follows:

- The Eurekahedge North American Hedge Fund Index has a positive coefficient which is consistent with business intuition: as Hedge Funds performance improves and attracts more capital, BNY Mellon would expect more deposits. An alternate variable that was suggested by the line of business is total assets under management by hedge funds
- The TED spread had a negative coefficient while the coefficient on S&P volatility index is positive. This was surprising to the line of business as they expected that both variables would have positive coefficients as BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress. The modeling team hypothesized that the TED spread variable could have been offsetting a particularly large positive S&P volatility variable coefficient. Because of a lack of alternative models that passed the statistical tests, this was selected as the final model

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in Figure 96.

Figure 96: Candidate models for AIS/GCS DDA

Alternative Investment Services / Global Collateral Services DDA
Candidate models

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Equity markets					MSCI WORLD Index (% MoM, 1M Lag)
General economic health	Real GDP growth (Level)				
Hedge fund index			Eurekahedge NA HF Index (Diff YoY)		
Market volatility/ uncertainty (equity)	S&P Vol (30D MAVG) (% QoQ)	S&P Vol (30D MAVG) (% QoQ)	Market Vol (% QoQ)	S&P Vol (30D MAVG) (% MoM)	Market Vol (% QoQ)
Monetary base				US M1 (% MoM, 1M Lag)	
Banking system risk	TED Spread (Diff QoQ)	TED Spread (Diff QoQ)	TED Spread (Diff QoQ)		
Short-term rates		Prime rate (Diff MoM)			
Variation in balances explained through estimated first differences	**88%**	**85%**	**76%**	**87%**	**82%**
R-squared (differences)	**30%**	**29%**	**23%**	**18%**	**17%**

Final model

Additional drivers tested: Assets under custody, Relative creditworthiness of BNYM, Market volatility/ uncertainty (rates), Financial stability of US government

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.4.3.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.4.3.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Alternative Investment Services/Global Collateral Services DDA series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 97.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 98.

Table 97: Unit root tests and stationarity tests including a trend variable on balances

AIS/GCS DDA – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	7	-1.6	>0.10	Fail to Reject unit root
Phillips-Perron	1	-2.1	0.57	Fail to Reject unit root
KPSS	5	0.15	0.05	Reject stationarity

Table 98: Unit root tests and stationarity tests including a constant on first differences

AIS/GCS DDA – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-7.1	<0.01	Reject unit root
Phillips-Perron	1	-7.1	<0.01	Reject unit root
KPSS	2	0.07	0.76	Fail to Reject stationarity

Stationarity tests for AIS/GCS DDA balances uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the AIS/GCS DDA deposit balances are modeled on their first differences.

5.4.3.3.2. Historical data review

In addition to checking for stationarity of dependent variables, we also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the AIS/GCS DDA segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the AS business.

5.4.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 99 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Each of the coefficient estimates in the AIS/GCS DDA model is statistically significant, but the the joint F-test is found to be statistically insignificant. The intercept is also found to be statistically insignificant.

Table 99: Statistical significance tests of model and variables for AIS/GCS DDA

AIS/GCS DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	18%	10%	Statistically not significant
EH_HF_index_DYoY	14.519	10%	10%	Statistically significant
Market_Vol_PQoQ	17.377	4%	10%	Statistically significant
TED_Spread_DQoQ	-1075.890	3%	10%	Statistically significant
Intercept	-339.709	17%	10%	Statistically not significant

5.4.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

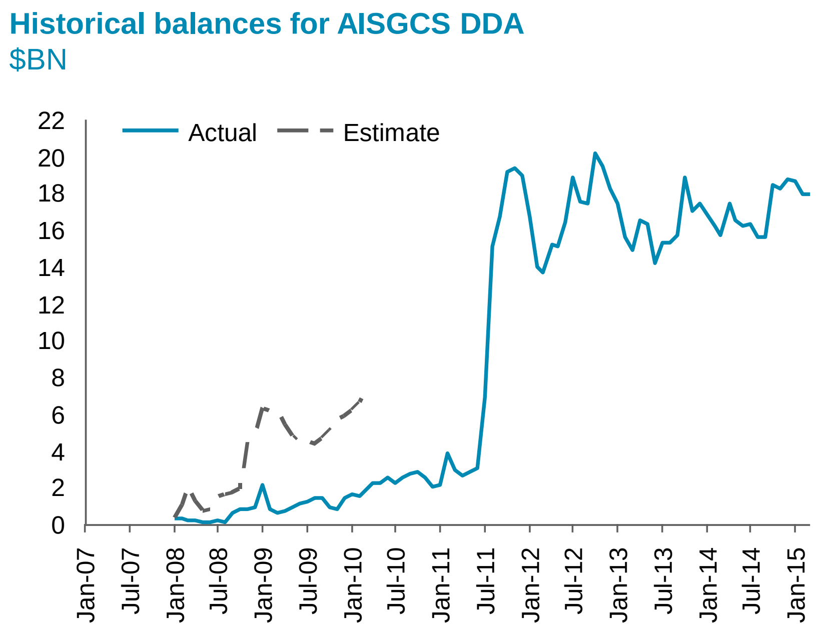
Table 100: AIS/GCS DDA Model Diagnostics

AIS/GCS DDA (in USD MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	23%	-	-
	Adjusted R-squared	20%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	3%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.58	5	No multicollinearity
Linearity	RESET test	2%	10%	Linear specification inappropriate

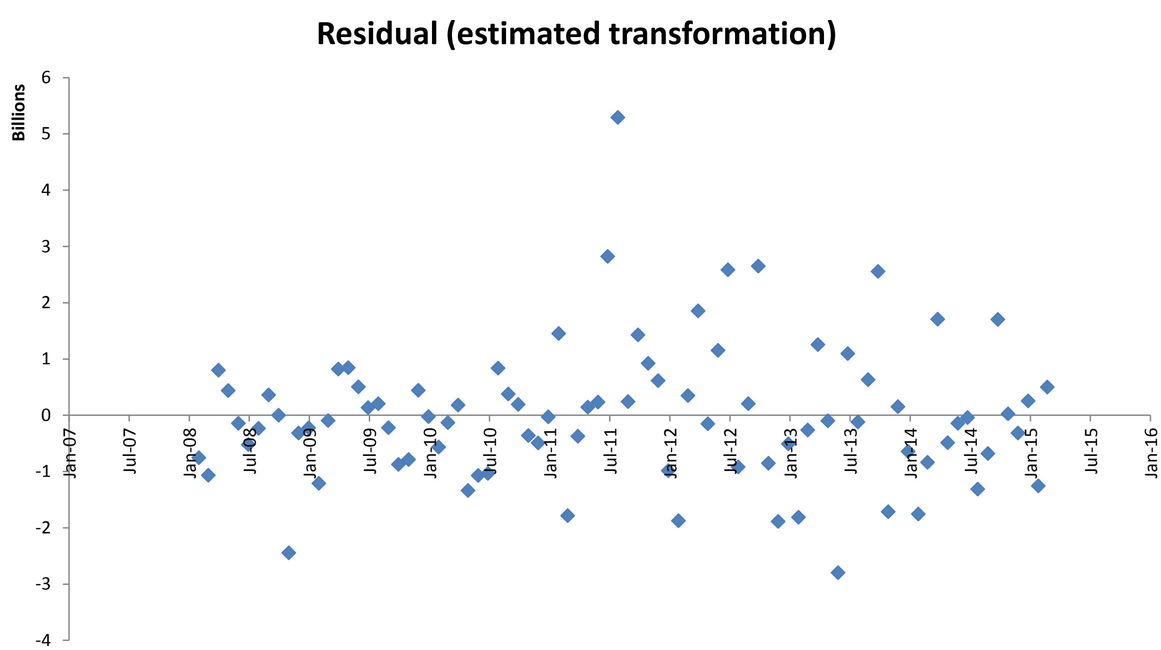
The model suffers from serial correlation. Also, the model fails the RESET test which tests for linearity. This was tolerated since there were no alternative models that were intuitive and passed statistical tests. This is noted as a key model limitation.

Figure 97: AIS/GCS DDA 9Q In-Sample Prediction



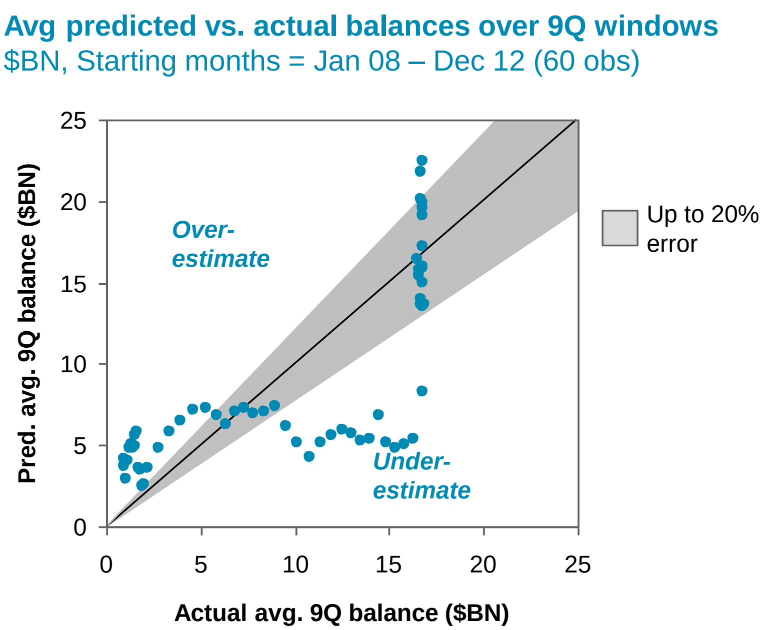
The in-sample back test of the model starting from January 2008 shows a much higher increase in balances than the actual deposits. Given that the majority of balance growth was captured in a 6-month period in 2011 due to a political event it is not surprising that the model will overestimate balance growth during all other periods.

Figure 98: AIS/GCS DDA Residual Plot ($ BN)



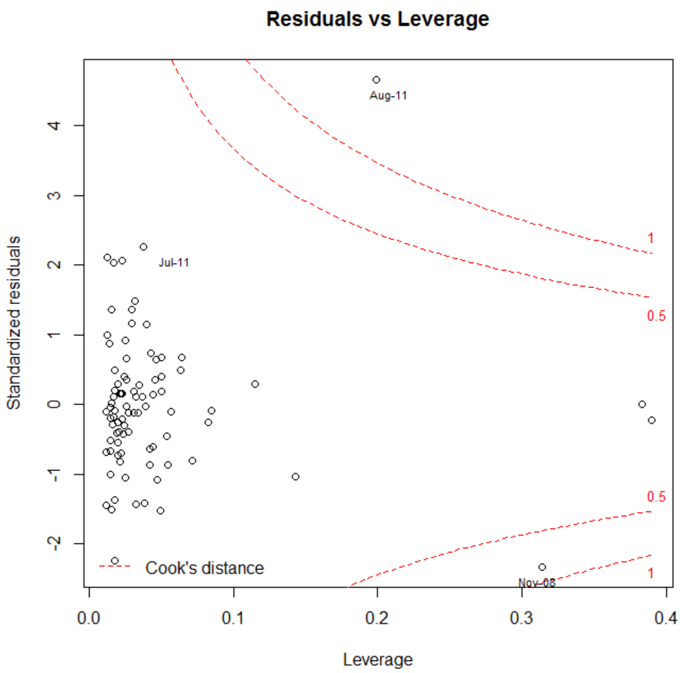
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 99: AIS/GCS DDA Balance Estimation Scatterplot



The points of overestimation on Figure 99 occur in the period prior to the 2011 debt crisis. The model overestimates the model intercept trend as the balance increase due to this idiosyncratic event was not captured by the model. The points of underestimation are following the 2011 US debt ceiling crisis.

Figure 100: Influential points for AIS/GCS DDA



For this segment August 2011 is a highly influential point. This is not surprising because of the high growth in balances during the 2011 debt ceiling crisis. The model is not able to fully capture these dynamics, a weakness documented below.

5.4.3.6. Model sensitivity

5.4.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 101. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 101: Sensitivity to changes to independent variables for AIS/GCS DDA

AIS/GCS DDA (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
EH_HF_index_DYoY	First difference – YoY	Index	0.20	19.53	0.28
Market_Vol_PQoQ	Percent change – QoQ	Index	0.60	48.74	0.85
TED_Spread_DQoQ	First difference – QoQ	%	-0.34	0.44	-0.48
Intercept	-	$ MM	N/A	N/A	N/A

In the AIS GCS DDA model, the Market Volatility Index (S&P 500) variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the quarterly percentage changes of Market Volatility results in a 0.60 standard deviation ($0.85 BN) increase in the predicted monthly change of the AIS/GCS DDA deposits.

5.4.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 102.

Table 102: Statistical sensitivity tests for AIS/GCS DDA

AIS/GCS DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
EH_HF_index_DYoY	14.519	16.944	0.16	Statistically insignificant
Market_Vol_PQoQ	17.377	18.321	0.45	Statistically insignificant
TED_Spread_DQoQ	-1075.890	-1120.550	0.13	Statistically insignificant
Intercept	-339.709	-367.210	0.18	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.00	Statistically significant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.4.3.6.3. Sensitivity to stressed independent variable scenarios

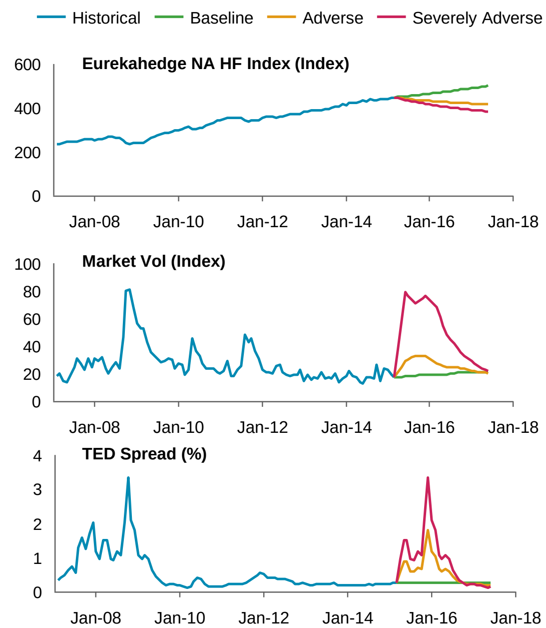
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model’s forecast behavior was tested for different macroeconomic scenarios.

Figure 101: AIS/GCS Demand Deposit Account Model Forecast

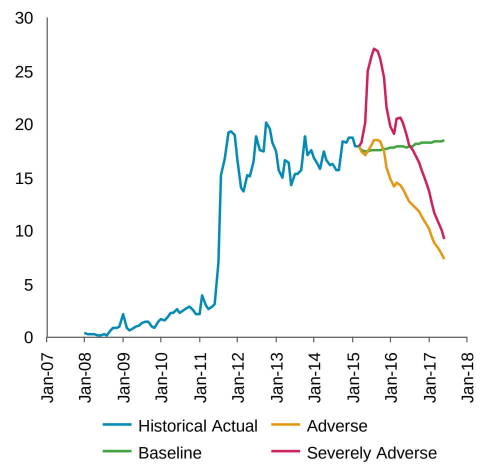
Alternative Investment Services / Global Collateral Services DDA: Model 3
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for AISGCS DDA
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008
Start to 9Q end	0.53 (3%)	-10.66 (-60%)	-8.77 (-49%)	-
Start to peak	0.53 (3%)	0.61 (3%)	9.17 (51%)	1.74 (499%)
Start to trough	-0.56 (-3%)	-10.66 (-60%)	-8.77 (-49%)	-0.27 (-77%)



The Working Group considered the forecast behavior for the selected AIS/GCS DDA model as reasonable.

The model forecasts are illustrated on Figure 101.

- **Severe recession (Severely Adverse) scenario:** The model initially predicts a significant increase in deposits but is followed by larger decline. In a review of the forecasts with the line of business, it was noted that the decline was not directionally consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. The line of business suggested that the magnitude and direction of the change in balances should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts a deposits run-off. This was consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment
- **Baseline scenario:** The baseline scenario largely remains flat with a mild decline, which is consistent to business intuition that a significant change in balances is not expected

5.4.3.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The AIS/GCS DDA balances proved challenging to model since:

- It is a new business that underwent growth during the modelling period
- The segment balances exhibited an extremely large and rapid increase during the 2011 debt ceiling crisis. Not surprisingly, the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently

Given the particular difficulty in modeling this segment, there was a limited set of candidate models to select from. The selected model has two key limitations:

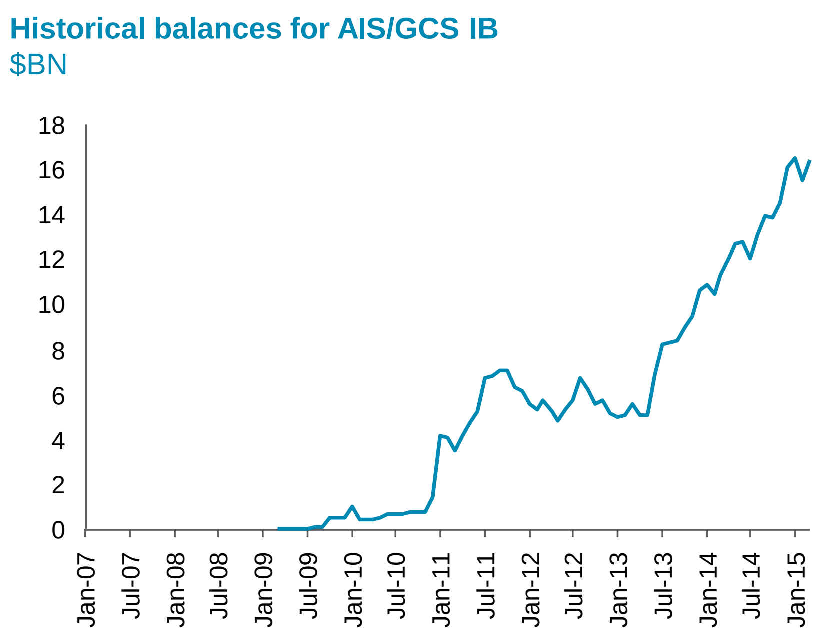
- The selected model suffers from model misspecification, which was only tolerated given the lack of alternatives
- The model contains a Hedge Fund performance index variable. An alternate variable suggested by the line of business that may more accurately capture the performance of hedge funds is an assets under management variable. The modeling team suggests investigating whether more preferable models can be found using such a variable

5.4.4. Alternative Investment Services and Global Collateral Services IB

5.4.4.1. Deposit balance overview

Similar to the AIS/GCS DDA segment, Alternative Investment Services and Global Collateral Services Interest Bearing (AIS/GCS IB) deposits is a relatively new segment that has experienced large and sudden increases in balances during times of economic stress. The most notable case was before and during the 2011 debt ceiling crisis when deposit balances grew from $1 BN to $8 BN (though about half of this increase can be attributed to a data limitation discussed in Section 5.4.4.3.2). After this period balances remained flat until the second crisis in 2013 where they began a steady increase up to ~$17 BN up until the present.

Figure 102: Historical balances for AIS/GCS IB



5.4.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Alternative Investment Services/Global Collateral Services IB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the AIS/GCS IB deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 103.

Table 103: Coefficient estimates for the AIS/GCS IB model

AIS/GCS IB (in USD MM)

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
EH_HF_index_DYoY	First difference – YoY	Index	9.848	0.25
Tnote_Vol_10yr_DYoY	First difference – YoY	Index	82.149	0.30
UE_DMoM	First difference – MoM	%	-691.709	-0.18
Intercept	-	$ MM	-47.394	N/A

AIS/GCS IB (in USD MM)

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Dummy for July 2011		$ MM	855.599	N/A

The model contains the following drivers and variables:

- **Hedge Fund Index –** Eurekahedge North American Hedge Fund Index, a return index of hedge funds in North America
- **Market Volatility (rates) –** 10 Year T-Note Volatility index, a common benchmark of implied US rate volatility
- **General Economic Health –** US Unemployment Rate

The intuition for these variables is as follows:

- The Eurekahedge North American Hedge Fund Index has a positive coefficient which is consistent with business intuition: as Hedge Funds performance improves and attracts more capital, BNY Mellon would expect more deposits. An alternate variable suggested by the line of business that may more accurately capture the performance of hedge funds is a variable that captures total assets under management by hedge funds
- The T-Note volatility index has a positive coefficient which is consistent with business intuition as BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress/volatility
- The Unemployment Rate contains a negative coefficient which is also consistent as balances are expected to grow as general health of the economy improves

In addition to these variables, a dummy variable was used to address a specific issue identified in the historical data, which is discussed further in Section 5.4.4.3.2.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in Figure 103.

Figure 103: Candidate models for AIS/GCS IB

Alternative Investment Services / Global Collateral Services IB
Candidate models

	Candidate models		
Drivers Considered	**1**	**2**	**3**
General economic health	Unemp rate (Diff MoM)	Unemp rate (Diff MoM)	
Hedge fund index	Eurekahedge NA HF Index (Diff YoY)		Eurekahedge NA HF Index (Diff YoY)
Market volatility/ uncertainty (equity)		Market Vol (Diff YoY)	
Market volatility/ uncertainty (rates)	10 Year US T-Note Volatility Index (Diff YoY)	10 Year US T-Note Volatility Index (Diff YoY)	10 Year US T-Note Volatility Index (% QoQ)
Variation in balances explained through estimated first differences	**96%**	**94%**	**91%**
R-squared (differences)	**19%**	**19%**	**14%**

Final model

Additional drivers tested: Assets under custody, Monetary base, Relative creditworthiness of BNYM, Equity markets, Short-term rates, Perceived credit risk, Financial stability of US government
Models include dummy on July 2011, as GCS Cash Reserves data only starts from this date.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.4.4.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.4.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The AIS/GCS IB series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed Table 104.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 105.

Table 104: Unit root tests and stationarity tests including a trend variable on balances

AIS/GCS IB – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-0.9	>0.10	Fail to reject unit root

Phillips-Perron	1	-1.5	0.82	Fail to reject unit root
KPSS	5	0.16	0.04	Reject stationarity

Table 105: Unit root tests and stationarity tests including a constant on first differences

AIS/GCS IB – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-6.9	<0.01	Reject unit root
Phillips-Perron	1	-7.2	<0.01	Reject unit root
KPSS	3	0.26	0.18	Fail to reject stationarity

Stationarity tests for AIS/GCS IB balances uniformly reject stationarity across all three tests. These results suggest the AIS/GCS IB balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the AIS/GCS IB deposit balances are modeled on their first differences.

5.4.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the AIS/GCS IB segment. However, the regression model for the segment contains a dummy variable of the month of July 2011. The reason is that data for one component in that segment, the Global Collateral Services Cash Reserves, only became available in the available dataset at starting in July 2011. Although balances for this segment existed prior, they were not captured in the systems used for modeling. The Global Collateral Services Cash Reserves sub-segment contained $3.5 BN of deposits in July 2011. Since the dependent variable is a difference month over month transformation, a single dummy is used to treat this data limitation, which results in a large artificial increase in balances in the historical data in this month. All candidate models considered for this segment contain this dummy variable. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the AIS/GCS business.

5.4.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold

- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 106 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the AIS/GCS IB model are statistically significant.

Table 106: Statistical significance tests of model and variables for AIS/GCS IB

AIS/GCS IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
EH_HF_index_DYoY	9.848	<1%	10%	Statistically significant
Tnote_Vol_10yr_DYoY	82.149	<1%	10%	Statistically significant
UE_DMoM	-691.709	4%	10%	Statistically significant
Intercept	-47.394	76%	10%	Statistically not significant
Dummy for July 2011	855.599	N/A	N/A	N/A

5.4.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

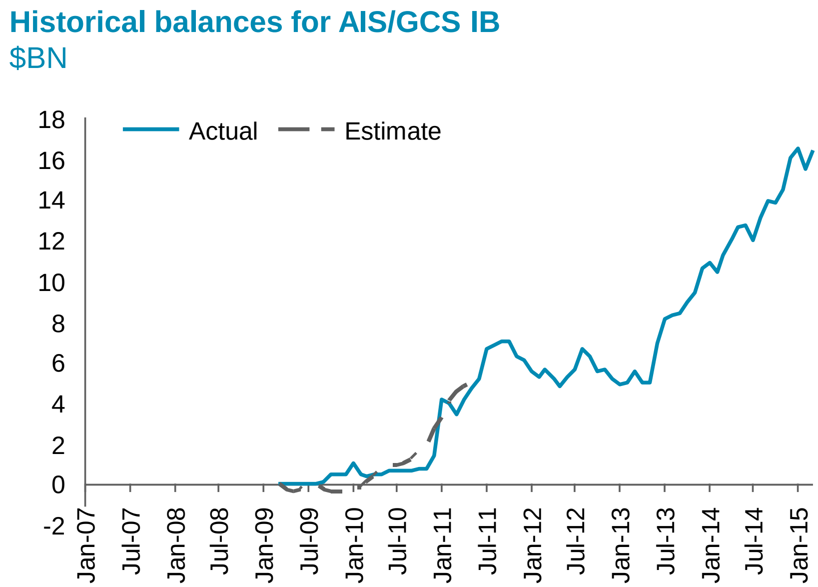
Table 107: AIS/GCS IB Model Diagnostics

AIS/GCS IB – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	19%	-	-
	Adjusted R-squared	15%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	14%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.17	5	No multicollinearity
Linearity	RESET test	22%	10%	Linear specification appropriate

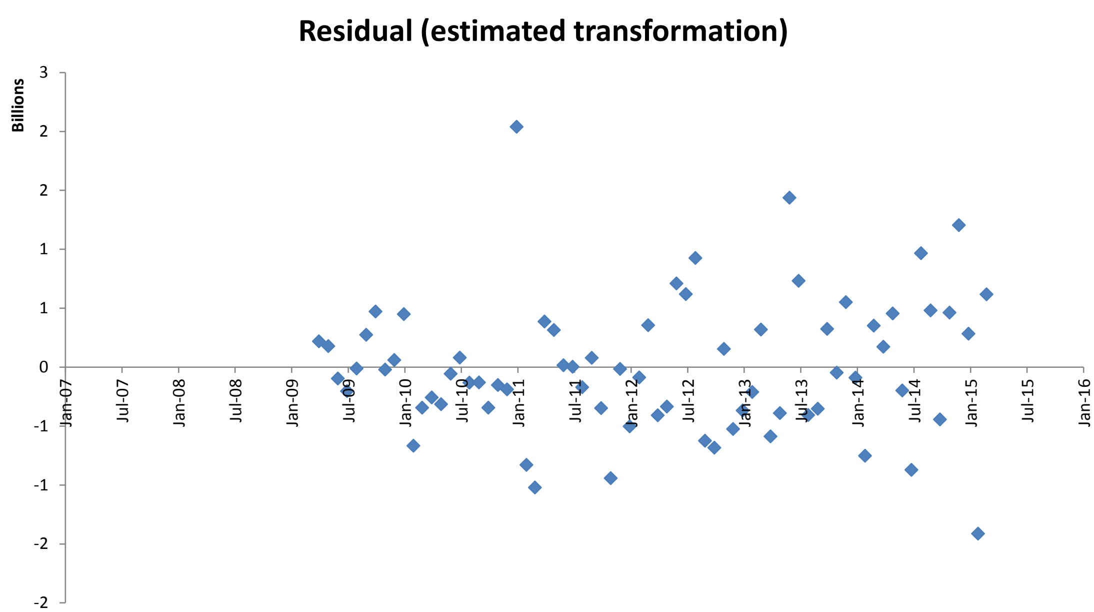
The model passes all model diagnostic tests that were evaluated, except the Breusch-Godfrey test for serial correlation.

Figure 104: AIS/GCS DDA 9Q In-Sample Prediction



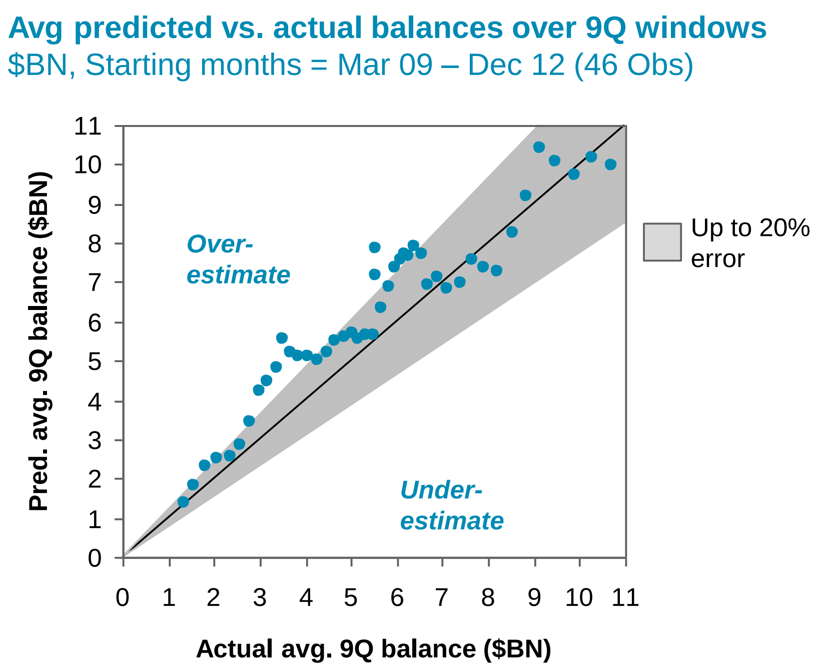
The in-sample back test of the model starting from January 2008 closely follows the trend of the historical balances and through 9 quarters ends closely to where the actual balances were at the time.

Figure 105: AIS/GCS IB Residual Plot ($ BN)



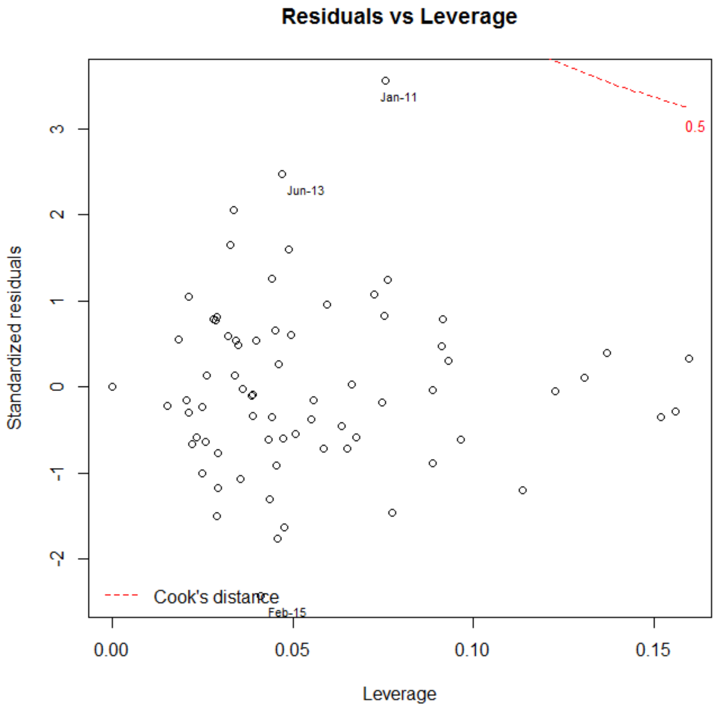
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 106: AIS/GCS IB Balance Estimation Scatterplot



The points of overestimation on Figure 106 occurred following the 2011 debt ceiling crisis as well as some variation in deposit balances shortly after.

Figure 107: Influential points for AIS/GCS IB



The segment does not contain any highly influential points.

5.4.4.6. Model sensitivity

5.4.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 108. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 108: Sensitivity to changes to independent variables for AIS/GCS IB

AIS/GCS IB – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
EH_HF_index_DYoY	First difference – YoY	Index	0.25	16.16	0.16
Tnote_Vol_10yr_DYoY	First difference – YoY	Index	0.30	2.32	0.19
UE_DMoM	First difference – MoM	%	-0.18	0.16	-0.11
Intercept	-	$ MM	N/A	N/A	N/A

In the AIS/GCS IB model, the 10 Year T-Note Volatility variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the yearly changes of the

T-Note Volatility results in a 0.30 standard deviation ($0.19 BN) increase in the predicted monthly change of the AS DDA deposits.

5.4.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results are shown in Table 109.

Table 109: Statistical sensitivity tests for AIS/GCS IB

AIS/GCS IB (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
EH_HF_index_DYoY	9.848	8.221	<0.01	Statistically significant
Tnote_Vol_10yr_DYoY	82.149	61.108	0.90	Statistically insignificant
UE_DMoM	-691.709	-398.462	0.66	Statistically insignificant
Intercept	-47.394	807.711	0.95	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.40	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant with the exception of the Eurekahedge North American Hedge Fund Index variable. This suggests the model may not remain stable when removing observations from the development data.

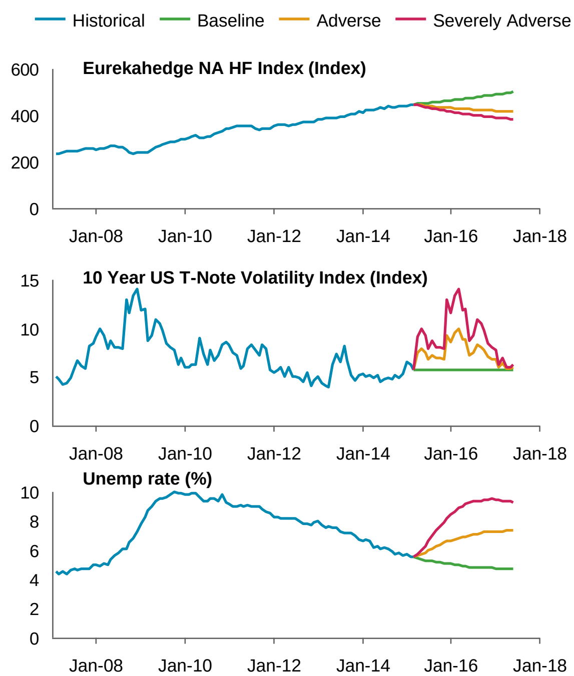
5.4.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

Figure 108: AIS/GCS IB Model Forecast

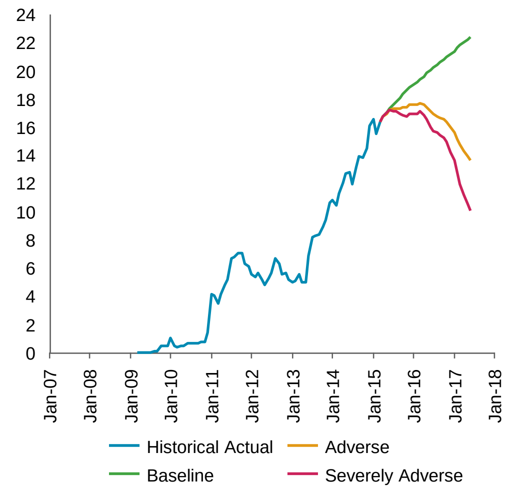
Alternative Investment Services / Global Collateral Services IB: Model 1
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for AISGCS IB
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	6.03 (37%)	-2.77 (-17%)	-6.32 (-39%)	-
Start to peak	6.03 (37%)	1.3 (8%)	0.79 (5%)	N/A
Start to trough	N/A	-2.77 (-17%)	-6.32 (-39%)	N/A



The Working Group considered the forecast behavior for the selected AIS/GCS IB model as reasonable.

The model forecasts are illustrated on Figure 108.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant deposit run-off. In a review of the forecasts with the line of business, this was noted to be not directionally consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. It was noted by the line of business that the sharp runoff in balances in the severe recession scenario should be reviewed closely as well, as a flight to quality increase in the deposits in times of severe market stress is expected
- **Interest rate shock (Adverse) scenario:** The model predicts a deposits run-off. This was consistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment
- **Baseline scenario:** The baseline scenario shows a significant increase in balances. While this increase is in line with historic growth, a significant change in balances is not expected therefore the scenario should be reviewed closely as well

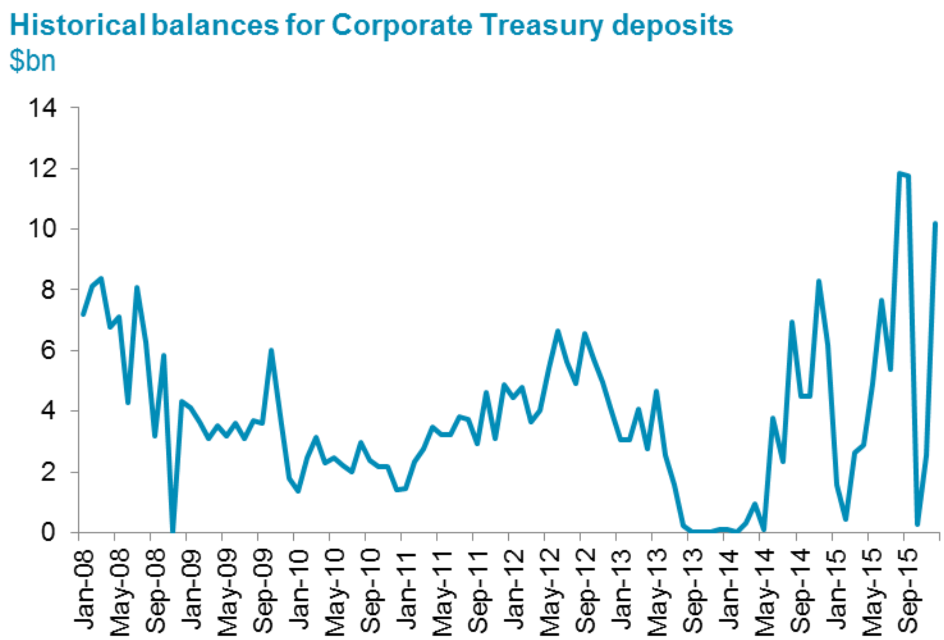
5.4.4.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

5.5. Corporate Treasury deposit balance

5.5.1. Historical data

Figure 109 Historical balances for Corporate Treasury deposits



5.5.2. General data issues

The historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Corporate Treasury deposits. As discussed previously, the data was sourced from the MAQ, which is also used for regulatory reporting purposes.

5.5.3. Summary of approach

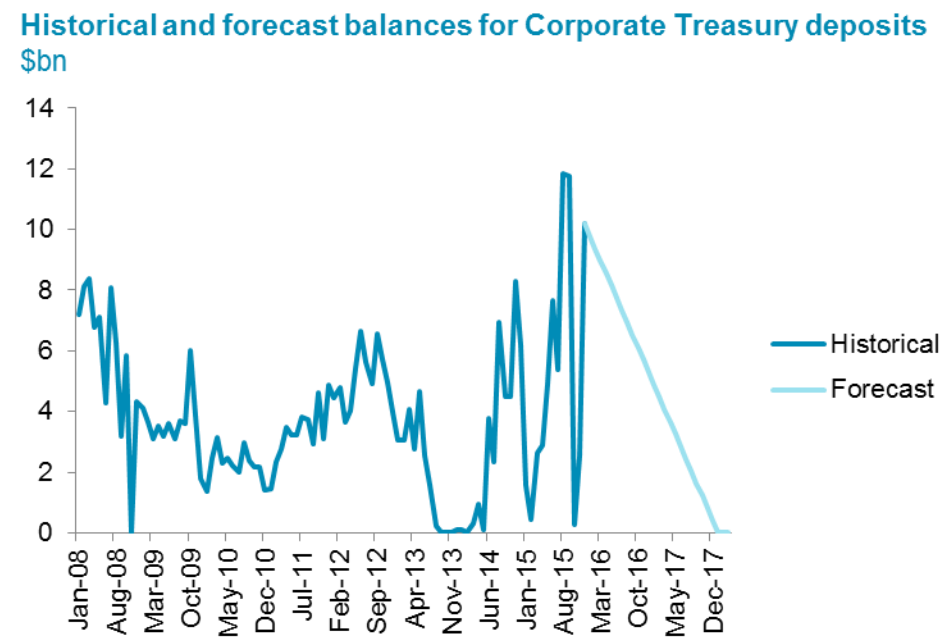
5.5.3.1. Approach

A qualitative framework is applied for the Corporate Treasury deposits segment.

Under normal course of buisness, Corporate Treasury solicits deposit balances to gain incremental NII by holding them at the Federal Reserve and earning an excess spread. This function will have come to an end in January 2018 when the new SLR regulation takes effect. As a consequence, the qualitative framework linearly interpolates from the balance at the beginning of the forecast period to zero in January 2018, and then holds the balance at zero until the end of the forecasting period.

However, if additional funding is needed during the forecast period, the amortization above is not to be programmed. Instead the decision tree as described in Investment Portfolio (Section 9) is applied period after period in which Corporate Treasury deposits may serve as a source of additional funding.

Figure 110Influential point: Historical and forecast balances for Corporate Treasury deposits



5.5.3.2. Previous Statistical approach

The modeling team first attempted to develop a statistical model for this segment.

The Corporate Treasury deposit model failed to capture the high volatility of the segment and had a relatively poor in-sample fit. Moreover, the segment's balances are management driven. The Corporate Treasury team that manages Corporate Treasury deposits and Fed Funds Purchased and Repos balances explained that balances are in large part solicited when there is room in the leverage ratio and Corporate Treasury decides to repo out securities or purchase deposits. These balances then earn incremental NII when they are left at the Federal Reserve and earn interest above the purchase price for deposits or the interest rate for repos, and have little to do with macroeconomic variables. The statistical model also misses an important aspect of the future business outlook for both balances, namely, that they are expected to wind down in light of new, more restrictive regulation concerning the leverage ratio that takes effect in January 2018 (new SLR regulation). As more restrictive leverage ratio regulation takes effect in January

2018 and there is less room in the bank's leverage ratio, this activity is likely to come to an end in the upcoming years. Finally, this segment's balances serve a funding function when additional funding is needed. Subsequently, a qualitative framework was developed.

5.6. Wealth Management deposit balance models

5.6.1. Business overview and segments

The Wealth Management business provides various finance-related services to high net worth individuals, families, endowments and foundations. Core services include investment management, wealth and estate planning, private banking, and asset servicing & information management. As of April 30, 2015, the Wealth Management line of business has deposits totaling $14.1 BN.

For ALM management purposes, Wealth Management deposits are separated into three segments, as described in Table 110: non-interest bearing USD deposits (WM DDA), interest bearing USD deposits (WM Personal), and interest bearing Sweep (WM Sweep). As described earlier in Section 3.1.2, this segmentation was adopted for the purposes of balance sheet forecasting as well, to align the segmentation with those used for other business purposes.

Table 110: Segment description for Wealth Management

Segments for Wealth Management

Segments	Size ($ BN)[27]	Description
WM DDA	1.9	Composed entirely of USD denominated non-interest bearing balances in demand deposit accounts.
WM Personal	5.8	Contains all interest bearing Wealth Management deposits denominated in USD currency. The products contained in this segment are Wealth Management Checking with Interest (CWIs), WM Private Banking Money Market Deposit Accounts (MMDAs), WM Savings, Wealth Management Cash Management Access Accounts (CMAAs), and WM Time Deposits. All these deposits are managed within the US
WM Sweep	6.4	Uninvested cash held in fiduciary or custody accounts that are swept into a short-term bank time deposit.

5.6.2. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team and the line of business, a list of driver hypotheses were developed and refined over time. Figure 111 illustrates the initial driver hypotheses that were identified through conversations with the lines of business and the ALM team in advance of the modeling process. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

[27] Month-end spot balances from April 30, 2015

Figure 111: Summary of Wealth Management deposit balance drivers

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit balances increase when general economic health improves	• Real GDP growth, unemployment rate, real disposable income
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase as BNYM is perceived as a relative "safe haven"	• Spread of BNYM debt rate to industry peer rate
	Banking system risk	• Deposit balances increase as banking credit risk increases, as BNYM is perceived as a relative "safe haven"	• Overnight Libor, TED Spread, Libor OIS spread
	Equity markets	• Deposit balances may increase as investor wealth grows together with the market • Deposit balances may decrease as market returns increase and the relative cost of keeping cash increases	• DJI, MSCI Global, KBW Bank Index
	Mutual Fund cash flow	• Deposits balances increase as stock and bond and income mutual funds increase activity • Deposit balances decrease as Money Market funds are attracting more capital	• Bond and Income MF CF, Money market MF CF, Stock MF CF
	Market volatility/ uncertainty	• Deposit balances increase as market volatility and uncertainty increases • Deposit balances decrease when financial markets are trending up, as leaving cash in low/zero yield deposits becomes less attractive	• VIX, 10 Year T-Note volatility index, US LIBOR-OIS spread
Rates	**Short-term rates**	• Deposit balances decrease in higher rate environments as depositors chase higher yielding products	• Prime Rate, Fed Funds effective rate, 1 & 3 month Treasury rate, Overnight Repo rate, T-Bill index spread with Fed funds effective rate
	Long-term rates	• Deposit balances decrease in higher rate environments as depositors chase higher yielding products	• Treasury yields, US swaps
	Corporate credit rates	• Deposit balances may increase as credit risk in the economy increases • Deposit balances may decrease as depositors chase higher yielding products in higher rate environments	• Corporate BAA, BAA to Treasury spread
	Treasury Yield Spread	• Deposit balances decrease when yield spreads widen as longer term investment yields become more attractive	• 3 month – 5 year and 3 month – 10 year Treasury yield spread

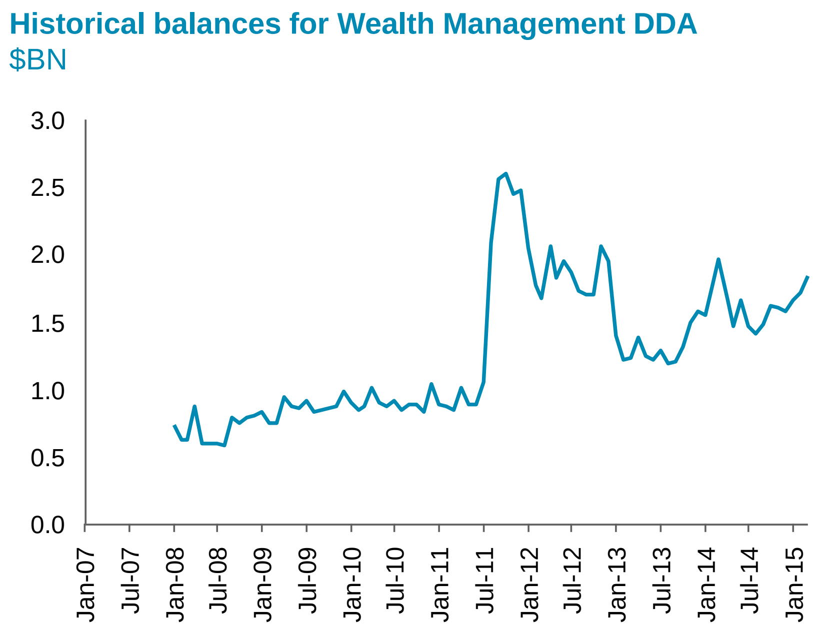
The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

5.6.3. Wealth Management DDA

5.6.3.1. Deposit balance overview

Over the modeling time period, Wealth Management Demand Deposit Account (Wealth Management DDA, or WM DDA) deposit balances have shown an overall growth trend with a few steep increases. The WM DDA balances remain largely flat until July 2011, when the balance more than doubles in a span of a few months. The businesses confirmed that this increase was largely driven by an idiosyncratic action taken by a single large client.

Figure 112: Historical balances for Wealth Management DDA



5.6.3.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Wealth Management DDA segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the WM DDA deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 111.

Table 111: Coefficient estimates for selected Wealth Management DDA model

Wealth Management DDA (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Corp_Baa_DMoM	First difference – MoM	%	-275.204	-0.28
Market_Vol_PQoQ	Percent change – QoQ	Index	1.926	0.49
Real_Dis_Inc	-	%	5.447	0.18
Intercept	-	$ MM	-11.576	N/A

The model contains the following drivers and variables:

- **Corporate credit rates** – Moody's Corporate Baa bond yield
- **Market volatility (equities)** – The maximum close-of-day value of S&P 500 volatility index (i.e. the VIX), a common benchmark of conceived market uncertainty in the broad US equity market
- **General economic health** – US real disposable income

The intuition of these variables is as follows:

- The Corporate Baa bond yield has a negative coefficient, which is consistent with business intuition that deposit balances decrease as bond yields increase. WM DDA are non-interest bearing deposits, and as such BNY Mellon expects clients to seek alternative higher-yielding products
- The market volatility shows a positive coefficient, which is consistent with business intuition that WM clients increase their deposits with BNY Mellon when market volatility and uncertainty rises
- The real disposable income variable has a positive coefficient. This is consistent with business intuition that an improvement in general economic health will result in higher WM balances. The more disposable income is available to WM clients, the more money will be held in BNY Mellon accounts

Besides the selected model above, a few alternative models were considered for the WM DDA segment. Figure 113 displays an overview of candidate models for WM DDA.

Figure 113: Candidate Models for Wealth Management Demand Deposit Account

Wealth Management DDA
Candidate models

Drivers Considered	Candidate models 1	2	3	4
Corporate credit		Baa Corporate Yield (Diff MoM)	Baa Corporate Yield (Diff MoM)	
General economic health	Real Disposable Income Growth (Level)	Real Disposable Income Growth (Level)		Real Disposable Income Growth (Level, 1M Lag)
Long-term rates				20Y Treasury (Diff MoM)
Market volatility/ uncertainty (equity)	Market Vol (% QoQ)	Market Vol (% QoQ)	Market Vol (% QoQ)	
MF Cash Flow	Money Market Fund Cash Flow (Diff QoQ)			
Variation in balances explained through estimated first differences	**40%**	**76%**	**71%**	**62%**
R-squared (differences)	**24%**	**22%**	**19%**	**10%**

Final model

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.6.3.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.6.3.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Wealth Management DDA series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 112.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 113.

Table 112: Unit root tests and stationarity tests including a trend variable on balances

Wealth Management DDA (in USD MM) – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-2.5	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.7	0.26	Fail to reject unit root
KPSS	5	0.14	0.06	Reject stationarity

Table 113: Unit root tests and stationarity tests including a constant on first differences

Wealth Management DDA (in USD MM) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-7.6	<0.01	Reject unit root
Phillips-Perron	1	-7.6	<0.01	Reject unit root
KPSS	1	0.04	0.94	Fail to reject stationarity

Wealth Management DDA balances do not pass any of the stationarity or unit roots tests. These results suggest the WM DDA balances are likely to be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the WM DDA deposit balances are modeled on their first differences.

5.6.3.3.2. Historical data review

In addition to checking for stationarity of dependent variables, we also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were made for the WM DDA segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the WM business.

An additional analysis was conducted, however, to investigate whether removing the balances of the large client that drove the balances up in 2011 would lead to a better performing model. The analysis, however, did not result in a better performing model and the client was not separated out.

5.6.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 114 reports the results of the significance tests.

Heteroskedasticity was detected in this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Each of the coefficient estimates in the Wealth Management DDA model is statistically significant, but the coefficient for the joint f-test is found to be statistically insignificant. The intercept is also found to be statistically insignificant.

Table 114: Statistical significance tests of model and variables for Wealth Management DDA

Wealth Management DDA (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	17%	10%	Statistically not significant
Corp_Baa_DMoM	-275.204	7%	10%	Statistically significant
Market_Vol_PQoQ	1.926	6%	10%	Statistically significant
Real_Dis_Inc	5.447	9%	10%	Statistically significant
Intercept	-11.576	56%	10%	Statistically not significant

5.6.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

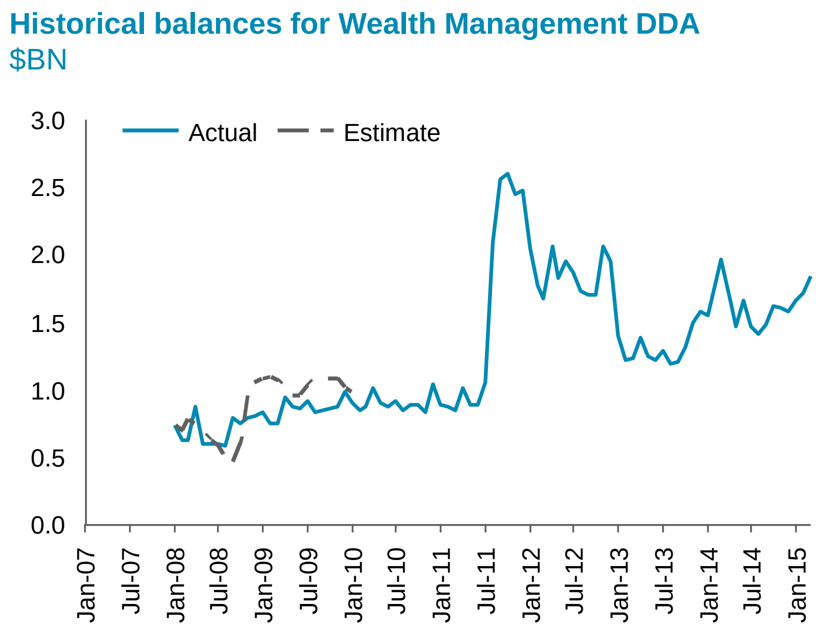
Table 115: Wealth Management DDA Model Diagnostics

Wealth Management DDA – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	22%	-	-
	Adjusted R-squared	19%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	24%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.28	5	No multicollinearity
Linearity	RESET test	72%	10%	Linear specification appropriate

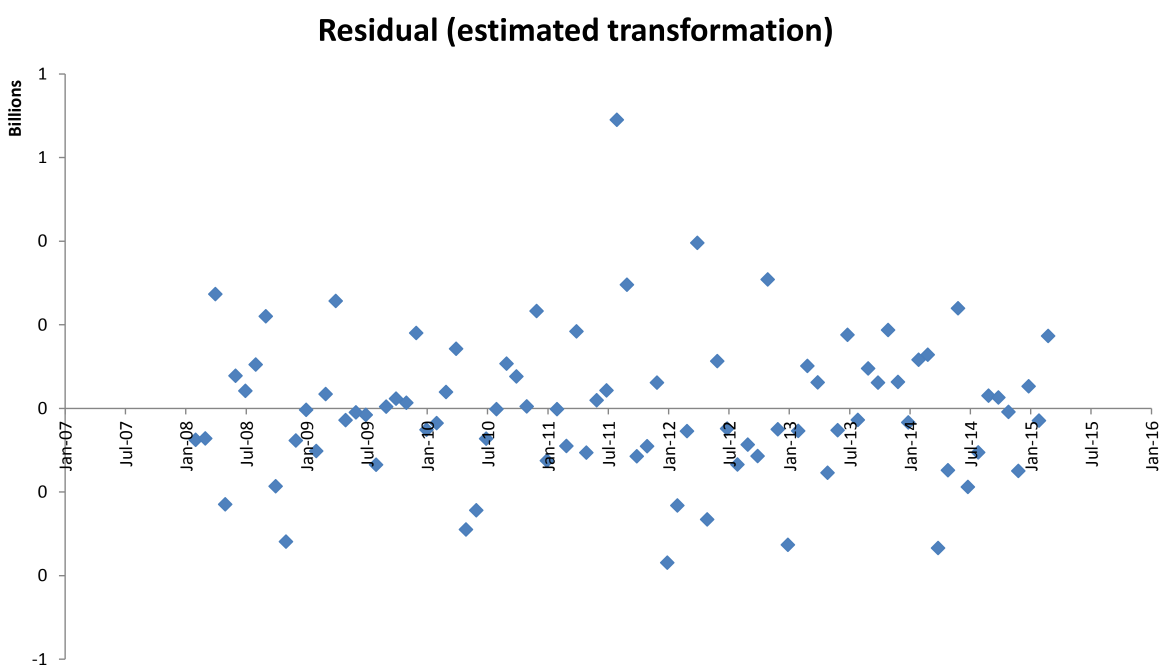
The model passes most model diagnostic tests that were evaluated but fails the Breusch-Pagan test for heteroskedasticity.

Figure 114: Wealth Management DDA 9Q In-Sample Prediction



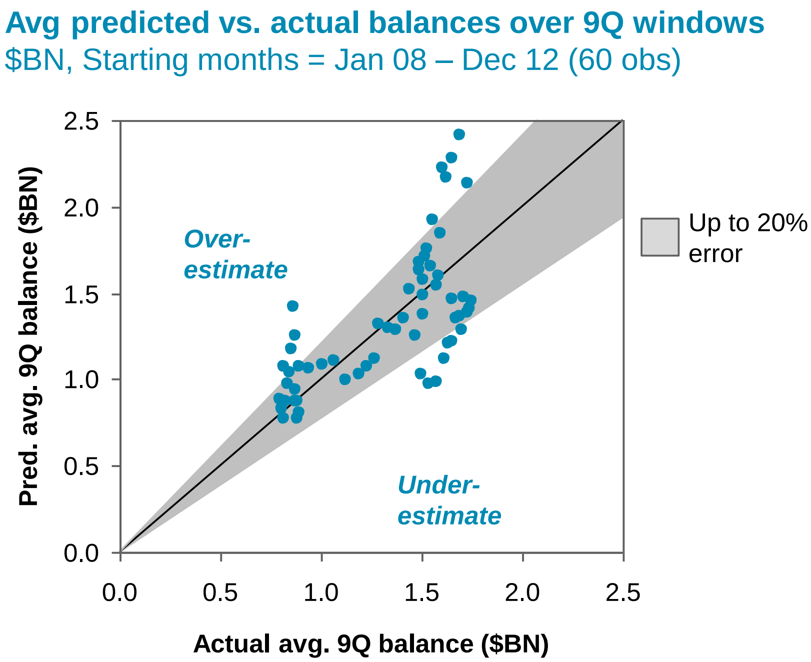
The in-sample back test of the model starting from January 2008 follows the balance fairly closely.

Figure 115: Wealth Management DDA Residual Plot ($ BN)



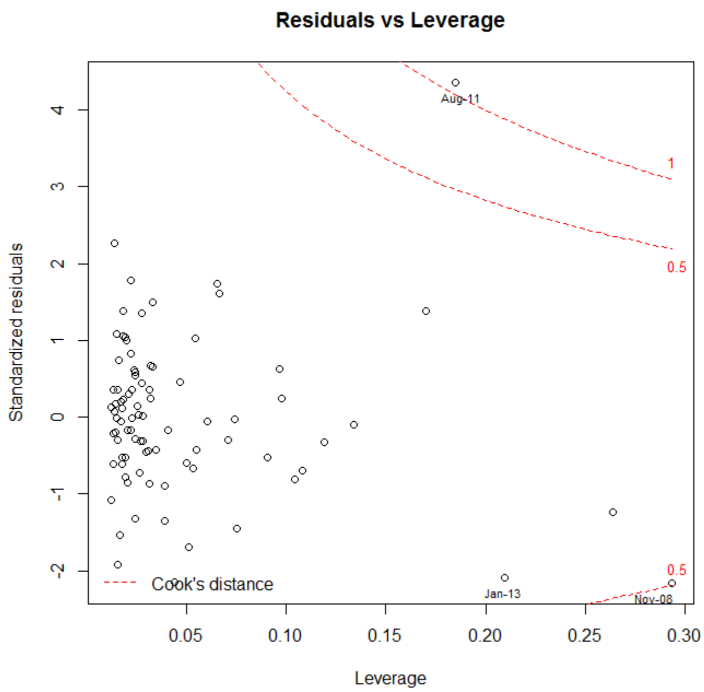
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 116: Wealth Management DDA Balance Estimation Scatterplot



The points of overestimation and underestimation on Figure 116 are mainly driven by the volatility of the balances caused by idiosyncratic balance movements triggered by large clients.

Figure 117: Influential points for Wealth Management DDA



The segment does not contain any highly influential points.

5.6.3.6. Model sensitivity

5.6.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 116. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 116: Sensitivity to changes to independent variables for Wealth Management DDA

Wealth Management DDA (in USD MM) – model sensitivity					
Independent variable	**Transformation**	**Unit**	**Standardized coefficient**	**Std. dev of independent variable**	**Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)**
Corp_Baa_DMoM	First difference – MoM	%	-0.28	0.19	-0.05
Market_Vol_PQoQ	Percent change – QoQ	Index	0.49	48.74	0.09
Real_Dis_Inc	-	%	0.18	6.57	0.04
Intercept	-	$ MM	N/A	N/A	N/A

In the WM DDA model, the market volatility variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the quarterly percentage changes of market volatility results in a 0.49 standard deviation ($0.09 BN) increase in the predicted monthly change of the WM DDA deposits.

5.6.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 117.

Table 117: Statistical sensitivity tests for Wealth Management DDA

Wealth Management DDA (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Corp_Baa_DMoM	-275.204	-303.454	0.86	Statistically insignificant
Market_Vol_PQoQ	1.926	2.027	0.77	Statistically insignificant
Real_Dis_Inc	5.447	6.156	0.38	Statistically insignificant
Intercept	-11.576	-16.132	0.41	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.17	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.6.3.6.3. Sensitivity to stressed independent variable scenarios

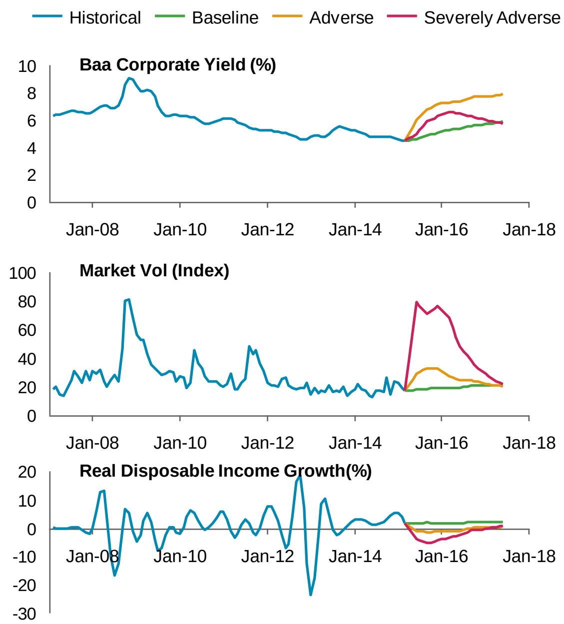
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 118: Wealth Management Demand Deposit Account Model Forecast

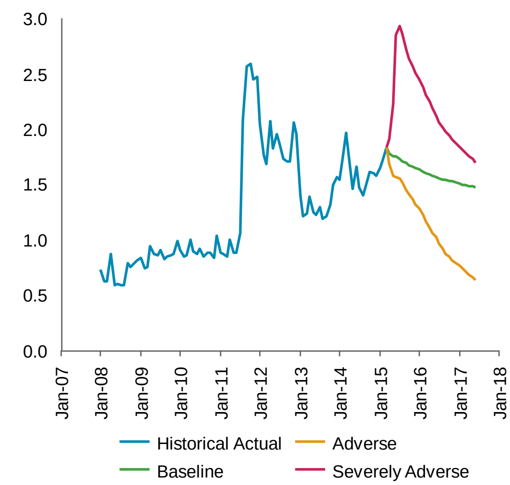
Wealth Management DDA: Model 2
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Wealth Management DDA, $BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-0.37 (-20%)	-1.2 (-66%)	-0.14 (-8%)	-
Start to peak	N/A	N/A	1.1 (60%)	0.26 (35%)
Start to trough	-0.37 (-20%)	-1.2 (-66%)	-0.14 (-8%)	-0.14 (-20%)



The Working Group considered the forecast behavior for the selected WM DDA model as reasonable.

The model forecasts are illustrated on Figure 118:

- **Severe recession (Severely Adverse) scenario:** The model predicts an initial increase in balances followed by a balance decrease. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations. The line of business suggested that the magnitude of the initial increase should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts a deposits run-off. This was consistent with business intuition, as BNY Mellon would expect clients to seek out alternative investments in a rising rates environment. The line of business suggested that the magnitude of the initial increase should be monitored closely when the final outputs for submission are generated
- **Baseline scenario:** The baseline scenario largely remains flat with a mild decline, which is consistent to business intuition that a significant change in balances is not expected

5.6.3.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The WM DDA balances exhibited large and rapid increases and decreases during the modeling period due to idiosyncratic shifts in balances from a single client. The WM DDA balance more than doubled in mid-2011, when a major client deposited nearly $1.5 BN into their account within a span of few months. Not surprisingly, the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently.

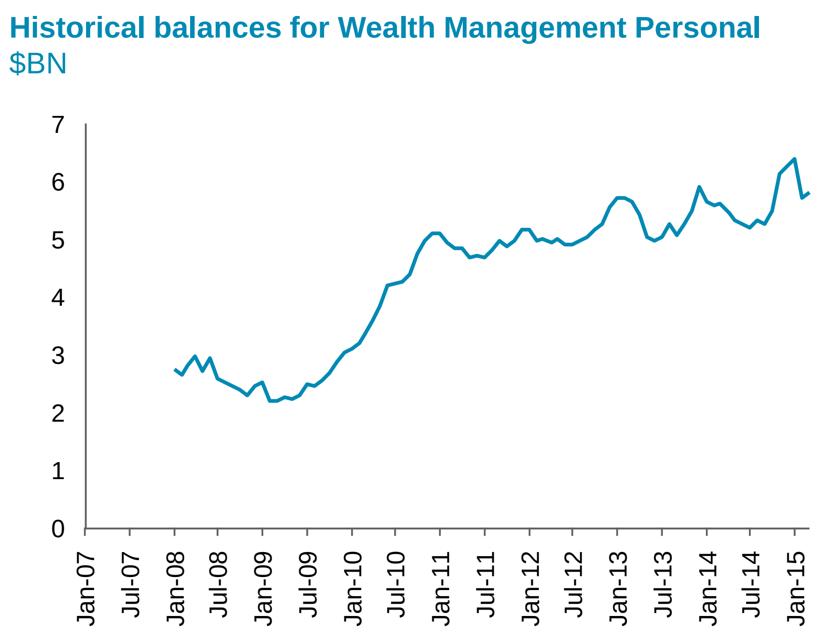
As discussed in a prior section, an attempt was made to model the segment balances by removing the balances from a large client that drove large shifts in the overall segment balances, but this analysis did not yield a better model.

5.6.4. Wealth Management Personal

5.6.4.1. Deposit balance overview

Over the modeling time period, Wealth Management Personal (WM Personal) balances have shown a steady growth trend. The WM Personal balances remain largely flat until July 2009, when the balance almost doubled in a span of two years. The businesses confirmed that the steep increase in WM balances were due to idiosyncratic actions taken by large clients, especially in the WM MMDA product.

Figure 119: Historical balances for Wealth Management Personal



5.6.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Wealth Management Personal segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the WM Personal deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 118.

Table 118: Coefficient estimates for selected Wealth Management Personal model

Wealth Management Personal (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Real_GDPL1	-	%	17.466	0.27
US_5yr_swap_DQoQ	First difference – QoQ	%	-76.901	-0.20
Intercept	-	$ MM	7.942	N/A

The model contains the following drivers and variables:

- General economic health – US Real GDP growth
- Long term rates – US 5-year swap, a measure of US long-term rates

The intuition of these variables is as follows:

- The real GDP growth has a positive coefficient, which is consistent with business intuition that deposit balances increase as general economic performance improves and the more wealth the WM clients will have to deposit
- The US 5-year swap has a negative coefficient, which is consistent with business intuition that deposit balances decrease as long-term rates increase. BNY Mellon expects clients to seek other institutions and instruments with higher yields when rates rise

Besides the selected model above, a few alternative models were considered for the WM Personal segment. Figure 120 displays an overview of candidate models for WM Personal.

Figure 120: Candidate Models for Wealth Management Personal

Wealth Management Personal
Candidate models

Drivers Considered	Candidate models 1	2	3	4	5
Corporate credit	Baa to Treasury Spread (Diff YoY)				
General economic health		Real GDP growth (Level, 1M Lag)	Real GDP growth (Level, 1M Lag)	Real GDP growth (Level)	Real GDP growth (Level, 1M Lag)
Long-term rates	5Y US Swap (Diff QoQ)	5Y US Swap (Diff QoQ)			5Y US Swap (Diff QoQ)
Market volatility/ uncertainty (equity)				Market Vol (% MoM, 1M Lag)	
MF Cash Flow	Stock Mut Fund Cash Flow (Diff MoM)	Stock Mut Fund Cash Flow (Diff MoM)	Stock Mut Fund Cash Flow (Diff MoM)		
Banking system risk				TED Spread (Diff YoY)	
Yield spread			3M to 10Y T Spread (Level)		
Variation in balances explained through estimated first differences	**92%**	**80%**	**93%**	**89%**	**82%**
R-squared (differences)	**13%**	**12%**	**11%**	**10%**	**8%**

Final model (model 5)

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.6.4.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

5.6.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Wealth Management Personal series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 119.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 120.

Table 119: Unit root tests and stationarity tests including a trend variable on balances

Wealth Management Personal (in USD MM) – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-1.9	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.3	0.44	Fail to reject unit root
KPSS	5	0.22	0.01	Reject stationarity

Table 120: Unit root tests and stationarity tests including a constant on first differences

Wealth Management Personal (in USD MM) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	11	-2	0.31	Reject unit root
Phillips-Perron	1	-13	<0.01	Reject unit root
KPSS	2	0.07	0.73	Fail to reject stationarity

Wealth Management Personal balances do not pass any of the stationarity or unit roots tests. These results suggest the WM Personal balances are likely to be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the WM Personal deposit balances are modeled on their first differences.

5.6.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, we also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the WM Personal segment. As discussed previously, the data was primarily sourced from MAQ, with one sub-segment sourced from Microstrategy to remove the effects of an accounting adjustment that created significant outlier data values. Its accuracy was confirmed with the WM business.

5.6.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 121 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the WM Personal model are statistically significant.

Table 121: Statistical significance tests of model and variables for Wealth Management Personal

Wealth Management Personal (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	3%	10%	Statistically significant
Real_GDPL1	17.466	2%	10%	Statistically significant
US_5yr_swap_DQoQ	-76.901	8%	10%	Statistically significant
Intercept	7.942	72%	10%	Statistically not significant

5.6.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

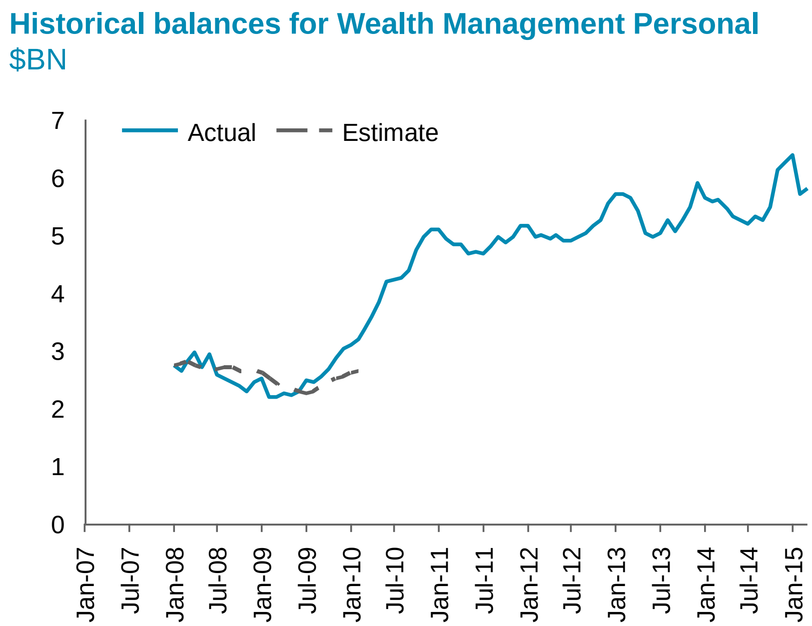
Table 122: Wealth Management Personal Model Diagnostics

Wealth Management Personal – Model diagnostics

Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	8%	-	-
	Adjusted R-squared	6%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.60	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	30%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.10	5	No multicollinearity
Linearity	RESET test	93%	10%	Linear specification appropriate

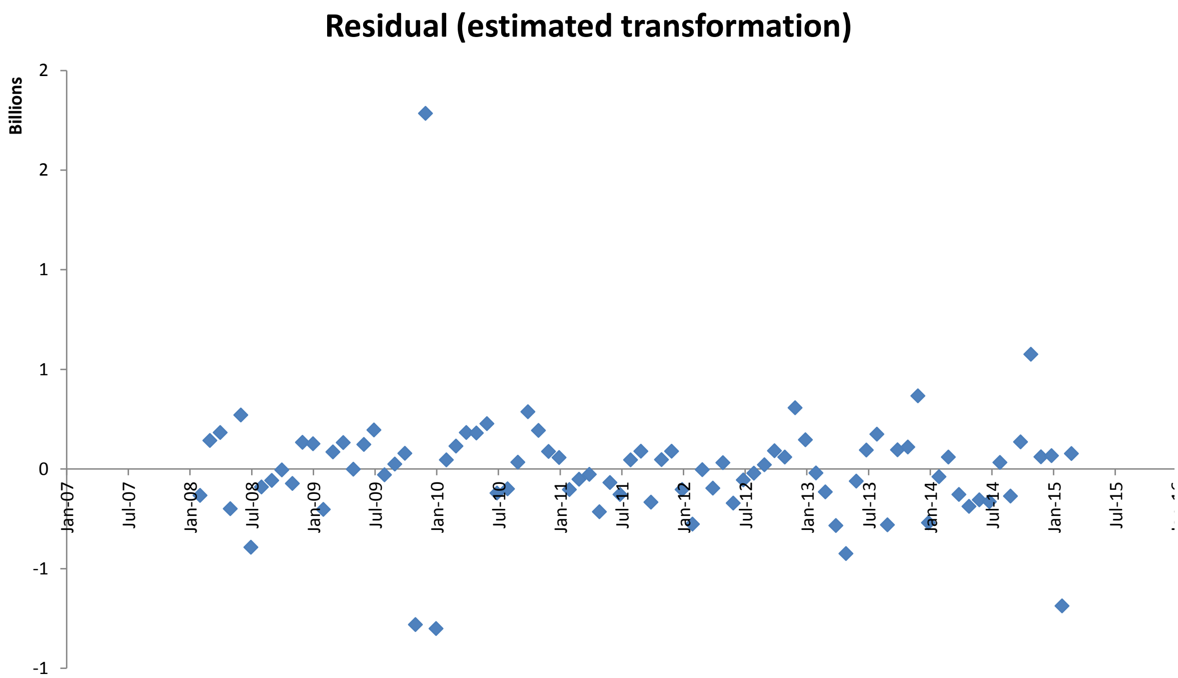
The model passes all model diagnostic tests that were evaluated, except the Breusch-Godfrey test for serial correlation.

Figure 121: Wealth Management Personal 9Q In-Sample Prediction



The in-sample back test of the model starting from January 2008 captures the balance fairly closely during the first few quarters, but only partially captures the increase in 2010. Given this increase was driven by idiosyncratic client movement, it is not unexpected that the model would not be able to fully capture the change in balances.

Figure 122: Wealth Management Personal Residual Plot ($ BN)



As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 123: Wealth Management Personal Balance Estimation Scatterplot

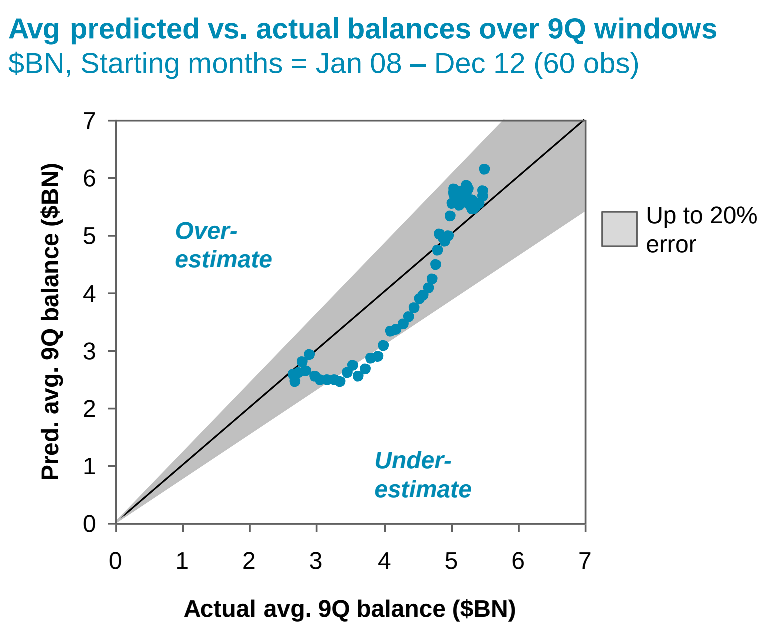
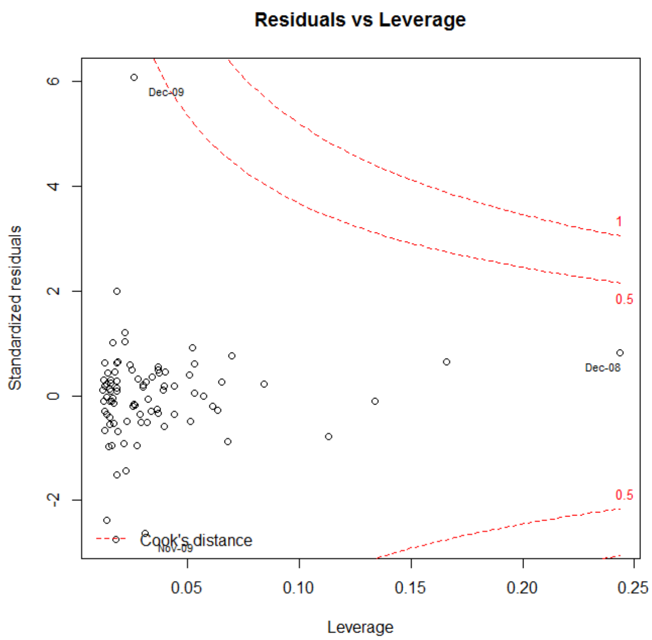


Figure 123 shows that most predictions are generally in line with the actual balances of Wealth Management Personal.

Figure 124: Influential points for Wealth Management Personal



The segment does not contain any highly influential points.

5.6.4.6. Model sensitivity

5.6.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 123. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 123: Sensitivity to changes to independent variables for Wealth Management Personal

Wealth Management Personal (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Real_GDPL1	-	%	0.27	2.93	0.08
US_5yr_swap_DQoQ	First difference – QoQ	%	-0.20	0.48	-0.06
Intercept	-	$ MM	N/A	N/A	N/A

In the WM Personal model, the real GDP growth variable has the standardized coefficient with the largest magnitude. We find that a one standard deviation increase in the real GDP growth results in a 0.27 standard deviation ($0.08BN) increase in the predicted monthly change of the WM Personal deposits.

5.6.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 124.

Table 124: Statistical sensitivity tests for Wealth Management Personal

Wealth Management Personal (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Real_GDPL1	17.466	13.737	0.48	Statistically insignificant
US_5yr_swap_DQoQ	-76.901	1.098	0.66	Statistically insignificant
Intercept	7.942	37.875	0.27	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.66	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.6.4.6.3. Sensitivity to stressed independent variable scenarios

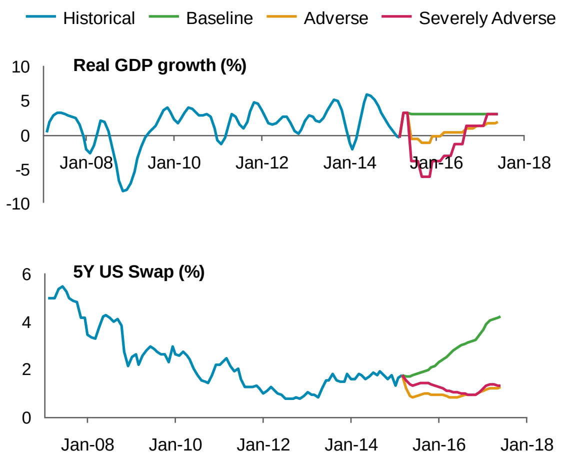
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model's forecast behavior was tested for different macroeconomic scenarios.

Figure 125: Wealth Management Personal Model Forecast

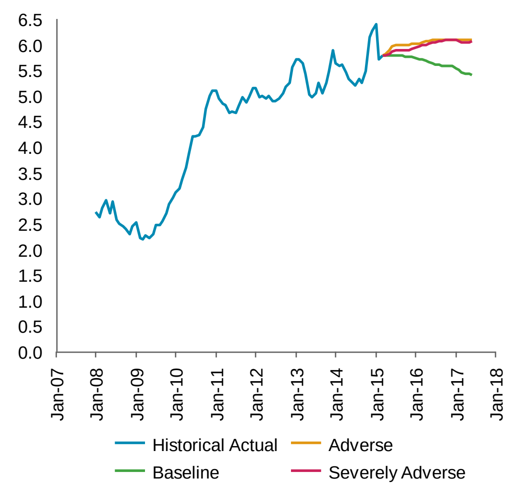
Wealth Management Personal: Model 5
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Wealth Management Personal, $BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-0.39 (-7%)	0.29 (5%)	0.27 (5%)	-
Start to peak	N/A	0.31 (5%)	0.31 (5%)	0.28 (10%)
Start to trough	-0.39 (-7%)	N/A	-0.01 (0%)	-0.55 (-20%)



The Working Group considered the forecast behavior for the selected WM Personal model as reasonable.

The model forecasts are illustrated in Figure 125:

- **Severe recession (Severely Adverse) scenario:** The model predicts a mild increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as, unlike the WM non-interest bearing accounts, WM interest-bearing accounts are expected continue its mild growth trend through severe recession
- **Interest rate shock (Adverse) scenario:** The model predicts a mild increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as, unlike the WM non-interest bearing accounts, WM interest-bearing accounts are expected to be stable through severe recession
- **Baseline scenario:** The baseline scenario largely remains flat with a mild decline, which is consistent to business intuition that a significant change in balances is not expected

5.6.4.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

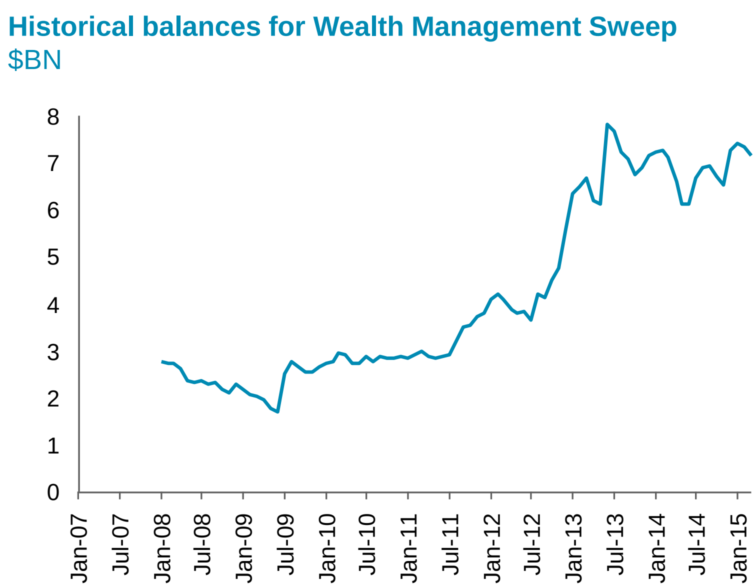
The WM Personal balances exhibited large and rapid increases and decreases during the modeling period. For instance, the WM Personal increased at a steep curve from 2009 to 2011 due to idiosyncratic actions taken by large clients. Not surprisingly, the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently.

5.6.5. Wealth Management Sweep

5.6.5.1. Deposit balance overview

Over the modeling time period, Wealth Management Sweep (WM Sweep) balances have experienced an overall growth trend. The WM Sweep balances increase mildly until July 2012, when the balance more than doubles in a span of a year. This was due to management's decision to move the balances from money market accounts, which were off-balance sheet, to cash sweep vehicles.

Figure 126: Historical balances for Wealth Management Sweep



5.6.5.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Wealth Management Sweep segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the WM Sweep deposit balances, which is found to be stationary

- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 125.

Table 125: Coefficient estimates for selected Wealth Management Sweep model

Wealth Management Sweep (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
BAA_TSpread_DMoM	First difference – MoM	%	-452.482	-0.33
SP_Vol_DQoQ	First difference – QoQ	Index	94.626	0.25
Tspread_3m_5yr	-	%	-127.830	-0.22
Intercept	-	$ MM	236.292	N/A

The model contains the following drivers and variables:

- **Corporate credit rates** – Baa-to-Treasury spread, which is a measure of corporate credit controlling for the rate environment
- **Market volatility (equities)** – Moody's S&P 500 volatility index (30 day moving average), a common benchmark of conceived market uncertainty in the broad US equity market
- **Treasury yield spread** – Treasury 3 month-to-5 year spread, which is a measure of spread between short-term and long-term rates

The intuition of these variables is as follows:

- The Baa-to-Treasury spread has a negative coefficient, which is consistent with business intuition business intuition that deposit balances decrease as long-term corporate bond yields become more attractive
- The S&P 500 volatility index has a positive coefficient, which is consistent with business intuition that deposit balances increase as under a volatile market environment. The more volatility in equity markets, the more likely the portfolio managers are to leave uninvested cash for the sweep accounts
- The Treasury 3-month-to-5-year spread has a negative coefficient, which is consistent with business intuition that deposit balances decrease as long-term investments become increasingly more attractive

Besides the selected model above, a few alternative models were considered for the WM Sweep segment. Figure 127 displays an overview of candidate models for WM Sweep.

Figure 127: Candidate Models for Wealth Management Sweep

Wealth Management Sweep
Candidate models

Drivers Considered	Candidate models 1	2	3	4
Corporate credit	Baa to Treasury Spread (Diff MoM)	Baa to Treasury Spread (Diff MoM)		Baa Corporate Yield (Diff MoM, 1M Lag)
Market volatility/ uncertainty (equity)		S&P Vol (30D MAVG) (Diff QoQ)		
MF Cash Flow	Bond and Income Mut Fund Cash Flow (Diff MoM, 1M Lag)		Money Market Fund Cash Flow (Diff YoY)	Bond and Income Mut Fund Cash Flow (Diff MoM, 1M Lag)
Banking system risk			TED Spread (Diff YoY)	
Yield spread	3M to 5Y T Spread (Level)	3M to 5Y T Spread (Level)	3M to 10Y T Spread (Level, 1M Lag)	
Variation in balances explained through estimated first differences	**95%**	**94%**	**96%**	**85%**
R-squared (differences)	**8%**	**8%**	**7%**	**6%**

Final model

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

The Working Group had initially selected Model 3. During the line of business review, feedback was provided that an equity volatility variable was strongly preferred over a Money Market Mutual Fund cash flow variable. Therefore, Model 2 was selected instead as the final model.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.6.5.3. Dependent variable construction

Dependent variable construction consistent of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.6.5.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Wealth Management Sweep series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 126.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 127.

Table 126: Unit root tests and stationarity tests including a trend variable on balances

Wealth Management Sweep (in USD MM) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	5	-1.5	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.5	0.32	Fail to reject unit root
KPSS	5	0.25	<0.01	Reject stationarity

Table 127: Unit root tests and stationarity tests including a constant on first differences

Wealth Management Sweep (in USD MM) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	5	-3.1	0.03	Reject unit root
Phillips-Perron	1	-7.7	<0.01	Reject unit root
KPSS	3	0.18	0.32	Fail to reject stationarity

Wealth Management Sweep balances do not pass any of the stationarity or unit roots tests. These results suggest the WM Sweep balances are likely to be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the WM Sweep deposit balances are modeled on their first differences.

5.6.5.3.2. Historical data review

In addition to checking for stationarity of dependent variables, we also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the WM Sweep segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the WM business.

An additional analysis was conducted, however, to investigate whether removing the balances of the large client that drove the balances up starting in 2012 would help lead to a better performing model. The analysis, however, did not result in a better performing model and the large client was not separated out.

5.6.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 128 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

All of the coefficient estimates in the WM Sweep model are statistically significant.

Table 128: Statistical significance tests of model and variables for Wealth Management Sweep

Wealth Management Sweep (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
BAA_TSpread_DMoM	-452.482	<1%	10%	Statistically significant
SP_Vol_DQoQ	94.626	<1%	10%	Statistically significant
Tspread_3m_5yr	-127.830	3%	10%	Statistically significant
Intercept	236.292	2%	10%	Statistically significant

5.6.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

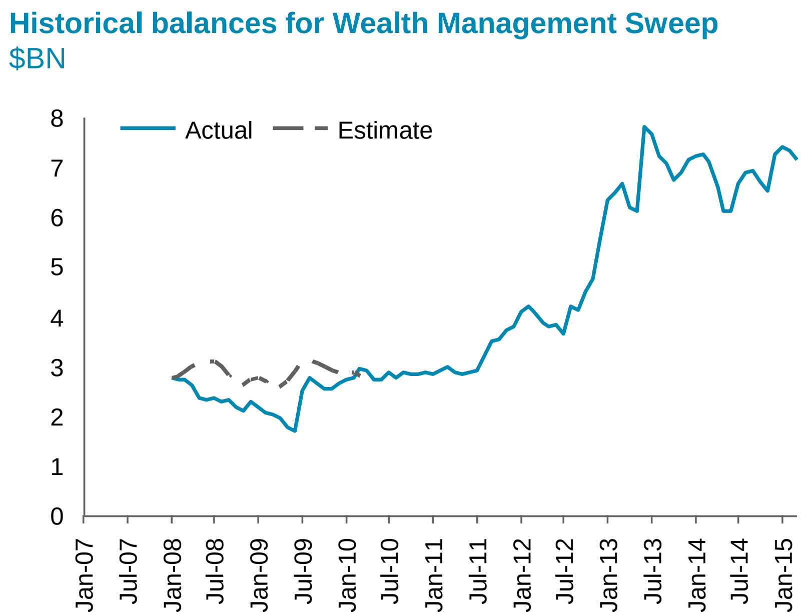
Table 129: Wealth Management Sweep Model Diagnostics

Wealth Management Sweep – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	8%	-	-
	Adjusted R-squared	4%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	29%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	2%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	2.26	5	No multicollinearity
Linearity	RESET test	23%	10%	Linear specification appropriate

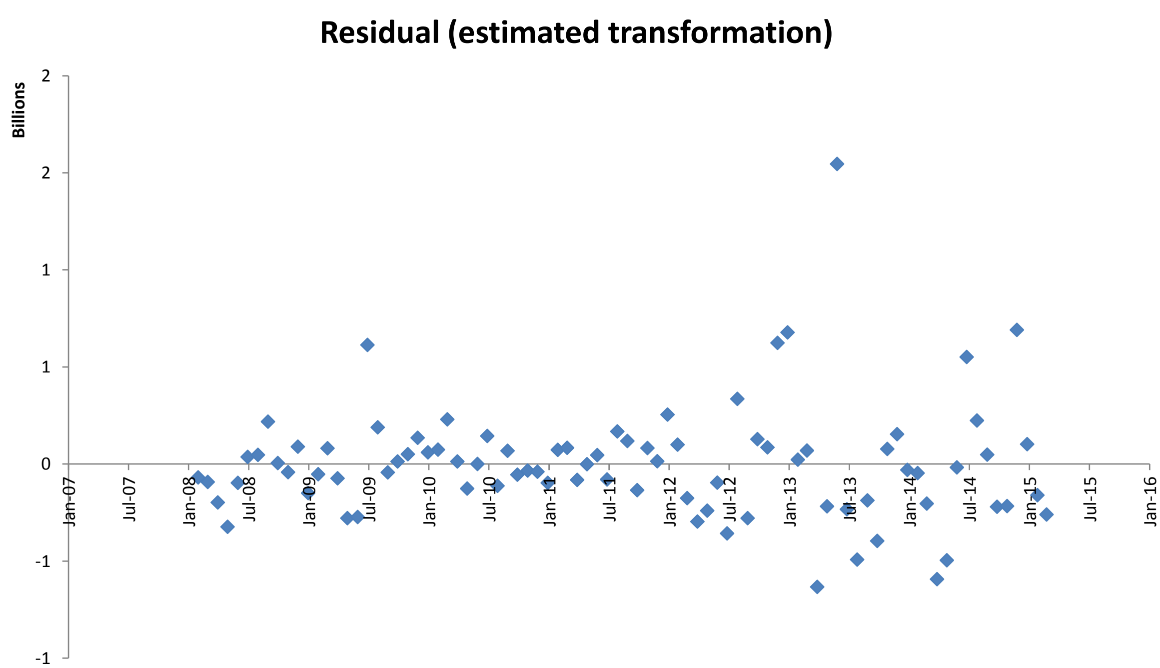
The model passes all model diagnostic tests that were evaluated, except the Breusch-Godfrey test for serial correlation.

Figure 128: Wealth Management Sweep 9Q In-Sample Prediction



The in-sample back test of the model starting from January 2008 tracks the balance fairly closely during the first 9 quarters. The model overestimates balance during this period, since it is calibrated on a series that experiences a steep increase in 2012–2013.

Figure 129: Wealth Management Sweep Residual Plot ($ BN)



As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 130: Wealth Management Sweep Balance Estimation Scatterplot

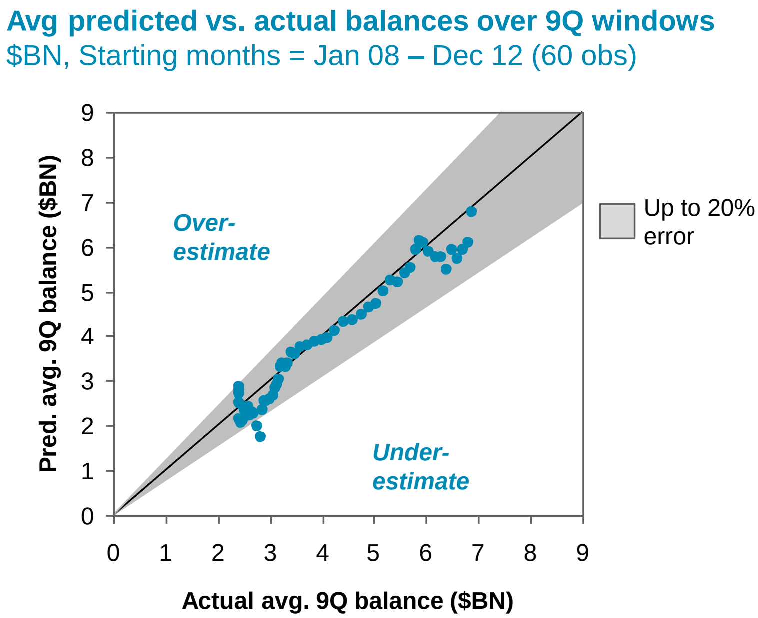
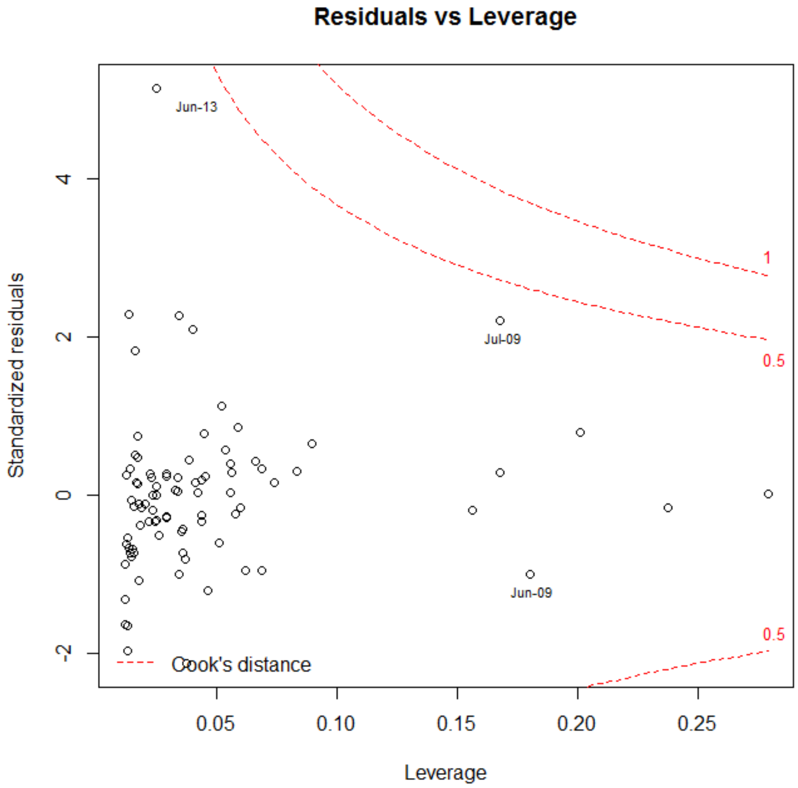


Figure 130 shows that most predictions are generally in line with the actual balances of Wealth Management Sweep.

Figure 131: Influential points for Wealth Management Sweeps



The segment does not contain any highly influential points.

5.6.5.6. Model sensitivity

5.6.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 130. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 130: Sensitivity to changes to independent variables for Wealth Management Sweep

Wealth Management Sweep (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
BAA_TSpread_DMoM	First difference – MoM	%	-0.33	0.23	-0.10
SP_Vol_DQoQ	First difference – QoQ	Index	0.25	0.83	0.08
Tspread_3m_5yr	-	%	-0.22	0.53	-0.07
Intercept	-	$ MM	N/A	N/A	N/A

In the WM Sweep model, the Baa-to-Treasury spread variable has the standardized coefficient with the largest magnitude. We find that a one standard deviation increase in the changes of the Baa-to-Treasury spread results in a 0.33 standard deviation ($0.1 BN) decrease in the predicted monthly change of the WM Personal deposits.

5.6.5.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 131.

Table 131: Statistical sensitivity tests for Wealth Management Sweep

Wealth Management Sweep (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of coefficients	P-value of shortened period coefficient	Conclusion
BAA_TSpread_DMoM	-452.482	-439.205	0.94	Statistically insignificant
SP_Vol_DQoQ	94.626	86.305	0.25	Statistically insignificant
Tspread_3m_5yr	-127.830	-122.235	0.89	Statistically insignificant
Intercept	236.292	244.361	0.78	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.65	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

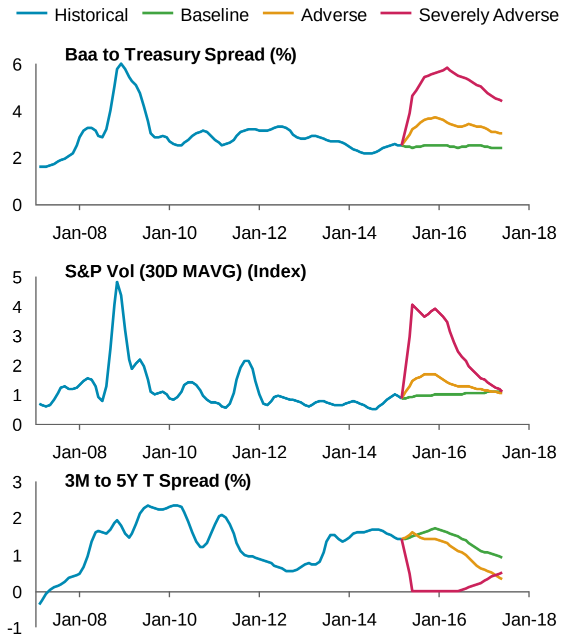
5.6.5.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

Figure 132: Wealth Management Sweep Model Forecast

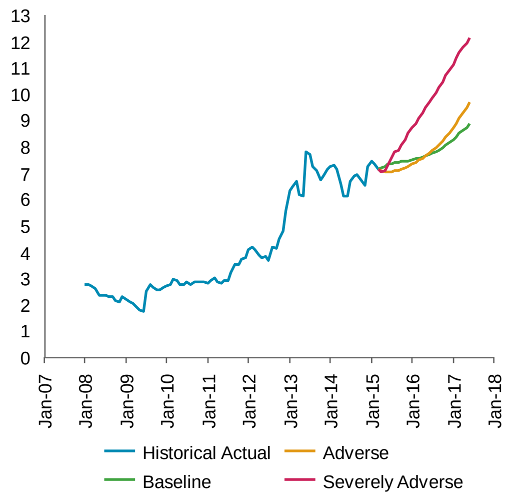
Wealth Management Sweep: Model 2
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Wealth Management Sweep, $BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	1.71 (24%)	2.54 (36%)	4.99 (70%)	-
Start to peak	1.71 (24%)	2.54 (36%)	4.99 (70%)	0 (0%)
Start to trough	N/A	-0.1 (-1%)	-0.11 (-2%)	-1.05 (-38%)



The Working Group considered the forecast behavior for the selected WM Personal model as reasonable.

The model forecasts are illustrated in Figure 132.

- **Severe recession (Severely Adverse) scenario:** The model predicts a steep increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as WM Sweep balances will increase under high market volatility/uncertainty environment given that cash sweep vehicles are considered to be risk-free. The line of business suggested that the magnitude of the initial increase should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts a considerable increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as WM Sweep balances will continue its general growth trend even under interest rate shock scenario
- **Baseline scenario:** The model predicts a considerable increase in deposits under baseline scenario. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as WM Sweep balances will continue its general growth trend

5.6.5.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The WM Sweep balances exhibited large and rapid increases during the modeling period due to management actions. BNY Mellon management decided to move cash from off-balance sheet items to cash sweep vehicles in 2012, contributing to a two-fold increase in balances. Not surprisingly, the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently.

The segment also experienced idiosyncratic balance shifts driven by a single large client that coincided with the management action described above in 2012.

As discussed in a prior section, an attempt was made to model the segment balances by removing the balances from a large client that drove large shifts in the overall segment balances, but this analysis did not yield a better model.

5.7. Broker Dealer Services balance model

5.7.1. Business overview and segments

Broker-Dealer Services offers security clearance and US tri-party repo-related services for broker-dealers. BNY Mellon clears transactions in over 100 markets globally and is the leading clearing agent for US government securities. Deposits are maintained by clients in order to facilitate the use of these products and services as well as comply with regulatory requirements.

For ALM management purposes, Broker Dealer Services deposits are maintained as one segment described in Table 132: non-interest bearing USD deposits (BDS DDA). As described earlier in Section 3.1.2, this segmentation was adopted for the purposes of balance sheet forecasting as well, to align the segmentation with those used for other business purposes.

Table 132: Segment description for Broker Dealer Services

Segment for Broker Dealer Services		
Segments	**Size ($ BN)[28]**	**Description**
BDS DDA	7.8	Composed entirely of USD denominated non-interest bearing balances in demand deposit accounts.

5.7.2. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team and the line of business, a list of driver hypotheses were developed and refined over time. Figure 133 illustrates the initial driver hypotheses that were identified through conversations with the lines of business and the ALM team in advance of the modeling process. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave

[28] Month-end spot balance from April 30, 2015

feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 133: Summary of Broker Dealer Services balance drivers

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit balances increase when general economic health improves	• US GDP growth, unemployment rate
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase as BNYM is perceived as a relative "safe haven"	• Spread of BNYM debt rate to industry peer rate
	Banking system risk	• Deposit balances increase as banking credit risk increases, as BNYM is perceived as a relative "safe haven"	• Overnight Libor, TED Spread, Libor OIS spread
	Market volatility/ uncertainty (equity/rates)	• Deposit balances increase as market volatility (i.e., transaction volume) increases	• VIX, Market Volatility Index, 10 Year T-Note volatility index
	Financial stability of US government	• Deposit balances increase when there is a shock decline to the perceived creditworthiness of the US government	• 1-3 month Treasury yield spread
Rates	**Short-term rates**	• Deposit balances may decrease as short-term interest rates increase, as spreads with competitors and alternative investments widen	• Overnight LIBOR, Prime Rate, Fed Funds rate,1 month and 3 month Treasury, SONIA, EONIA, repo rates

1. Corporate Credit and Treasury Yield spreads were also tested as extra drivers.

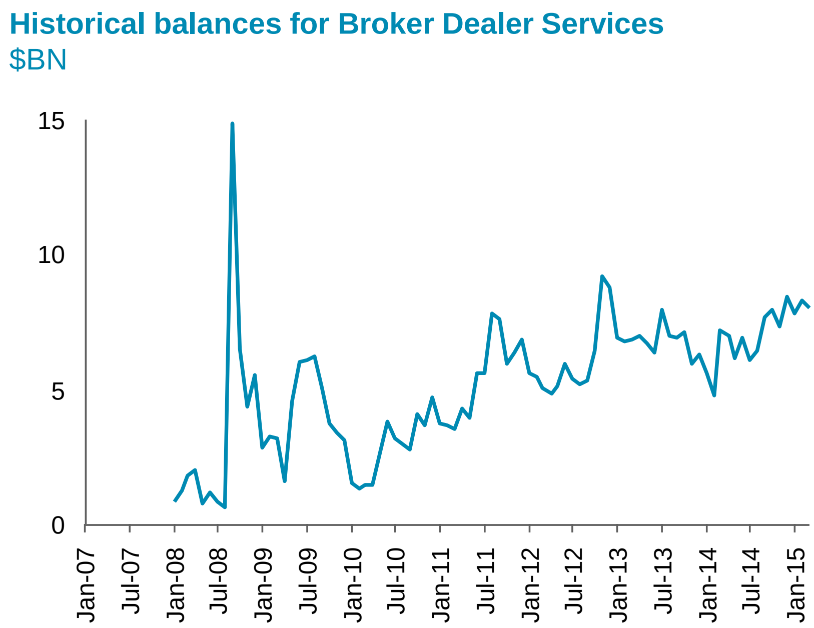
The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

5.7.3. Broker Dealer Services

5.7.3.1. Deposit balance overview

Over the modeling time period, Broker Dealer Services (BDS) deposit balances experienced large, sudden changes in balances in times of economic stress. Most notably during the financial crisis in 2008, deposit balances increase from less than $2 BN to $15 BN. The sharp increase in balances was shortly followed by a sharp decrease in balances. Since then, balances have shown a moderate upward trend. Starting in June 2015 the line of business has initiated structural changes to the business and begun an initiative to shrink deposits.

Figure 134: Historical balances for Broker Dealer Services



5.7.3.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Broker Dealer Services segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the AS DDA deposit balances, which is found to be stationary
- **Statistical significance:** The coefficient estimates of the selected model have coefficients that are only significant at the 20% threshold – this is noted as a significant limitation
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in Table 133.

Table 133: Coefficient estimates for the Broker Dealer Services model

Broker Dealer Services (in USD MM)				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Tnote_Vol_10yr_DQoQ	First difference – QoQ	Index	233.302	0.19
Intercept	-	$ MM	103.464	N/A

The model contains the following driver and variable:

- **Market Volatility (rates)** – 10 Year T-Note Volatility index, a common benchmark of implied US rate volatility

The intuition for this variable is as follows:

- The T-Note volatility index had a positive coefficient which is consistent with business intuition as BNY Mellon is perceived as a relative safe haven and its deposit balances are expected to increase during times of market stress

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient sign.

The final model was selected following the model-based approach described in Section 3.3.3. The other shortlisted candidate models for this segment are listed in Figure 135.

Figure 135: Candidate models for Broker Dealer Services

Broker Dealer Services
Candidate models

	Candidate models	
Drivers Considered	**1**	**2**
Corporate credit	Baa to Treasury Spread (Diff QoQ)	
Market volatility/ uncertainty (rates)	10 Year US T-Note Volatility Index (Diff QoQ)	10 Year US T-Note Volatility Index (Diff QoQ)
Variation in balances explained through estimated first differences	**32%**	**46%**
R-squared (differences)	**8%**	**4%**

Final model

Additional drivers tested: Housing prices, Equity markets, Exports, Perceived credit risk, Market volatility/uncertainty (equity), General economic health, Imports, Financial stability of US government, Yield spread

The Working Group had initially selected Model 1. During the line of business review, feedback was provided that the linkage between the BDS deposits and the corporate credit spread variable was unintuitive. Therefore, Model 2, which contains the 10-year US Treasury note volatility variable but not the corporate credit spread variable, was selected as the final model instead.

The details on statistical tests necessary to determine the transformation of the dependent variable, statistical diagnostic tests of the model, as well as sensitivity tests are described in the following sections.

5.7.3.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

5.7.3.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Broker Dealer Services series is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend. The results are listed in Table 134.

The first differences of the balances, that is, the month-over-month changes in the deposit balances, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in Table 135.

Table 134: Unit root tests and stationarity tests including a trend variable on balances

BDS – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	7	-2.4	>0.10	Fail to reject unit root
Phillips-Perron	1	-6	<0.01	Reject unit root
KPSS	4	0.06	0.46	Fail to reject stationarity

Table 135: Unit root tests and stationarity tests including a constant on first differences

BDS – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	6	-5.4	<0.01	Reject unit root
Phillips-Perron	1	-13	<0.01	Reject unit root
KPSS	29	0.18	0.31	Fail to reject stationarity

Stationarity tests for BDS balances yield mixed results: The ADF fails to reject the unit root while the PP tests reject a unit root and KPSS test fails to reject stationarity. These results suggest the BDS balances may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the BDS deposit balances are modeled on their first differences.

5.7.3.3.2. Historical data review

In addition to checking for stationarity of dependent variables, we also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical balance data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for the BDS segment. As discussed previously, the data was sourced from MAQ and its accuracy was confirmed with the BDS business.

5.7.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 136 reports the results of the significance tests.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

The coefficient estimate of T-Note Volatility in the BDS model is not statistically significant. This model was used despite the not statistically significant variable because of the lack of alternative viable models.

Table 136: Statistical significance tests of model and variables for Broker Dealer Services

Broker Dealer Services (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	19%	10%	Statistically not significant
Tnote_Vol_10yr_DQoQ	233.302	19%	10%	Statistically not significant
Intercept	103.464	64%	10%	Statistically not significant

5.7.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on balances)
- Residual plot (on estimated first differences)
- Error of average 9-quarter balances compared with actual average 9-quarter balances, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

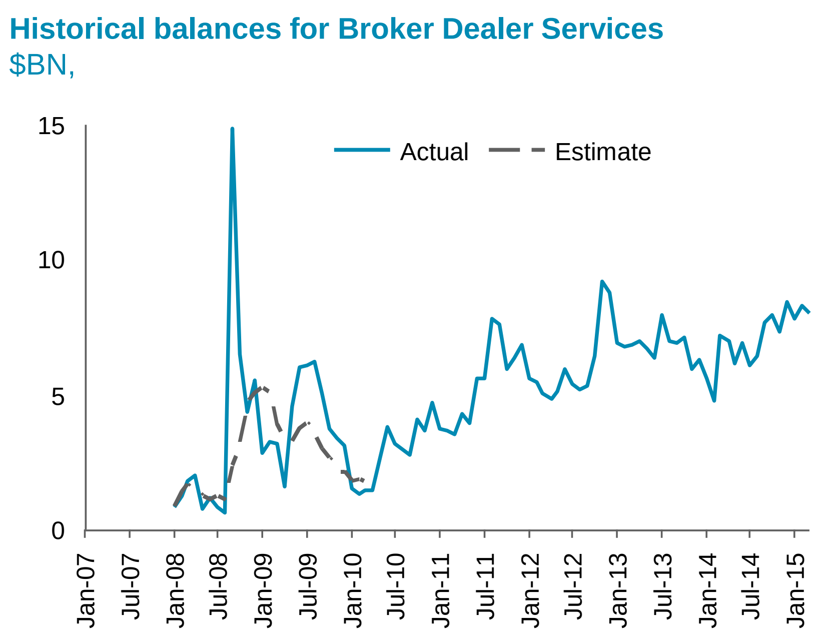
Table 137: BDS Model Diagnostics

BDS (in USD MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	4%	-	-
	Adjusted R-squared	3%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	34%	10%	Linear specification appropriate

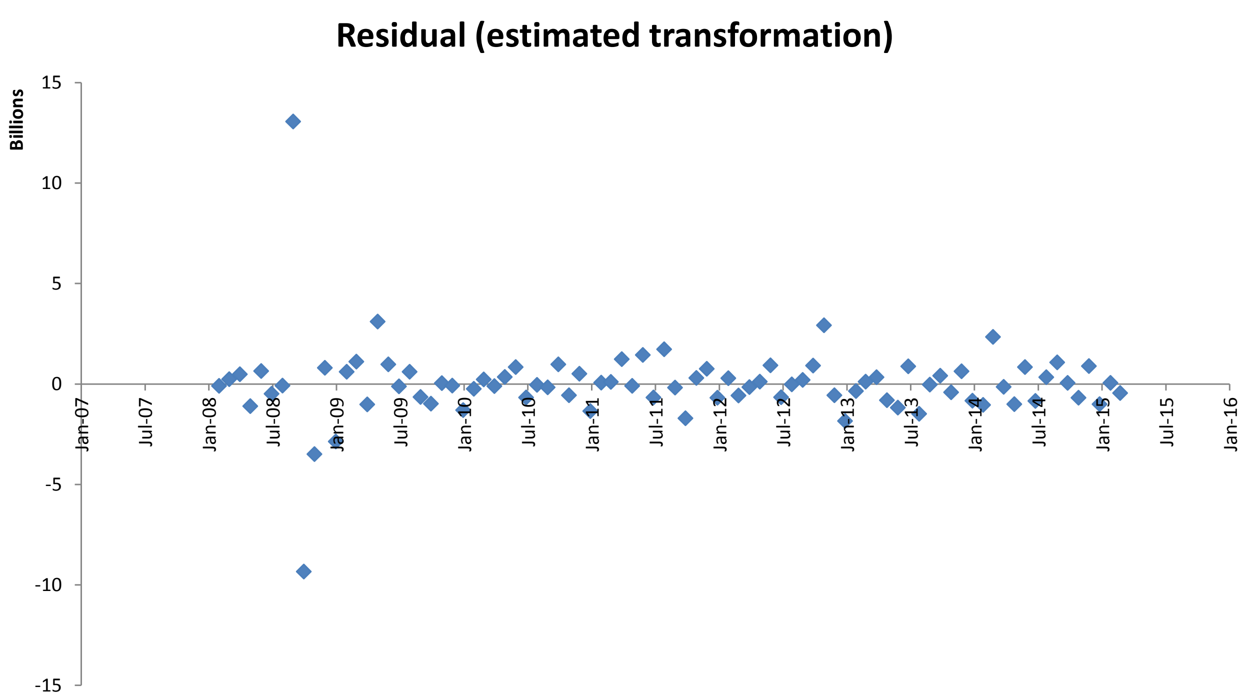
The model passes all model diagnostic tests that were evaluated, except the Breusch-Godfrey test for serial correlation.

Figure 136: Broker Dealer Services 9Q In-Sample Prediction



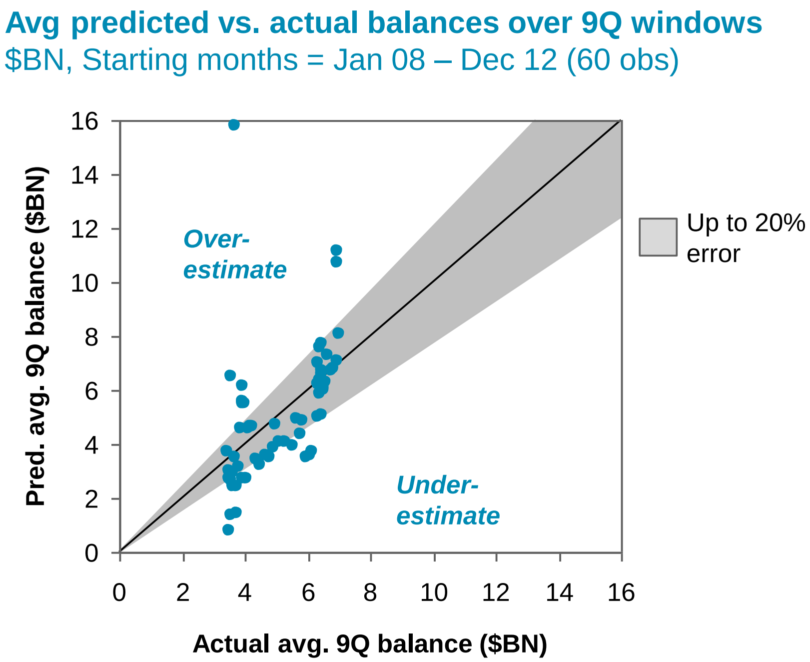
The in-sample back test of the model starting from January 2008 partially captures the increase and subsequent fall in balances, but is unable to capture the large increase in balances in 2008.

Figure 137: Broker Dealer Services Residual Plot ($ BN)



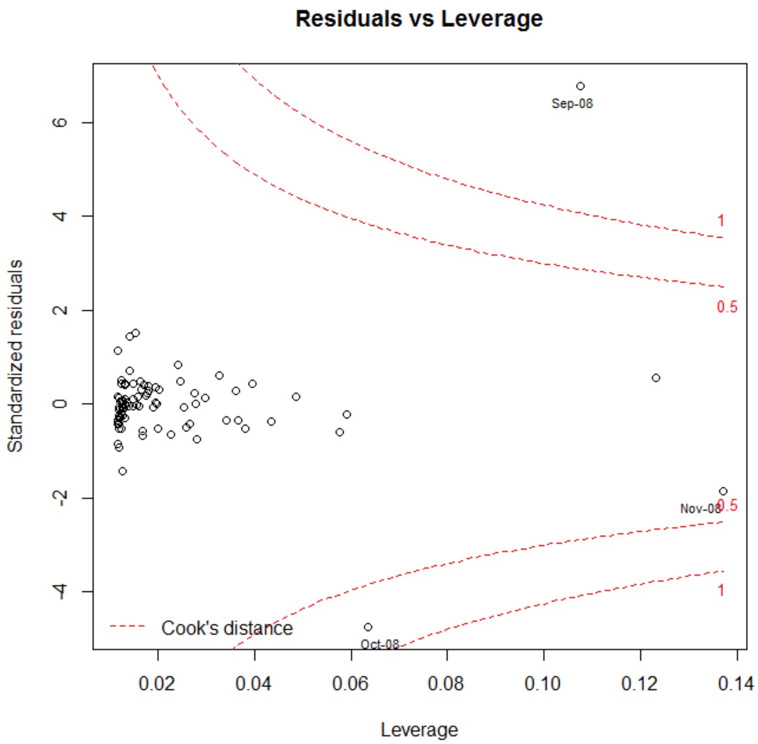
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 138: Broker Dealer Services Balance Estimation Scatterplot



The points of overestimation on Figure 138 occur following the 2008 financial crisis as the model does not fully capture the increase or decline in balances in the segment. The points of underestimation are around the 2011 debt crisis, as the balance increase due to this idiosyncratic event was not captured by the model.

Figure 139: Influential points for Broker Dealer Services



For this segment September 2008 is a highly influential point. However, this is not surprising because of the increase in balances due to the financial crisis and does not invalidate the model

5.7.3.6. Model sensitivity

5.7.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in Table 138. The standardized coefficient reported for each independent variable describes the standard deviation change in the predicted balances due to a one standard deviation increase in the independent variable.

Table 138: Sensitivity to changes to independent variables for Broker Dealer Services

Broker Dealer Services (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Tnote_Vol_10yr_DQoQ	First difference – QoQ	Index	0.19	1.70	0.40
Intercept	-	$ MM	N/A	N/A	N/A

In the BDS model, we find that a one standard deviation increase in the quarterly changes of the T-note volatility results in a 0.19 standard deviation ($0.40 BN) increase in the predicted monthly change of the BDS deposits.

5.7.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow-test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in Table 139.

Table 139: Statistical sensitivity tests for Broker Dealer Services

Broker Dealer Services (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
Tnote_Vol_10yr_DQoQ	233.302	276.589	0.39	Statistically insignificant
Intercept	103.464	151.499	0.62	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.52	Statistically insignificant

The coefficients of the shortened variables are statistically insignificant collectively. This suggests the model remains stable when removing observations from the development data.

5.7.3.6.3. Sensitivity to stressed independent variable scenarios

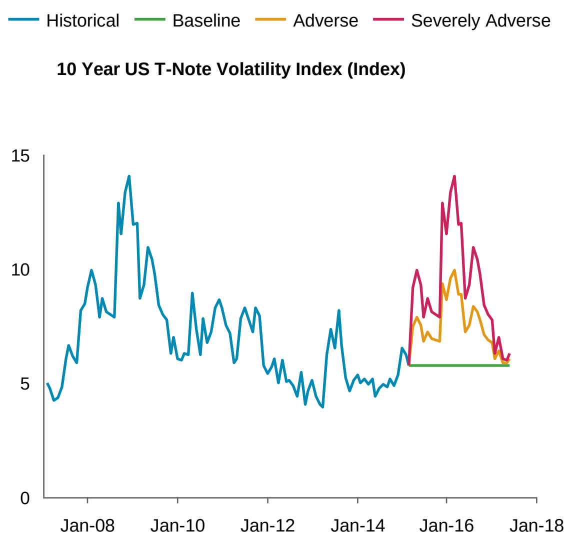
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

However, the model’s forecast behavior was tested for different macroeconomic scenarios.

Figure 140: Broker Dealer Services Model Forecast

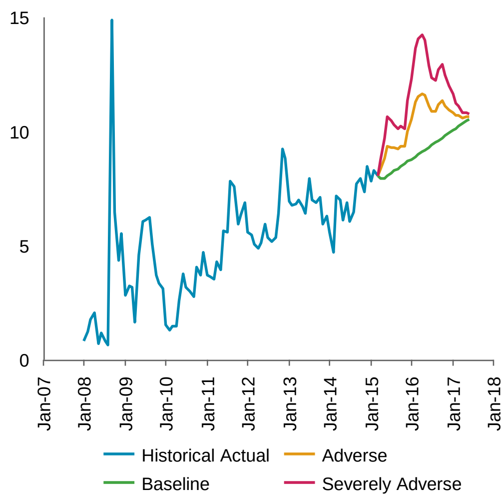
Broker Dealer Services: Model 2
Forecast balances under different scenarios

Historical and forecast independent variables



Historical and forecast balances for Broker Dealer Services
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	2.52 (31%)	2.63 (33%)	2.75 (34%)	-
Start to peak	2.52 (31%)	3.64 (45%)	6.21 (77%)	14.05 (1669%)
Start to trough	-0.07 (-1%)	N/A	N/A	-0.22 (-26%)



The Working Group determined that the forecast behavior for the selected Broker Dealer Services model requires higher scrutiny during management review.

The model forecasts are illustrated on Figure 140.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant increase in deposits. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations as clients would likely increase their cash holdings and increasingly seek out safer institutions such as BNY Mellon to hold their cash. The line of business suggested that the magnitude of the increase should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario:** The model predicts that balances increase. This is inconsistent with business intuition, as BNY Mellon would expect customers to seek out alternative investments in a rising rates environment. The line of business suggested that the direction of this forecast be closely monitored when the final outputs for submission are generated
- **Baseline scenario:** The baseline scenario shows a moderate increase in line with historic growth which is not consistent to business intuition as the line of business has begun an initiative to reduce segment balances starting in June 2015

5.7.3.7. Model limitations

The limitations applicable to all deposit models are discussed in Section 5.9.

The BDS balances exhibits large and rapid increases and decreases during the modeling period – the modeling team was unable to find macroeconomic variables that captured these dynamics sufficiently and the significance threshold of the model had to be relaxed. This is recognized as a significant limitation of this model.

5.8. Balance model for foreign deposits in currencies other than USD, Euro and GBP

5.8.1. Business overview and segments

Foreign deposits in currencies other than USD, Euro and GBP (Foreign Other, or FGN Other) are the aggregate balances of deposits denominated in currencies other than USD, Euro, or British Pound. These miscellaneous balances come from a variety of lines of business but are mainly composed of balances for the Asset Servicing business.

The individual currencies for this segment did not meet the materiality criteria. As a result they were collected in a single segment, particularly, because most of them are related to the Asset Servicing line of business.

Table 140: Segment description for Foreign Other

Segment for Foreign Other		
Segments	Size ($ BN)[29]	Description

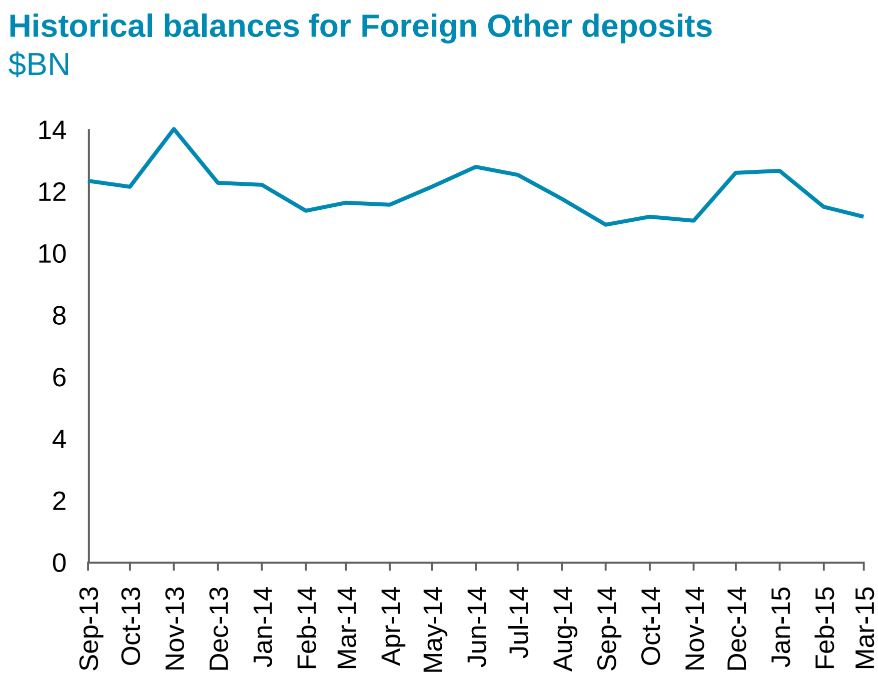
[29] Month-end spot balance from April 30, 2015

FGN Other	9.6	Composed entirely of balances in miscellaneous currencies

5.8.2. Historical data

Historical balances for this segment were only obtainable for 18 monthly observations, given the limitations for the data sources. The balances are represented in USD using end-of-month exchange rates, given the diverse nature of the currencies that fall into this segment. During this limited time period, balances have remained largely stable when aggregated and expressed in USD. The shortened time period does not cover historical events such as the 2008 financial crisis or the debt ceiling crises in 2011 and 2013.

Figure 141: Historical balances for Foreign Other

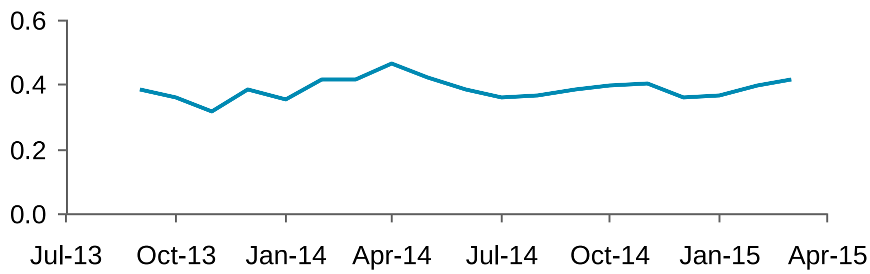


5.8.3. Summary of approach

As only 18 observations of data are available for the Foreign Other segment, any statistical models developed have significant limitations in capturing drivers that affect these balances. In addition, attempts were made to develop statistical models for this segment, but no statistically valid model with intuitive coefficients was found. Therefore, a simple model is developed for this segment.

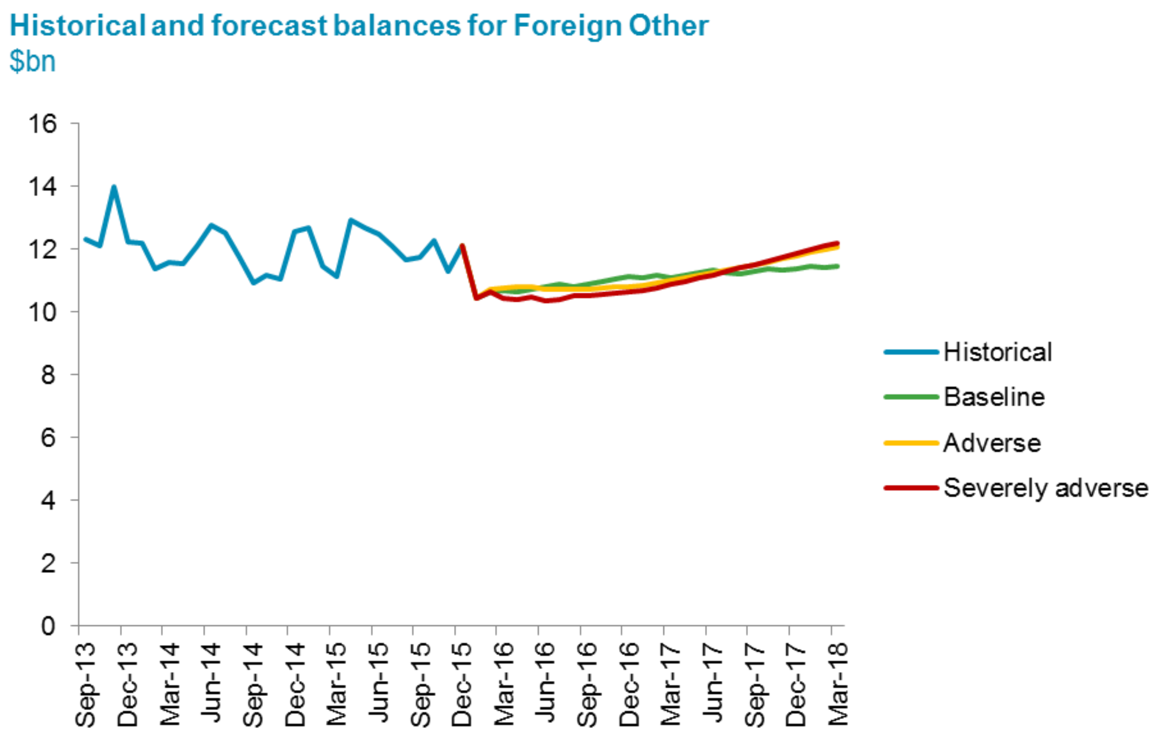
The line of business considers the balances in Foreign Other to be closely related to those in Nostro Placements. Over the 18 months of data available for the Foreign Other segment, the ratio between Foreign Other and Nostro Placements balances was constant.

Figure 142: Ratio between Nostro Placements and Foreign Other



To create the forecast for the Foreign Other segment the modeling team assumed that the ratio between Foreign Other and Nostro Placements would be constant and applied the average of the ratio to the forecasts of Nostro Placement to scale it to magnitude of Foreign Other.

Figure 143: Foreign Other Approach Forecast



5.8.4. Approach limitations

Because Foreign Other currently consists of only 18 observations, the modeling team had a small set of observations to test whether the ratio between Foreign Other and Nostro Placements remains constant over time. It is possible that with a longer set of data the ratio could be less consistent. In addition, because the approach follows the path of Nostro Placements, this approach will contain the weaknesses of that simple model as well.

5.9. Limitations to deposit balance models

The deposit models have key limitations. Due to the merger of Bank of New York and Mellon in 2007, data was only available starting in January 2008. As a result, the data only captures the end of a rate cycle followed by an extended period of very low interest rates. It is therefore possible that the models are not sufficiently well calibrated to accurately account for the key relationship between deposit balances and the rate environment.

Also, since the models are estimated on macroeconomic factors, any idiosyncratic events that materially that cannot be captured by macroeconomic variables will not be reflected in the estimated models. For example, increases in balances for some segments coinciding with the US debt ceiling crisis could not be fully captured by macroeconomic factors.

Another limitation, which is especially problematic for smaller segments such as the Wealth Management segments, is the material impact of large client balance movements to the overall segment balance. It is challenging to capture such movements with macroeconomic variables.

All the above limitation result in lower model fit metrics such as R^2 statistics.

Given these weakness, the modeling team recommends a close monitoring of the models and frequent re-estimation, especially when observations in a higher rate environment become available.

The aggregate deposit forecast is shown in Section 1.3, which is found to be intuitive both directionally and in magnitude.

6. Deposit rates

6.1. Business overview and segments

Deposit rate modeling is performed for each interest-bearing balance sheet segment. A description of each line of business can be found in the corresponding balance segments.

6.2. Driver hypotheses and selection of candidate variables

As discussed in Section 3.5 on methodology, a benchmark rate was identified for each of the rate segments, and a relationship between the benchmark rate and the deposit rate is estimated. This approach was reviewed by the appropriate lines of business and is in line with actual pricing practices. Table 141 contains the benchmark rate assigned for each segment.

Table 141: Deposit rates segments and the selected benchmark rate

Segment	Benchmark Rate
Asset Servicing IB	Fed Funds Target
Corporate Trust IB	Fed Funds Target
Wealth Management Personal	Fed Funds Target
Wealth Management Sweep	Fed Funds Target
AS/TS (EUR)	European Central Bank (ECB) Marginal rate
AS/TS (GBP)	Bank of England (BOE) Base rate
Corporate Trust (EUR)	ECB Marginal rate
Corporate Trust (GBP)	BOE Base rate
Treasury Services IB Deposits	Fed Funds Target
AIS/GCS IB	Fed Funds Target
Corporate Treasury	Fed Funds Target (Interest On Excess Reserves)
Foreign Deposits (Other)	Fed Funds Target

The benchmark rates are target rates set by central banks because the deposits are typically re-priced when there is a change in central bank target rates. In addition, in line with the majority of BNY Mellon's deposit offerings, benchmark rates are short duration rates.

Feedback received from the line of business indicated that for the Euro and GBP segments, the relationship between BNY Mellon's deposit rates and the overnight unsecured interbank effective rates (Euro Overnight Index Average – EONIA and Sterling Overnight Index Average – SONIA) should be monitored going forward as well in addition to the benchmark rates listed above.

6.3. Model overview

The summary of the rates models are illustrated in Table 142. The methodology used for modeling is described in Section 3.5. The modeling team considered two main approaches:

- Approach A refers to the approach using of the shorter MAQ data, which only contains a limited number of observations where deposit rates were higher than 50 basis points. The approach estimates one single relationship between the deposit rate and the benchmark rate over the modeling period
- Approach B refers to the use of the extended Pre-Merger Deposit Rates Dataset described in Section 4.1.3 and estimates separate relationships between the benchmark rate and the deposit rate for rising or falling rate environments

A model using Approach B was selected for a given segment if two conditions were met: 1) rates data for the segment extending to at least 2006 (and thereby capturing a rising rate environment) is available and 2) a statistically sound model was found. If these conditions were not met, a model using Approach A is selected.

Table 142: Summary of deposit rates models

			Effective sensitivity[1] (Δ in cust rate/ Δ in the benchmark rate)	
Segment	**Approach used**	**Benchmark Rate**	**Rising rate environment**	**Falling rate environment**
AS IB Deposits	**B**	Fed Funds Target	0.44	0.53
CT IB Deposits	**B**	Fed Funds Target	0.59	0.37
WM Personal	**B**	Fed Funds Target	0.68	0.56
WM Sweep	**B**	Fed Funds Target	1.00	0.69
Fgn AS/TS (EUR)	**A**	ECB Marginal rate		0.45
Fgn AS/TS (GBP)	**A**	BOE Base rate		0.45
Fgn CT (EUR)	**A**	ECB Marginal rate		0.41
Fgn CT (GBP)	**A**	BOE Base rate		0.24
TS IB Deposits	**A**	Fed Funds Target		0.85
AIS/GCS IB	*No viable statistical models were found due to data availability – a structural approach is required for these segments*			
Corp. Treasury				
Fgn Deposits (Other)				

1. Effective sensitivity is the cumulative effect of a 1% point change in the benchmark rate on the rate paid during the forecast period.

The effective sensitivity in Table 142 captures how much the deposit rate for a given segment changes when the benchmark rate for that segment changes. Several alternative variable transformations were used for the benchmark rates and the effective sensitivity calculation for each of these is given below:

- When there are multiple transformations of the same independent variable in a single model, the coefficients are added to derive the effective sensitivity. For example, assume a model contains two independent variables: a difference month-over-month and the lagged difference month-over-month, both transformations of the Federal Funds Target rate. The effective sensitivity of the deposit rate is then the sum of the coefficients of the two variables as a given change in the Federal Funds Target rate would impact the customer rate twice: first through the month-over-month variable and a month later through the lagged month-over-month variable
- The coefficient of a difference quarter-over-quarter transformation of the independent variable is multiplied by three. The reason is that the underlying data is monthly while the independent variable spans more than one month. For instance, if there is a change in the benchmark rate in January, this change will be reflected in the January, February and March difference quarter-over–quarter values. Therefore, any given unit change is accounted for three times by the difference quarter-over-quarter transformation

There are several key observations to note on the sensitivities that were found across the various lines of businesses.

- **Asset Servicing** and **Corporate Trust** have lower sensitivities as customers are not able to move deposits easily due to the operational complexities
  - The onboarding process for new Asset Servicing clients typically requires 3–6 months
  - Historically, Corporate Trust clients have relied on BNY Mellon for subsequent deals in order to maintain consistency in processes
- **Wealth Management** segments have higher sensitivities because unlike Asset Servicing and Corporate Trust, clients do not face a large operational barrier to move balances to competitor banks
- **Treasury Services** has relatively high sensitivity as the deposits in this line of business have historically been priced much more competitively as clients actively seek out higher yielding alternatives
- Generally, for the lines of business with higher rate sensitivity, the rising rate environment was found to have a larger sensitivity than falling rate environments, which suggests that in the sample period, the lines of business have been pricing competitively in both rising and falling rate environments

A viable statistical model could not be estimated for the following three segments, and a qualitative framework based on business judgment is required:

- AIS/GCS IB – proxy forecast using the rates forecasted for the AS IB segment
- Corporate Treasury – a 13 basis point spread below Interest on Excess Reserves paid by the central bank
- Foreign Other (foreign deposits in currencies other than Euro and GBP) – proxy forecast using the rates forecasted for the AS IB segment

The following sections provide details on each of the deposit rate models.

6.4. Asset Servicing IB Rates

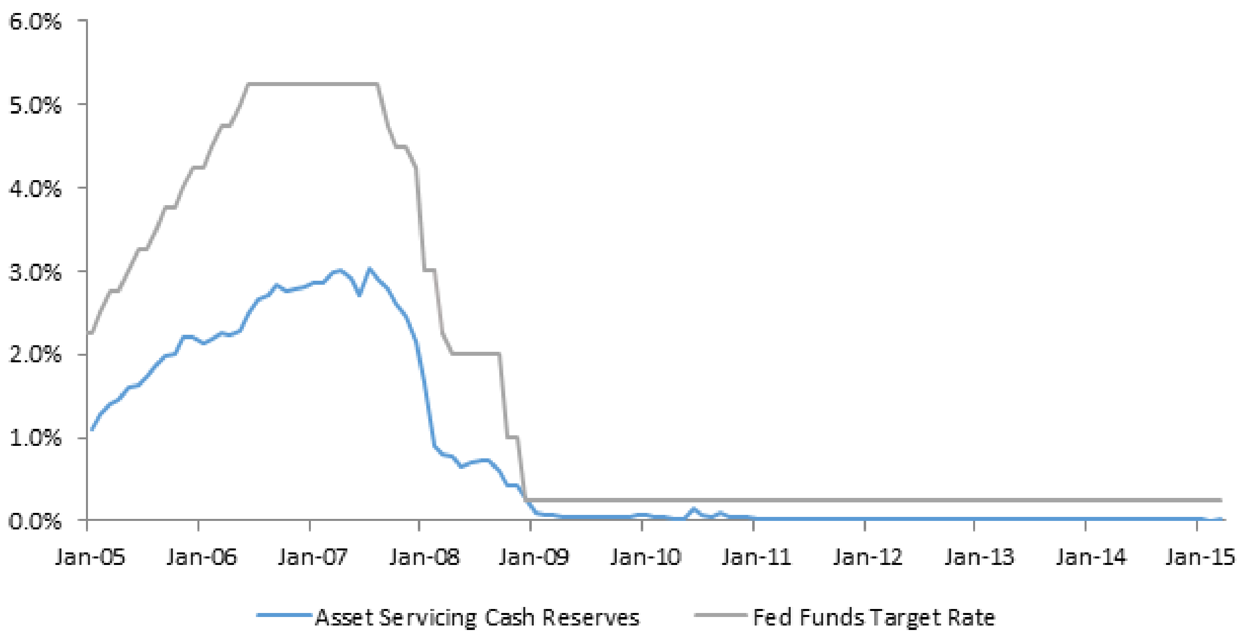
6.4.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Asset Servicing IB (AS IB) segment is modeled using the Asset Servicing Cash Reserves rates data series in the Pre-Merger Deposit Rates Database. Asset Servicing Cash Reserves accounts for 32% of the segment balance as of April 30, 2015. However, going forward, the foreign deposits denominated in USD, which accounts for 59% of the segment balance as of April 30, 2015, will be priced in the same way as the Cash Reserves. Therefore, the modeling team concluded that the Asset Servicing Cash Reserves product is an appropriate proxy for this segment.

The historical rates data for the segment is shown on Figure 144.

- The historical Asset Servicing Cash Reserves rate follows the directional movement of the Federal Funds Target rate, the segment's benchmark rate
- The differences between the two rates are generally larger when the benchmark rate is higher
- The increase in Asset Servicing Cash Reserves rate appears to be slower while the Fed Funds Target rate is increasing whereas decrease in the Asset Servicing Cash Reserves rate appears to be faster while the Fed Funds Target rate is decreasing
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 144: Historical rates for Asset Servicing Cash Reserves



6.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Asset Servicing IB rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits good in-sample fit

The coefficient estimates are displayed in Table 143. Note that Fed_Funds_t1 is the rising rate variable, and Fed_Funds_t2 is the falling rate variable. More details on the construction of these variables can be found on Section 3.3.3 on Methodology.

Table 143: Coefficient estimates for the Asset Servicing IB Rates model

Asset Servicing IB Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
Fed_Funds_t1_DMoM	First difference – MoM	%	0.437
Fed_Funds_t2_DMoM	First difference – MoM	%	0.239
Fed_Funds_t2_DMoML1	First difference – MoM, 1 lag	%	0.289
Intercept	None (level)	%	0.003

The Asset Servicing IB model is a three variable model containing one rising rate and two falling rate variables.

- In a rising rate environment, the deposit rate responds to a change in the benchmark rate in the same month. A 1.00% increase in the Fed Funds Target Rate results in a 0.44% increase of the AS IB deposits rate
- In a falling rate environment, the deposit rate responds partially in the same month (0.24%) and partially in the following month (0.29%). A 1.00% decrease in the Fed Funds Target Rate results in a 0.53% total decrease in the AS IB deposits rate

In a review and challenge meeting, the line of business generally confirmed the intuitiveness of the coefficient signs and estimates. The business indicated the fact that the sensitivity for the rising rate environment is lower than that of the falling rate environment is intuitive, as one would expect a higher sensitivity for BNY Mellon to decrease the deposit rate that it pays to its customers.[30]

Whenever the selected model uses the Pre-Merger Deposits Rates Dataset, a comparable model is estimated on the shorter MAQ data as a check. Given the MAQ data only captures observations in a falling and flat rate period, the comparable model is considered as the best fitting model (i.e. model with the highest R-squared) with the same transformation as the falling rate variable. For instance, if the falling rate variable is difference month-over-month transformation with one lag in the Pre-Merger Deposits Rates Dataset model, the comparable model on the shorter MAQ data would be a single variable model with difference month-over-month transformation with one lag.

The comparable model for AS IB model developed on the MAQ data has an effective sensitivity of 0.49, compared to the 0.53 in the extended data.

More details of the comparable model can be found in the Appendix.

Although the model using Approach B is selected as the final model for this segment, the modeling team recommends that both these models be monitored as more data points become available.

[30] The modeling team tested the rising rate environment coefficient of 0.437 against the sum of the falling rate environment coefficients of 0.528 (=.239+0.289) and the two were not statistically significantly different from each other. The calculated $F(1,118)$ statistic is 0.60 and results in a P-value of 0.44.

6.4.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 144 and Table 145.

Table 144: Unit root tests and stationarity tests including a constant on untransformed deposit rate

AS Cash Reserves – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	9	-1.9	0.34	Fail to Reject unit root
Phillips-Perron	2	-0.7	0.84	Fail to Reject unit root
KPSS	6	1.28	<0.01	Fail to Reject stationarity

Table 145: Unit root tests and stationarity tests including a constant on first differences

AS Cash Reserves – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	8	-2.5	0.12	Fail to Reject unit root
Phillips-Perron	2	-6.3	<0.01	Reject unit root
KPSS	5	0.17	0.34	Fail to Reject stationarity

Stationarity tests for AS Cash Reserve rate levels yield mixed results: The ADF and PP tests fail to reject a unit root while the KPSS test fails to reject stationarity. Since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be non-stationary.

The monthly first difference series also yields mixed results: The first differences passes two out of the three stationarity tests – the KPSS and PP tests. Since the KPSS test is the primary test reviewed for first differences, the AS Cash Reserves on first differences is determined to be stationary.

Given these results, the modeling team chose to model these rates on first differences.

6.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the AS IB deposit rates. Adjustments made to the MAQ data are described in Section 4.1.

6.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model –** The coefficient estimates in the models are tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individually using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 146 reports the results of the significance tests. All of the coefficient estimates in the AS IB rates model are statistically significant, both individually and collectively. The intercept is found to be statistically insignificant.

Table 146: Statistical significance tests of model and variables for Asset Servicing IB rates

AS IB Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Fed_Funds_t1_DMoM	0.437	<1%	10%	Statistically significant
Fed_Funds_t2_DMoM	0.239	<1%	10%	Statistically significant
Fed_Funds_t2_DMoML1	0.289	3%	10%	Statistically significant
Intercept	0.003	51%	10%	Statistically not significant

Heteroskedasticity was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

6.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in its residuals, autocorrelation in its residuals, multicollinearity of its variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of information regarding the model's historical fit were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests are displayed in Table 147.

Table 147: AS IB Rate Model Diagnostics

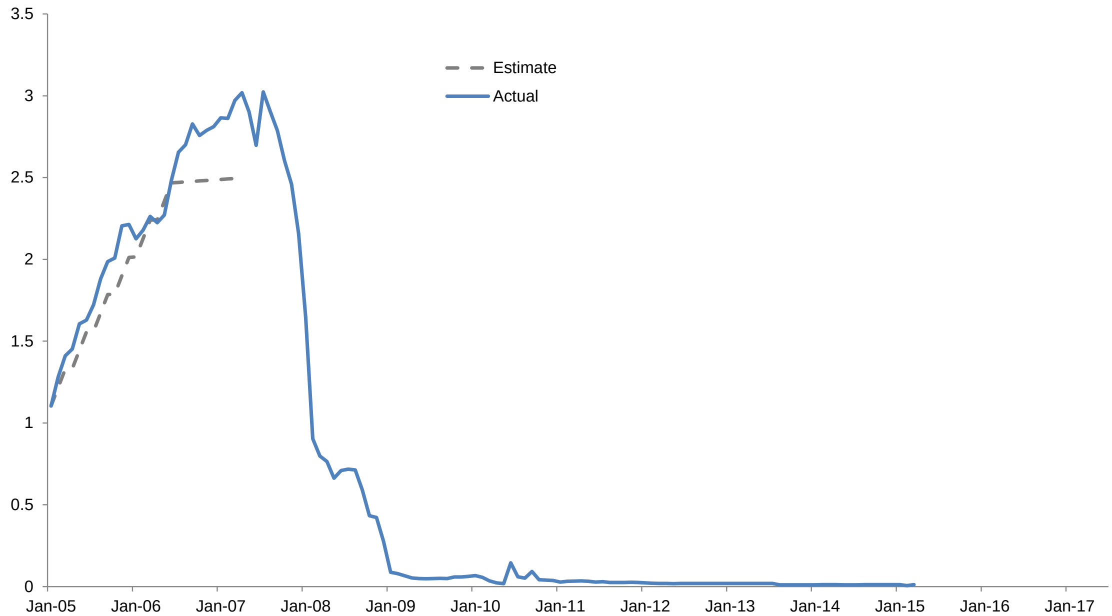
AS IB Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	52%	-	-
	Adjusted R-squared	51%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.00	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	51%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.03	5	No multicollinearity
Linearity	RESET test	0%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity in the residuals of the AS IB model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

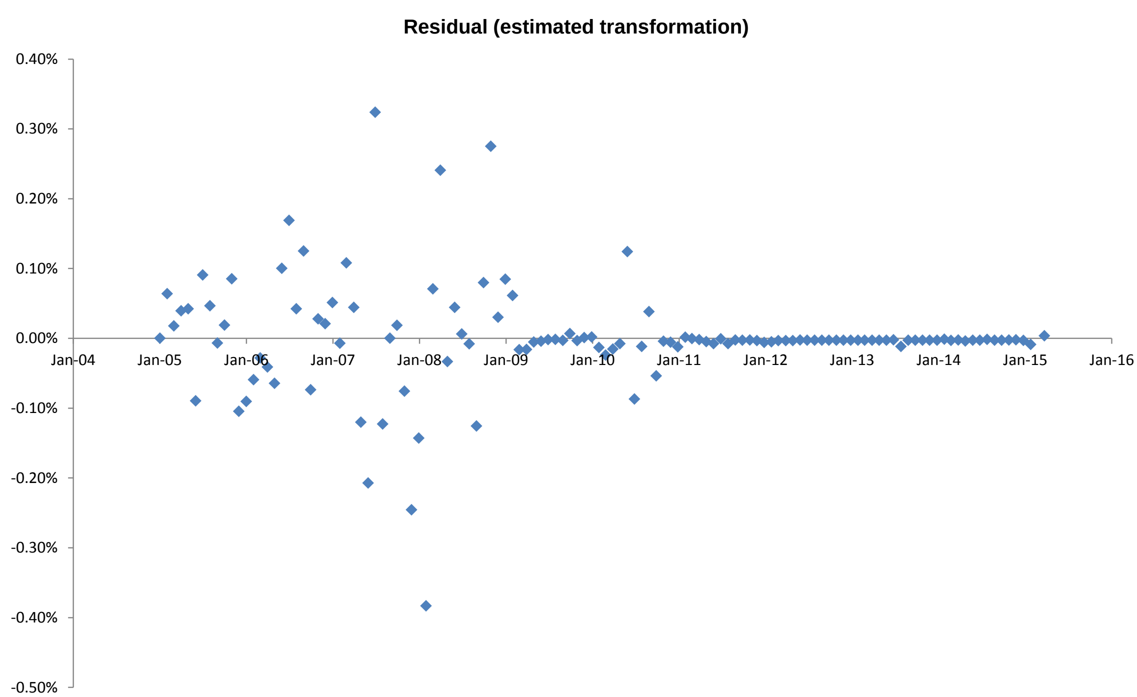
The model also fails the test for model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 145: Asset Servicing IB Rate 9Q In-sample Prediction



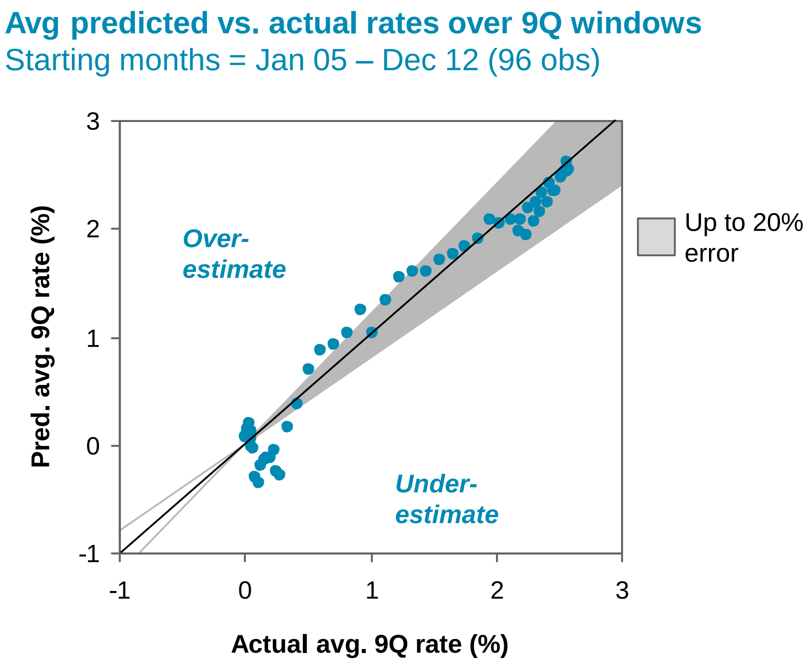
In the select 9Q in-sample prediction capturing the rate increase period, the model captures most of the rate increase of the rising rate period. It does not, however, capture the full increase.

Figure 146: Asset Servicing IB Rate Residual Plot (%)



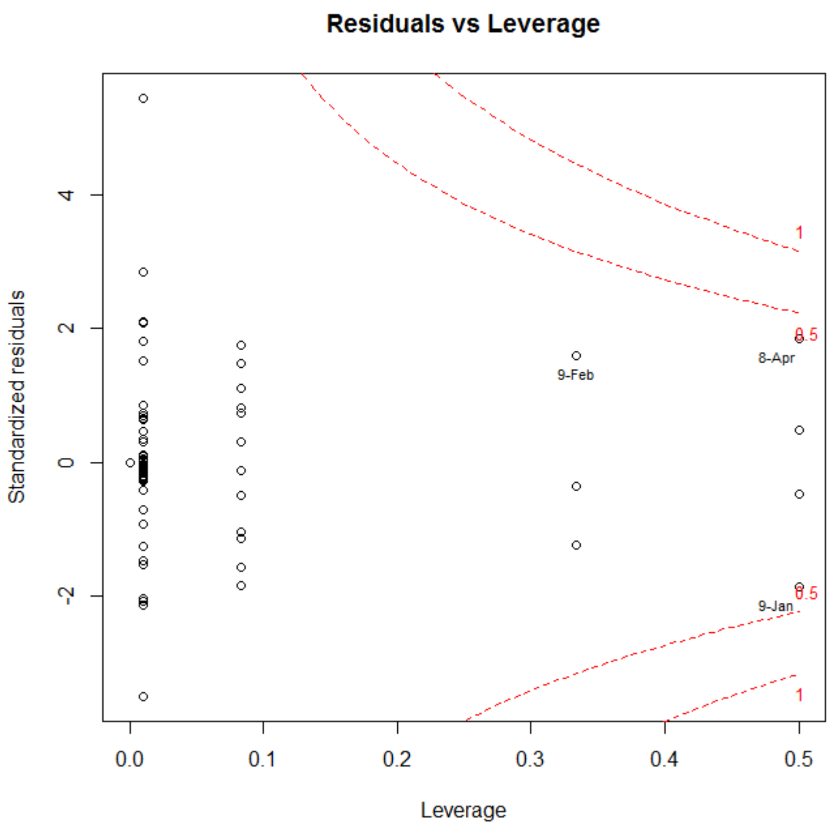
As seen on Figure 146, the residuals are randomly distributed around the horizontal axis. Starting 2009 the residuals become much closer to zero, as rates remain low and experience limited variation.

Figure 147: Asset Servicing IB Rate Estimation Scatterplot



As seen in Figure 345, the model estimates generally remain within 20% error. The points that do not remain within it mostly occur in 2007, when the model is being oversensitive to the decline of the benchmark rate.

Figure 148: Influential points for AS IB Rates



The segment does not contain any highly influential points.

6.4.6. Model sensitivity

6.4.6.1. Sensitivity to changes in independent variables

Given the deposit rates models only contain one type of independent variable (i.e. one or more transformations of the benchmark rate), the sensitivity can be directly interpreted from the coefficient estimates.

6.4.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

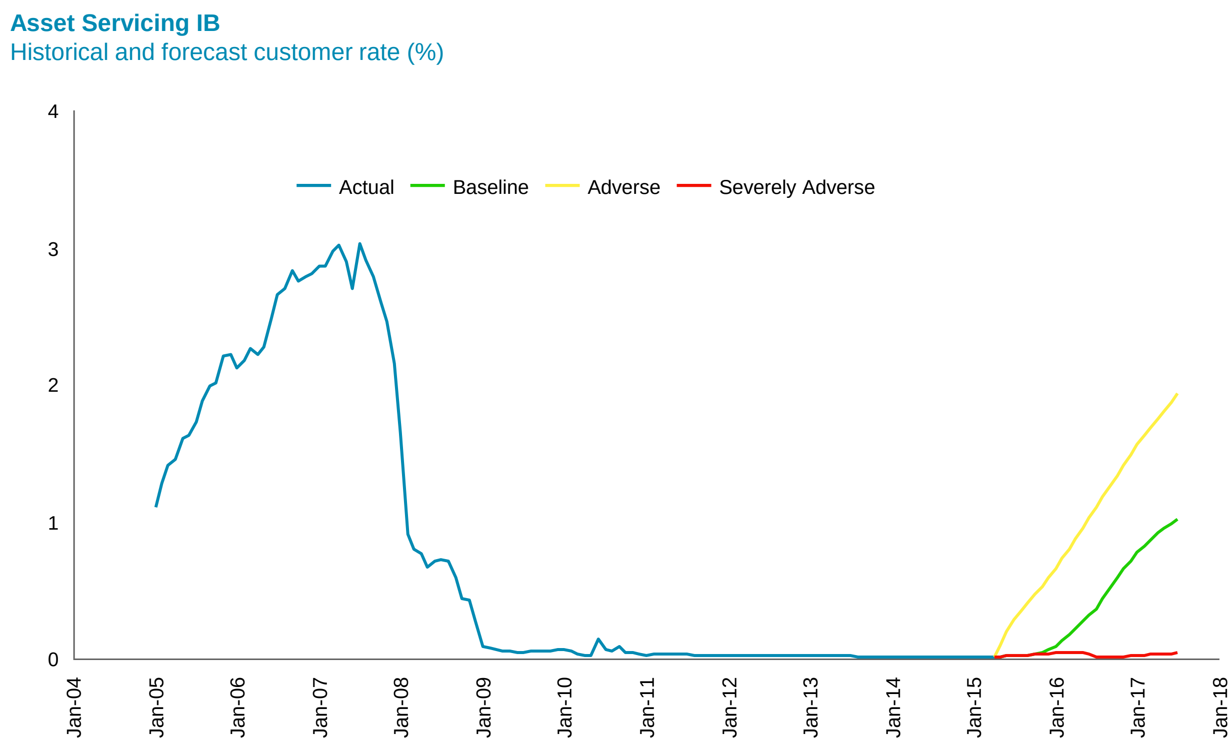
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

6.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used for model development given the limited data availability.

The forecasts output of the model is shown on Figure 149.

Figure 149: Asset Servicing IB Rates Model Forecast



The Working Group considered the forecast behavior for the selected AS IB model as requiring low scrutiny during management review, as the effective sensitivity of this model was considered to be intuitive. The model forecasts for the scenarios are in line with management expectations.

6.4.7. Model limitations

One limitation of this model is that the data from the Pre-Merger Deposit Rates Database are product rates whose collection is managed outside the management accounting system. Despite this limitation, the Pre-Merger Deposit Rates Database was preferred over MAQ data whenever available in pursuit of developing statistical models utilizing all available data. Due to the merger between Bank of New York and Mellon Financial in July 2007, MAQ data is only available from 2008 onward which does not contain a raising rate environment for most of the segments, a limitation that was resolved by using the Pre-Merger Deposit Rates Database.

The developed model assumes that the Asset Servicing Cash Reserves product is an appropriate proxy for the entire segment. The modeling team suggests reinvestigating whether an appropriate model can be estimated on the rates for all sub-segments as more observations become available.

6.5. Corporate Trust IB Rates

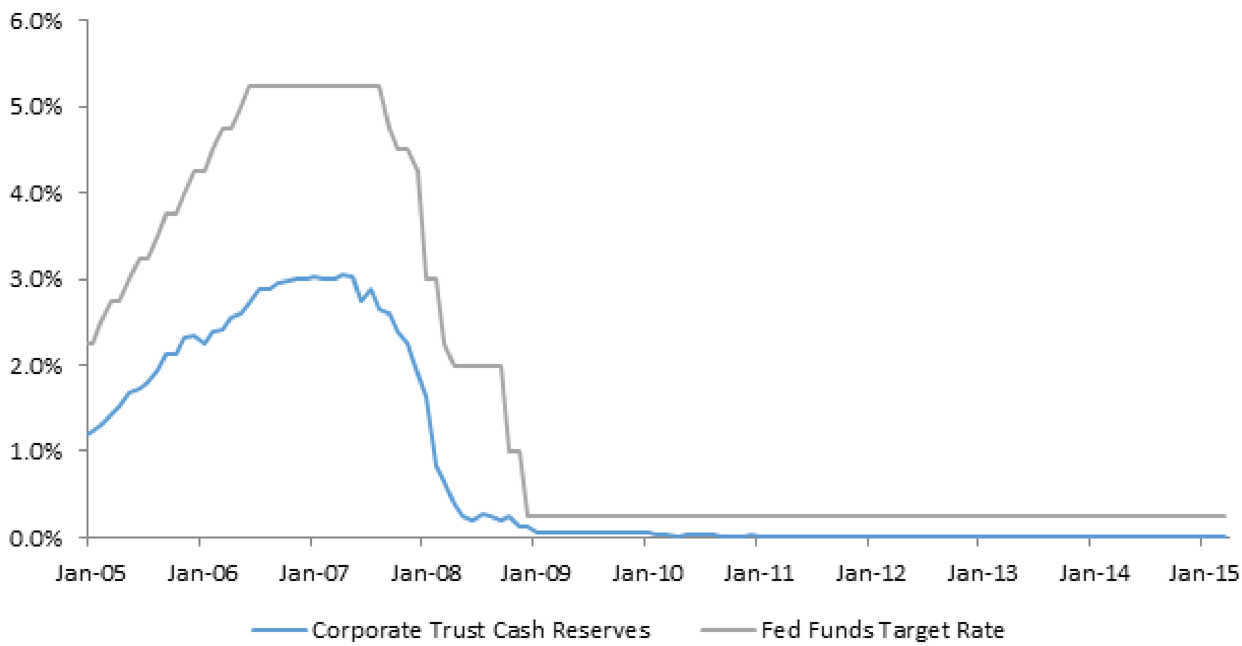
6.5.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Corporate Trust IB (CT IB) segment is modeled using the Corporate Trust Cash Reserves rates data series in the Pre-Merger Deposit Rates Database. Corporate Trust Cash Reserves accounts for 77% of the segment balance as of April 30, 2015. However, going forward, the foreign deposits denominated in USD, which accounts for 23% of the segment balance, will be priced in the same way as the Cash Reserves. Therefore, the modeling team concluded that the Corporate Trust Cash Reserves product is an appropriate proxy for this segment.

The historical rates data for the segment is shown on Figure 150.

- The historical Corporate Trust Cash Reserves rate follows the directional movement of the Federal Funds Target rate, the segment's benchmark rate
- The differences between the two rates are generally larger during times when the benchmark rate is higher
- The increase in Corporate Trust Cash Reserves rate appears to be slower while the Fed Funds Target rate is increasing whereas decrease in the Corporate Trust Cash Reserves rate appears to be faster while the Fed Funds Target rate is decreasing
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 150: Historical rates for Corporate Trust Cash Reserves



6.5.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Corporate Trust IB rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits good in-sample fit

The coefficient estimates are displayed in Table 148. Note that Fed_Funds_t1 is the rising rate variable, and Fed_Funds_t2 is the falling rate variable. More details on the construction of these variables can be found in Section 3.3.3 on Methodology.

Table 148: Coefficient estimates for the Corporate Trust IB Rates model

Corporate Trust IB Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
Fed_Funds_t1_DQoQ	First difference – QoQ	%	0.195
Fed_Funds_t2_DMoML1	First difference – MoM	%	0.369
Intercept	None (level)	%	-0.009

The Corporate Trust IB model is a two variable model containing one rising rate and one falling rate variable.

- In a rising rate environment, the deposit rate responds to a change in the benchmark rate in three months (a quarter after), a 1.00% increase in the Fed Funds Target Rate results in a 0.59% increase of the CT IB deposits rate
- In a falling rate environment the deposit rate responds in the following month. A 1.00% decrease in the Fed Funds Target Rate results in a 0.37% decrease in the CT IB deposits rate

In a review and challenge meeting, the line of business generally confirmed the intuitiveness of the coefficient signs and estimates. The fact that the deposit rates respond to increasing benchmark rates faster than falling benchmark rates was, however, found to be counterintuitive.

Whenever the selected model uses the Pre-Merger Deposits Rates Dataset, a comparable model is estimated on the shorter MAQ data as a check. Given the MAQ data only captures observations in a falling and flat rate period, the comparable model is considered as the best fitting model (i.e. model with the highest R-squared) with the same transformation as the falling rate variable. For instance, if the falling rate variable is difference month-over-month transformation with one lag in the Pre-Merger Deposits Rates Dataset model, the comparable model on the shorter MAQ data would be a single variable model with difference month-over-month transformation with one lag.

The comparable model for CT IB model developed on the MAQ data has an effective sensitivity of 0.56, compared to the 0.37 from the extended data.

Although the model using Approach B is selected as the final model for this segment, the modeling team recommends that both these models be monitored as more data points become available

More details of the comparable model can be found in the Appendix.

6.5.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.5.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 149 and Table 150.

Table 149: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Corporate Trust Cash Reserves – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-1.7	0.41	Fail to Reject unit root
Phillips-Perron	2	-0.7	0.846004	Fail to Reject unit root
KPSS	6	1.14	<0.01	Fail to Reject stationarity

Table 150: Unit root tests and stationarity tests including a constant on first differences

Corporate Trust Cash Reserves – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-3.2	0.03	Reject unit root
Phillips-Perron	2	-6.7	<0.01	Reject unit root
KPSS	6	0.19	0.3	Fail to Reject stationarity

Stationarity tests for CT IB rate levels yield mixed results: The ADF and PP tests fails to reject a unit root while the KPSS test fails to rejects stationarity. Since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be non-stationary.

In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Therefore, the modeling team uses first difference transformation for the model estimation.

6.5.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the CT IB deposit rates. Adjustments made to the MAQ data are described in Section 4.1.

6.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 151 reports the results of the significance tests. All of the coefficient estimates in the CT IB rates model are statistically significant. The intercept is found to be statistically insignificant.

Table 151: Statistical significance tests of model and variables for Corporate Trust IB rates

CT IB Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Fed_Funds_t1_DQoQ	0.195	<1%	10%	Statistically significant
Fed_Funds_t2_DMoML1	0.369	<1%	10%	Statistically significant
Intercept	-0.009	22%	10%	Statistically not significant

Serial correlation and heteroskedasticity was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

6.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 152: CT IB Rate Model Diagnostics

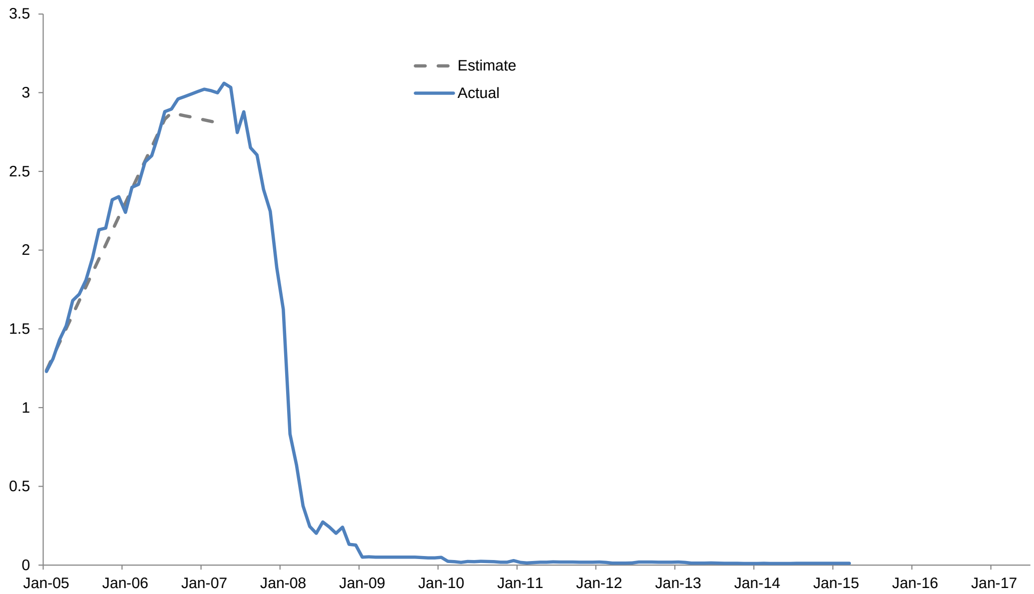
CT IB Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	54%	-	-
	Adjusted R-squared	53%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.01	5	No multicollinearity
Linearity	RESET test	1%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity and serial correlation in the residuals of the CT IB model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

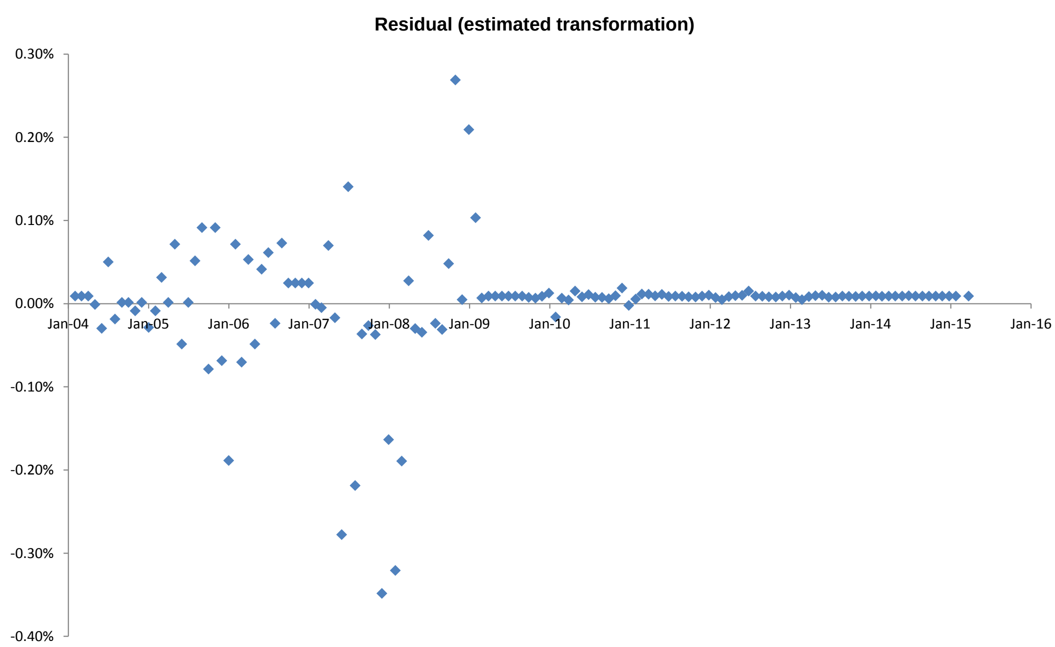
The model also suffers from model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 151: Corporate Trust IB Rate 9Q In-sample Prediction



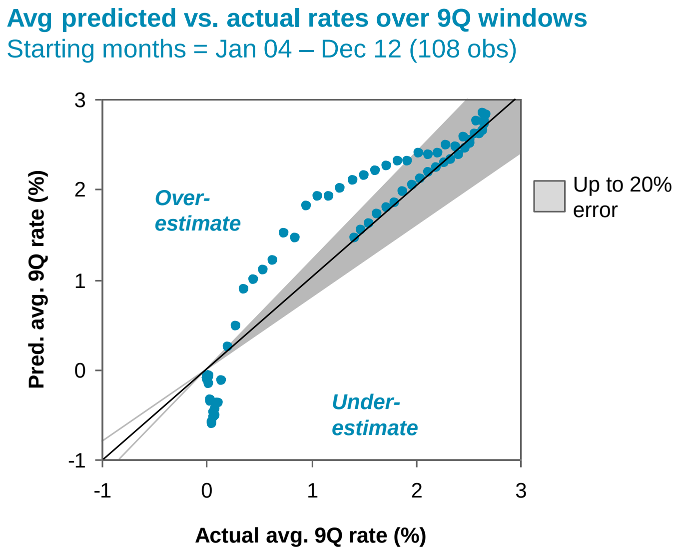
In the select 9Q in-sample prediction capturing the rate increase period, the model captures the rate increase well.

Figure 152: Corporate Trust IB Rate Residual Plot (%)



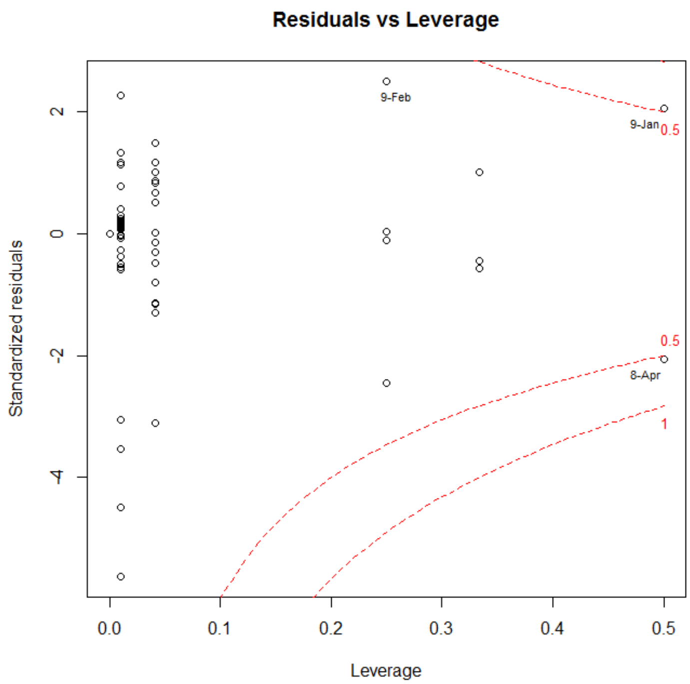
As seen on Figure 152, the residuals are randomly distributed around the horizontal axis. Starting 2009 the residuals become much closer to zero, as rates remain low and experience limited variation.

Figure 153: Corporate Trust IB Rate Estimation Scatterplot



As seen on Figure 153, the model estimates exhibit in-sample back test stability in higher rate environments. However, there are some back tests that result in an overestimation in higher rate environments.

Figure 154: Influential points for Corporate Trust IB rates



The segment did not contain an Influential point.

6.5.6. Model sensitivity

6.5.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable (i.e. one or more transformations of the benchmark rate) the sensitivity can be directly interpreted from the coefficient estimates.

6.5.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

6.5.6.3. Sensitivity to stressed independent variable scenarios

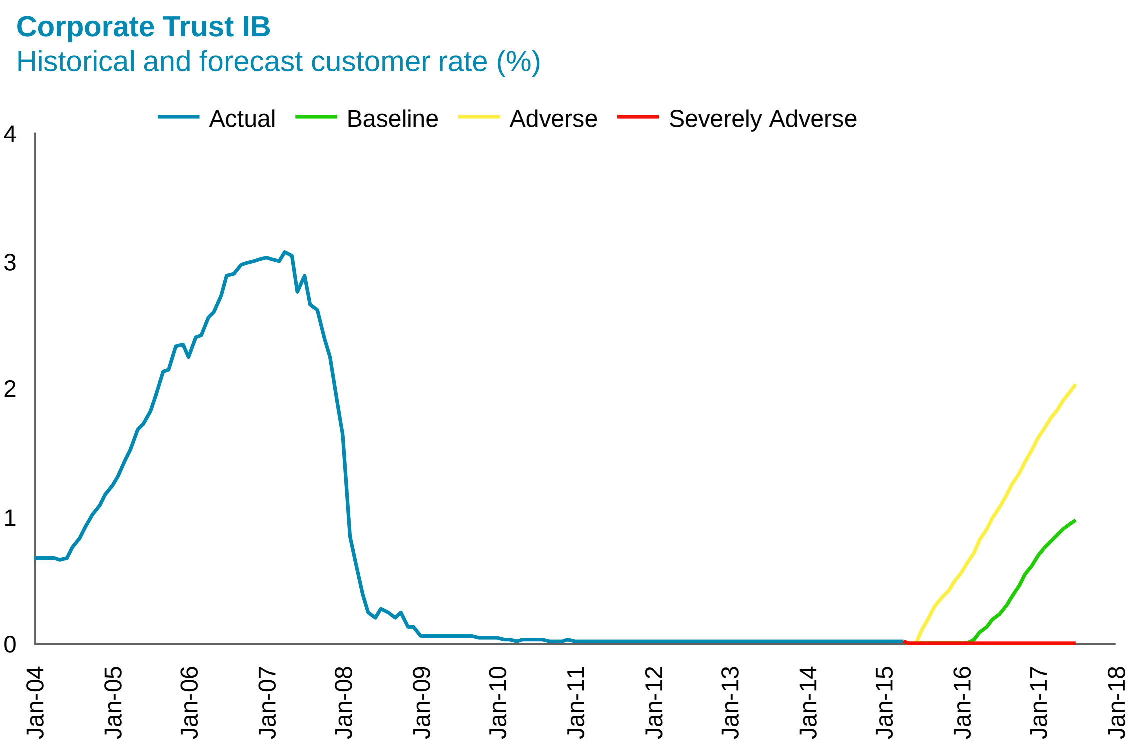
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 155.

The Working Group considered the forecast behavior for the selected CT IB model as requiring low scrutiny during management review, as the effective sensitivity of this model was considered to be intuitive.

The negative intercept in this model leads to some forecast observations falling below zero – hence, the model forecast is bounded to zero whenever the benchmark rate is not negative, as business intuition strongly suggests the deposit rate will not fall below zero unless the benchmark rate does.

Figure 155: Corporate Trust IB Rates Model Forecast



6.5.7. Model limitations

One limitation of this model is that the data from the Pre-Merger Deposit Rates Database are product rates whose collection is managed outside the management accounting system. Despite this limitation, the Pre-Merger Deposit Rates Database was preferred over MAQ data whenever available in pursuit of developing statistical models utilizing all available data. Due to the merger between Bank of New York and Mellon Financial in July 2007, MAQ data is only available from 2008 onward which does not contain a raising rate environment for most of the segments, a limitation that was resolved by using the Pre-Merger Deposit Rates Database.

6.6. Wealth Management Personal

6.6.1. Deposit rates overview

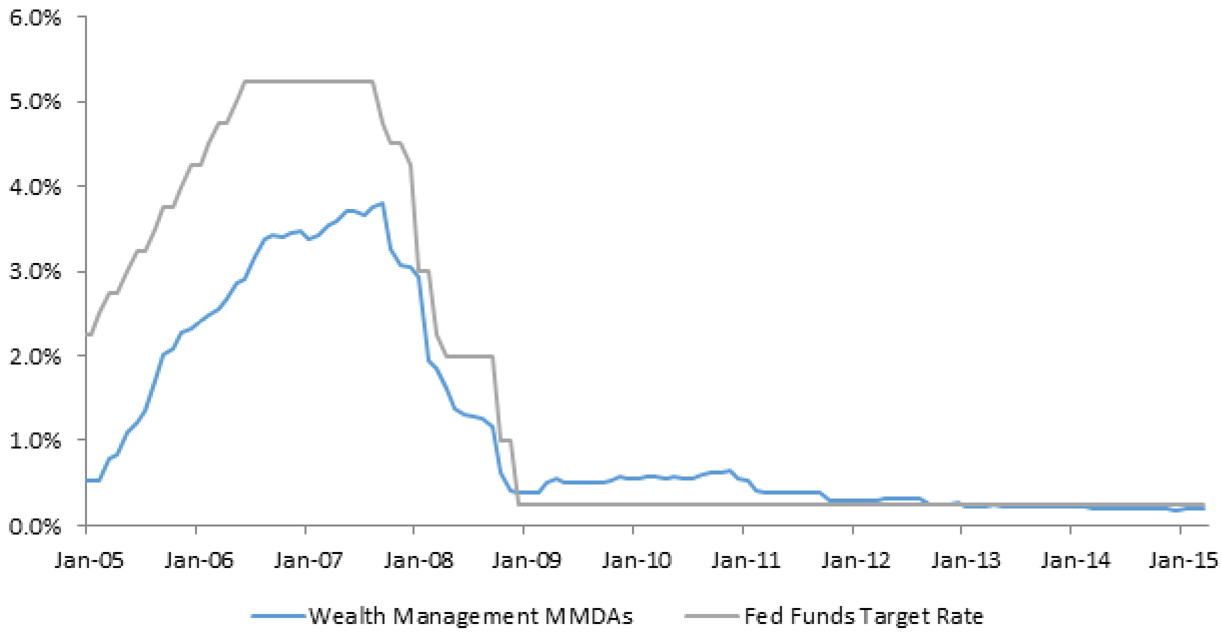
As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Wealth Management Personal (WM Personal) segment is modeled using the Wealth Management Private Banking MMDA rates data series in the Pre-Merger Deposit Rates Database. Wealth Management Private Banking MMDA accounts for 41% of the segment balance as of April 30, 2015. Of the remaining balance, WM CWIs is the second largest sub-segment that accounts for 36% of the total segment balance. While the Pre-Merger Deposit Rates Dataset contains data for this sub-segment, a statistically significant model could not be found with the benchmark rate.

Given this, the Working Group chose to use the extended data on the Private Banking MMDA accounts as a proxy for the entire segment.

The historical rates data for the segment is shown on Figure 156.

- The historical Wealth Management Private Banking MMDA rate follows the directional movement of the Federal Funds Target rate, the segment's benchmark rate
- The differences between the two rates are generally larger during times when the benchmark rate is higher
- The deposit rate seems to exhibit a slight lag to movements in the benchmark rate
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment.

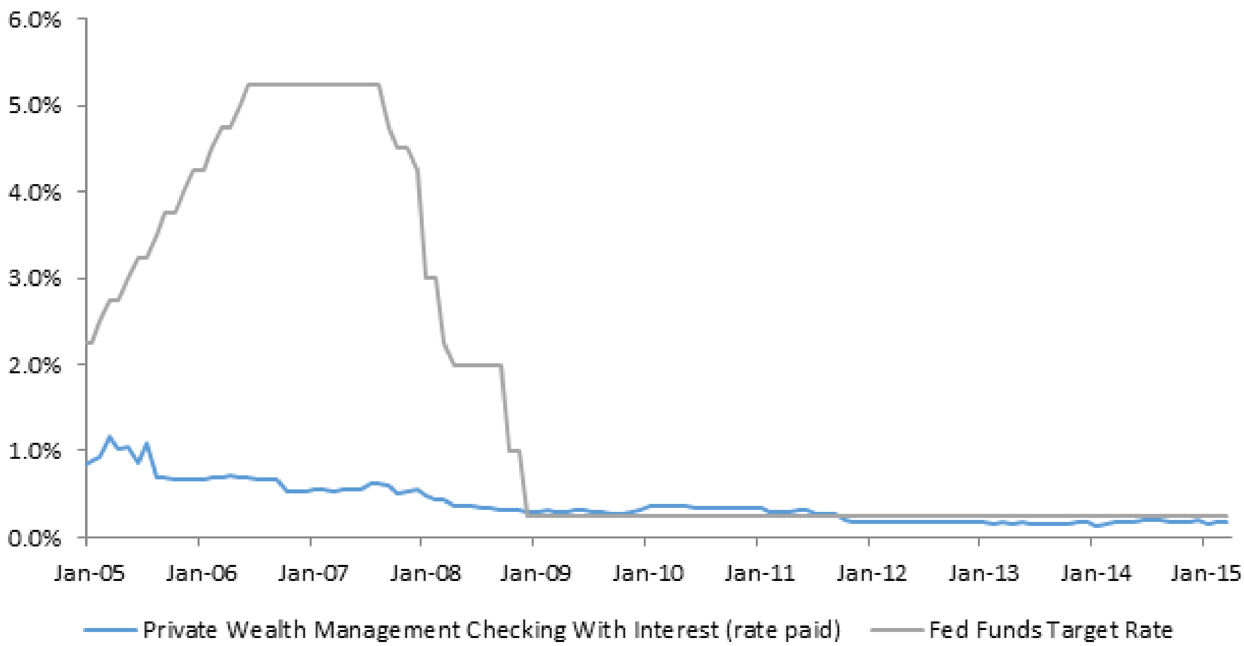
Figure 156: Historical rates for Wealth Management Private Banking MMDAs



The historical rates for the WM CWIs are shown in Figure 157. There is no apparent sensitivity to the deposit rate paid and the Fed Funds Target rate prior to 2009.

The choice to use the Private Banking MMDAs as a proxy for the WM Personal segment, therefore, is a conservative approach, as it assumes a greater sensitivity of the deposit rate to the benchmark rate than assuming a blended sensitivity using the WM CWIs. The business confirmed this conservatism intuitively as well, as they indicated the CWIs are less sensitive to the rate environment than the MMDAs.

Figure 157: Historical rates for Wealth Management CWIs



6.6.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Wealth Management Personal segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits good in-sample fit

The coefficient estimates are displayed in Table 153. Note that Fed_Funds_t1 is the rising rate variable, and Fed_Funds_t2 is the falling rate variable. More details on the construction of these variables can be found on Section 3.3.3 on Methodology.

Table 153: Coefficient estimates for the Wealth Management Personal Rates model

WM Personal Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
Fed_Funds_t1_DQoQ	First difference – QoQ	%	0.227
Fed_Funds_t2_DQoQ	First difference – QoQ	%	0.187
Intercept	None (level)	%	-0.001

The Wealth Management Personal rates model is a two variable model containing one rising rate and one falling rate variable. In both a rising rate and falling rate environment, the deposit rate responds to a change in the benchmark rate in the in three months (a quarter after).

- A 1.00% increase in the Fed Funds Target Rate results in a 0.68% increase of the WM Personal deposits rate.
- A 1.00% decrease in the Fed Funds Target Rate results in a 0.56% decrease in the WM Personal deposits rate

In a review and challenge meeting, the line of business generally confirmed the intuitiveness of the coefficient signs and estimates. The fact that the deposit rates respond to increasing benchmark rates faster than falling benchmark rates was, however, found to be counterintuitive.

Whenever the selected model uses the Pre-Merger Deposits Rates Dataset, a comparable model is estimated on the shorter MAQ data as a check. Given the MAQ data only captures observations in a falling and flat rate period, the comparable model is considered as the best fitting model (i.e. model with the highest R-squared) with the same transformation as the falling rate variable. For instance, if the falling rate variable is difference month-over-month transformation with one lag in the Pre-Merger Deposits Rates Dataset model, the comparable model on the shorter MAQ data would be a single variable model with difference month-over-month transformation with one lag.

The comparable model for WM Personal rates model developed on MAQ data has an effective sensitivity of 0.45, compared to the 0.56 from the extended data.

Although the model using Approach B is selected as the final model for this segment, the modeling team recommends that both these models be monitored as more data points become available

More details of the comparable model can be found in the Appendix.

6.6.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.6.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the rates are shown below.

Table 154: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Wealth Management MMDAs – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	8	-2.4	0.13	Fail to Reject unit root
Phillips-Perron	2	-0.9	0.801708	Fail to Reject unit root
KPSS	6	0.87	<0.01	Fail to Reject stationarity

Table 155: Unit root tests and stationarity tests including a constant on first differences

Wealth Management MMDAs – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	7	-2	0.27	Fail to Reject unit root
Phillips-Perron	2	-7.6	<0.01	Reject unit root
KPSS	5	0.26	0.18	Fail to Reject stationarity

Stationarity tests for WM Personal rate levels yield mixed results: The ADF and PP test fails to reject the unit root but the KPSS test rejects stationarity. However, since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be non-stationary.

Similarly, the first differences series yield mixed results: the ADF test fails to reject the unit root but the PP test rejects the unit root and the KPSS fails to reject stationarity. Since the KPSS test is the primary test reviewed for first differences, the WM MMDAs on first differences is determined to be stationary.

Given these results, the modeling team chose to model these rates on first differences.

6.6.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the WM Personal deposit rates. Adjustments made to the MAQ data are described in Section 4.1.

6.6.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 156 reports the results of the significance tests. All of the coefficient estimates in the WM Personal rates model are statistically significant. The intercept is found to be statistically insignificant.

Table 156: Statistical significance tests of model and variables for Wealth Management Personal rates

WM Personal Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Fed_Funds_t1_DQoQ	0.227	<1%	10%	Statistically significant
Fed_Funds_t2_DQoQ	0.187	<1%	10%	Statistically significant
Intercept	-0.001	91%	10%	Statistically not significant

Heteroskedasticity was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

6.6.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 157: Wealth Management Personal Rate Model Diagnostics

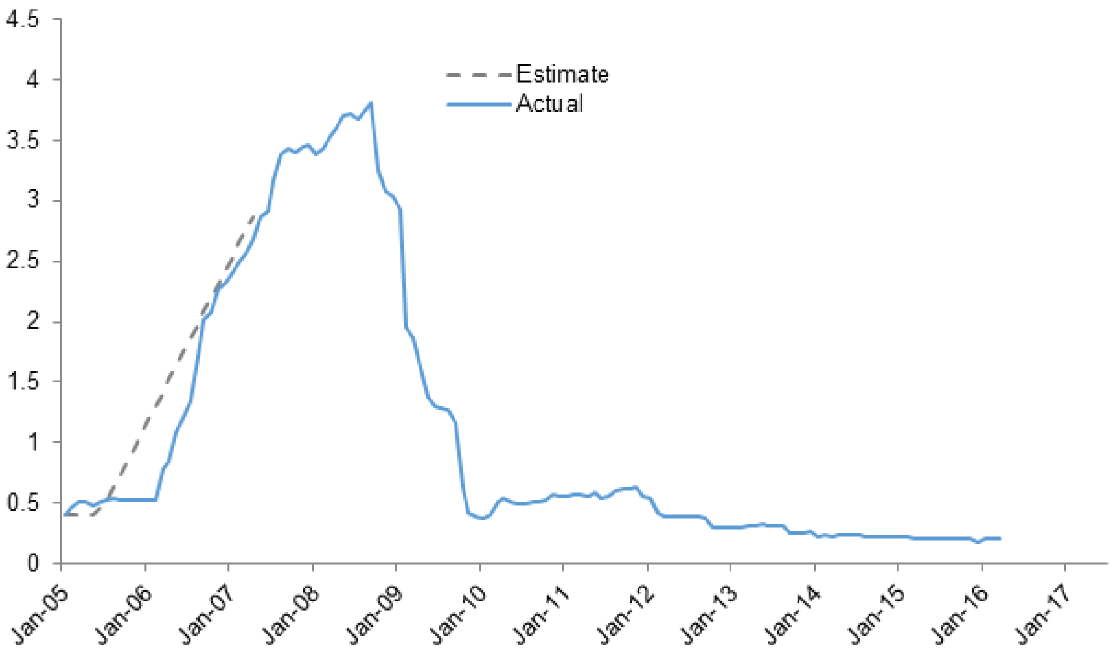
WM Personal Rates – Model diagnostics

Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	39%	-	-
	Adjusted R-squared	38%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	25%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.03	5	No multicollinearity
Linearity	RESET test	1%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity in the residuals of the Wealth Management Personal rates model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

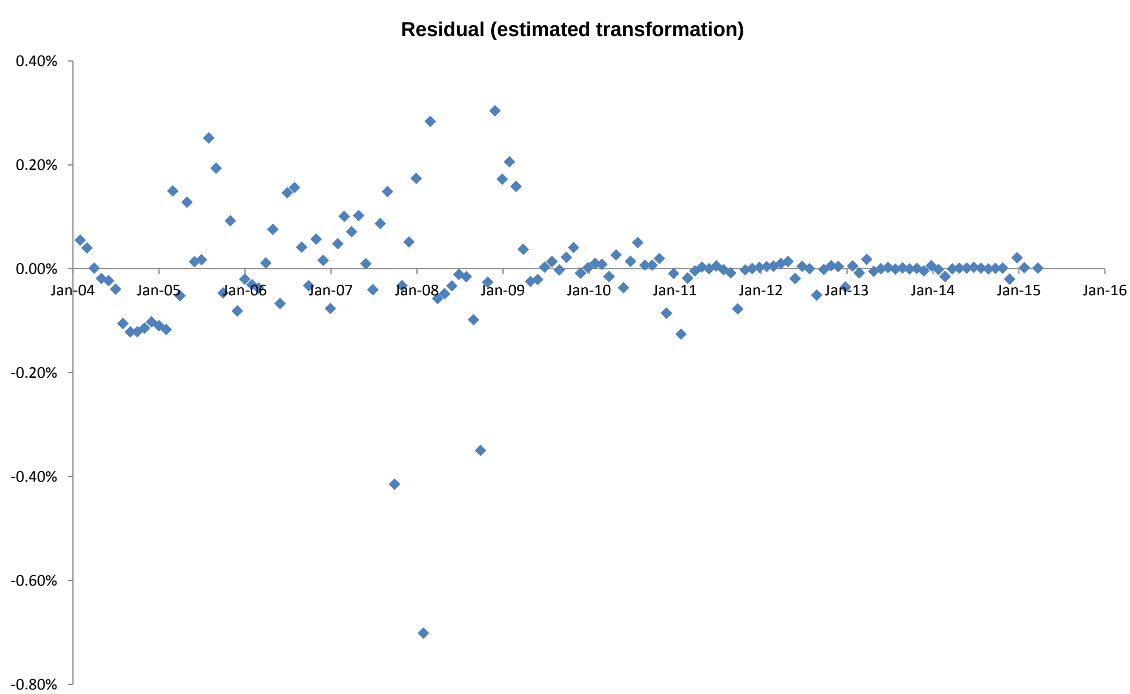
The model also suffers from model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 158: Wealth Management Personal Rate 9Q In-sample Prediction



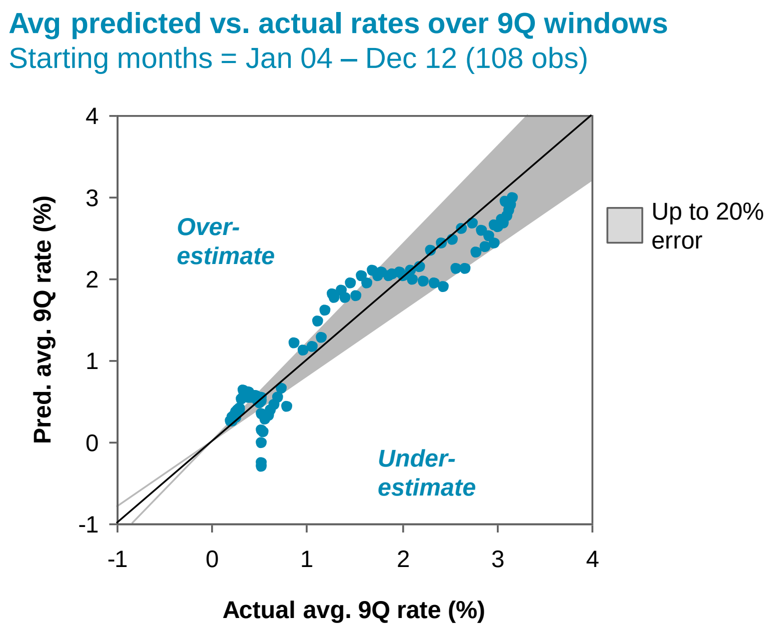
In the select 9Q in-sample prediction, the model captures the rate increase closely.

Figure 159: Wealth Management Personal Rate Residual Plot (%)



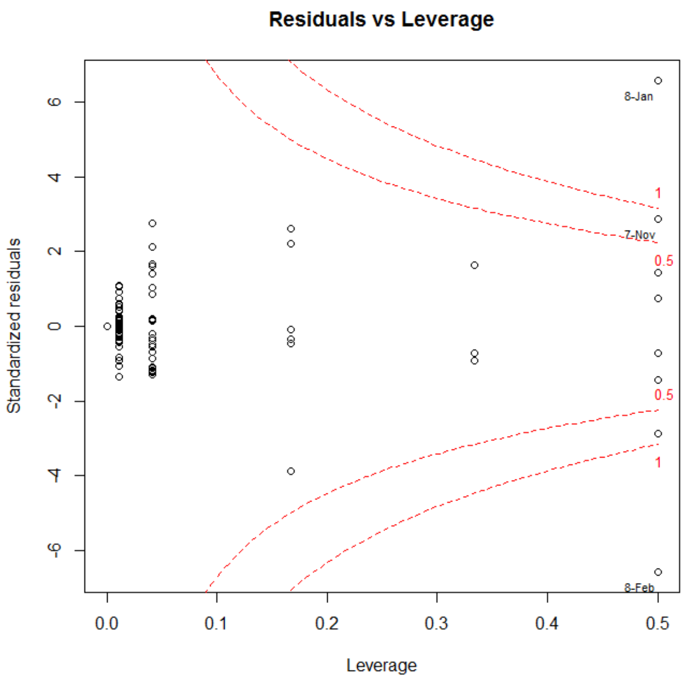
As seen on Figure 159, the residuals are generally randomly distributed across the x-axis, though there are more instances of residuals larger than ~0.1% in magnitude that are greater than zero (i.e. an underestimation), than those that are less than zero (i.e. an overestimation).

Figure 160: WM Personal Rate Estimation Scatterplot



On the other hand, Figure 160 illustrates that the back-test observations that do not remain within a 20% error to actuals on a 9Q average basis are mostly overestimates, especially in higher rate environments.

Figure 161: Influential points for Wealth management personal rates



For this segment January and February 2008 are highly influential points. However, this is not surprising because rates had high volatility during the crisis and does not invalidate the model

6.6.6. Model sensitivity

6.6.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable (i.e. one or more transformations of the benchmark rate), the sensitivity can be directly interpreted from the coefficient estimates.

6.6.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

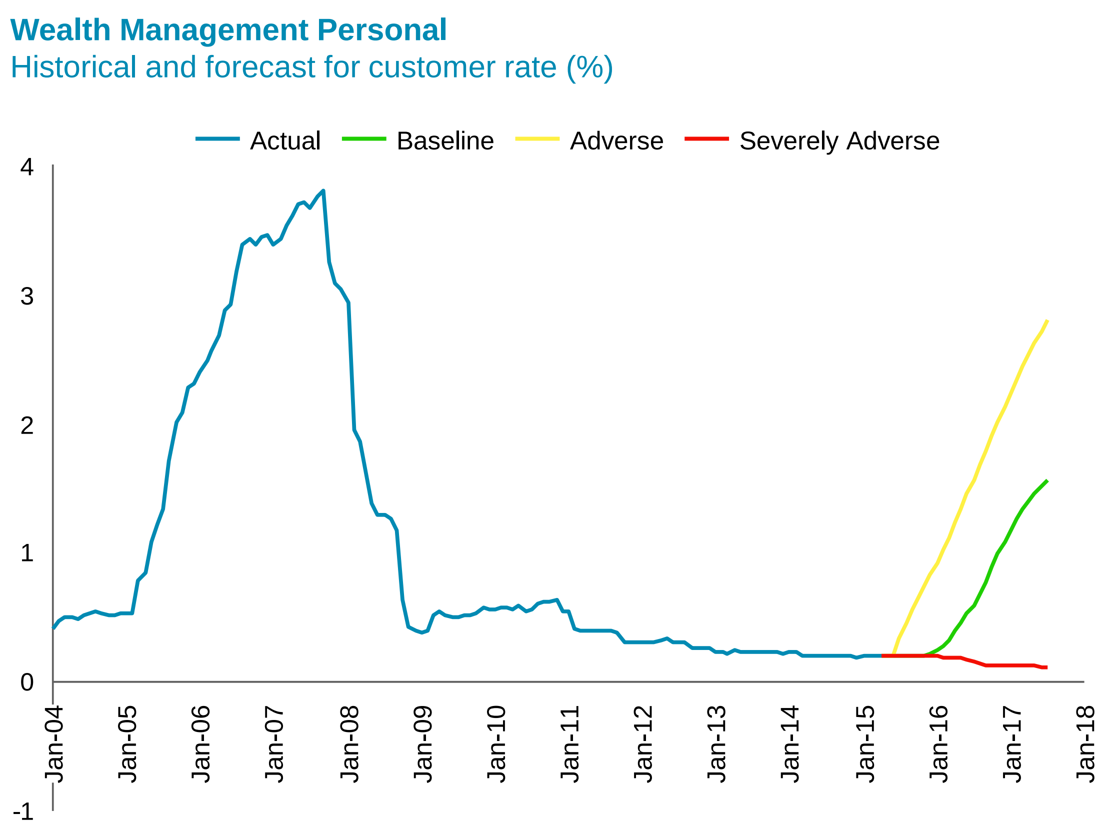
6.6.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 162.

The Working Group considered the forecast behavior for the selected WM Personal model as requiring low scrutiny during management review, as the effective sensitivity of this model was considered to be intuitive.

Figure 162: Wealth Management Personal Rates Model Forecast



6.6.7. Model limitations

One limitation of this model is that the data from the Pre-Merger Deposit Rates Database are product rates whose collection is managed outside the management accounting system. Despite this limitation, the Pre-Merger Deposit Rates Database was preferred over MAQ data whenever available in pursuit of developing statistical models utilizing all available data. Due to the merger between Bank of New York and Mellon Financial in July 2007, MAQ data is only available from 2008 onward which does not contain a raising rate environment for most of the segments, a limitation that was resolved by using the Pre-Merger Deposit Rates Database.

Also, the developed model assumes that the Wealth Management MMDAs product is an appropriate proxy for the entire segment. This decision is made following the principle of leverage the longer data whenever possible, but is certainly an assumption to monitor going forward. The modeling team suggests reinvestigating whether an appropriate model can be estimated on the rates for all sub-segments as more observations become available.

6.7. Wealth Management Sweep

6.7.1. Deposit rates overview

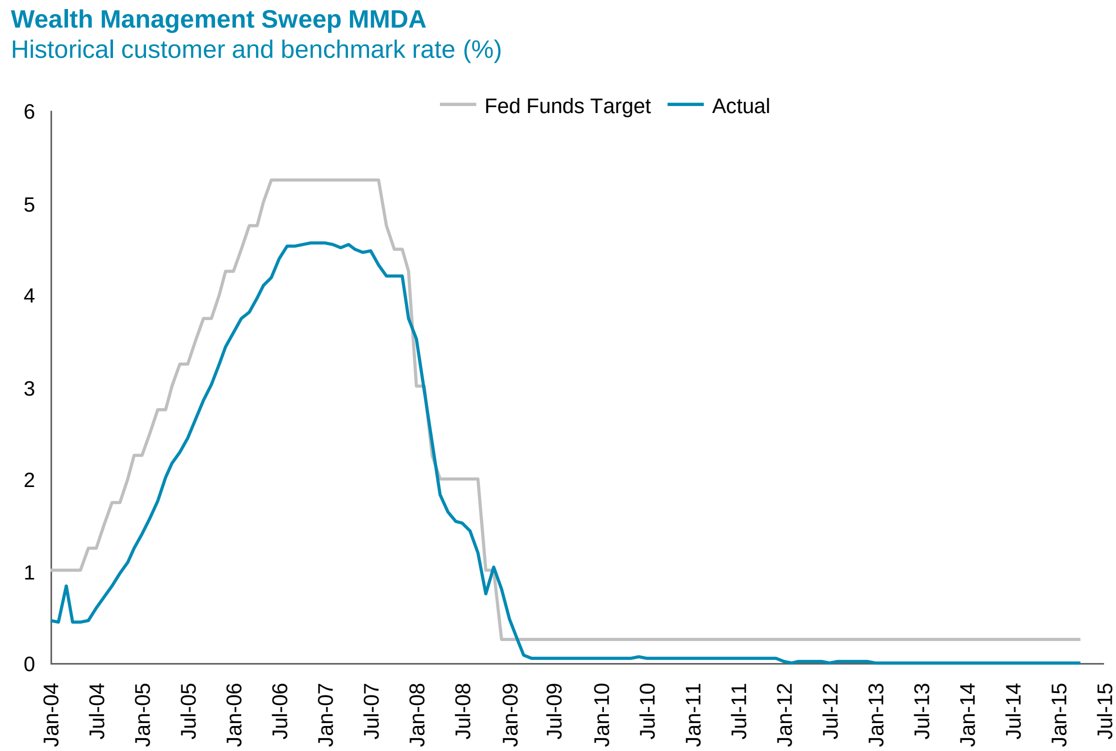
As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Wealth Management Sweep (WM Sweep) segment is modeled using the Wealth Management Sweep MMDA rates data series in the Pre-Merger Deposit Rates Database. Wealth Management Sweep MMDA accounts for 100% of the segment balance as of April 30, 2015. There are is a small amount of balances (~$1 MM) in an Escrow account, which are grouped together with these balances.

Given this, the modeling team chose to use the extended data on the Sweep MMDA accounts as a proxy for the entire segment.

The historical rates data for the segment is shown on Figure 163.

- The historical Wealth Management Sweep MMDA rate closely follows the movement of the Federal Funds Target rate, the segment’s benchmark rate
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 163: Historical rates for Wealth Management Sweep MMDAs



6.7.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Wealth Management Sweep segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits good in-sample fit

The coefficient estimates are displayed in Table 158. Note that Fed_Funds_t1 is the rising rate variable, and Fed_Funds_t2 is the falling rate variable. More details on the construction of these variables can be found on Section 3.3.3 on Methodology.

Table 158: Coefficient estimates for the Wealth Management Sweep Rates model

WM Sweep Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
Fed_Funds_t1_DQoQ	First difference – QoQ	%	0.336
Fed_Funds_t2_DQoQ	First difference – QoQ	%	0.229
Intercept	None (level)	%	-0.0085

The Wealth Management Sweep rates model is a two variable model containing one rising rate and one falling rate variable. In both a rising rate and falling rate environment, the deposit rate responds to a change in the benchmark rate three months after the change (a quarter after).

- A 1.00% increase in the Fed Funds Target Rate results in a 1.00% increase of the WM Sweep deposits rate
- A 1.00% decrease in the Fed Funds Target Rate results in a 0.69% decrease in the WM Sweep deposits rate

In a review and challenge meeting, the line of business generally confirmed the intuitiveness of the coefficient signs and estimates. The fact that the deposit rates respond to increasing benchmark rates faster than falling benchmark rates was, however, found to be counterintuitive.

Whenever the selected model uses the Pre-Merger Deposits Rates Dataset, a comparable model is estimated on the shorter MAQ data as a check. Given the MAQ data only captures observations in a falling and flat rate period, the comparable model is considered as the best fitting model (i.e. model with the highest R-squared) with the same transformation as the falling rate variable. For instance, if the falling rate variable is difference month-over-month transformation with one lag in the Pre-Merger Deposits Rates Dataset model, the comparable model on the shorter MAQ data would be a single variable model with difference month-over-month transformation with one lag.

The comparable model for WM Personal rates model has an effective sensitivity of 0.75, compared to the 0.69 from the extended data.

Although the model using Approach B is selected as the final model for this segment, the modeling team recommends that both these models be monitored as more data points become available

More details of the comparable model can be found in the Appendix.

6.7.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.7.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 159 and Table 160.

Table 159: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Wealth Management Sweep MMDAs – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-1.2	0.66	Fail to Reject unit root
Phillips-Perron	2	-0.6	0.86	Fail to Reject unit root
KPSS	6	1.05	<0.01	Fail to Reject stationarity

Table 160: Unit root tests and stationarity tests including a constant on first differences

Wealth Management Sweep MMDAs – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-3.9	<0.01	Reject unit root
Phillips-Perron	2	-5.9	<0.01	Reject unit root
KPSS	6	0.29	0.14	Fail to Reject stationarity

Stationarity tests for WM Sweep rate levels yield mixed results: The ADF and PP tests fails to reject a unit root while the KPSS test fails to rejects stationarity. However, since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be non-stationary.

In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Therefore, the modeling team uses first difference transformations for the model estimation.

6.7.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the WM Sweep deposit rates. Adjustments made to the MAQ data are described in Section 4.1.

6.7.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 161 reports the results of the significance tests. All of the coefficient estimates in the WM Personal rates model are statistically significant.

Table 161: Statistical significance tests of model and variables for Wealth Management Sweep rates

WM Sweep Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Fed_Funds_t1_DQoQ	0.336	<1%	10%	Statistically significant
Fed_Funds_t2_DQoQ	0.229	<1%	10%	Statistically significant
Intercept	-0.008	10%	10%	Statistically significant

Heteroskedasticity was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

6.7.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

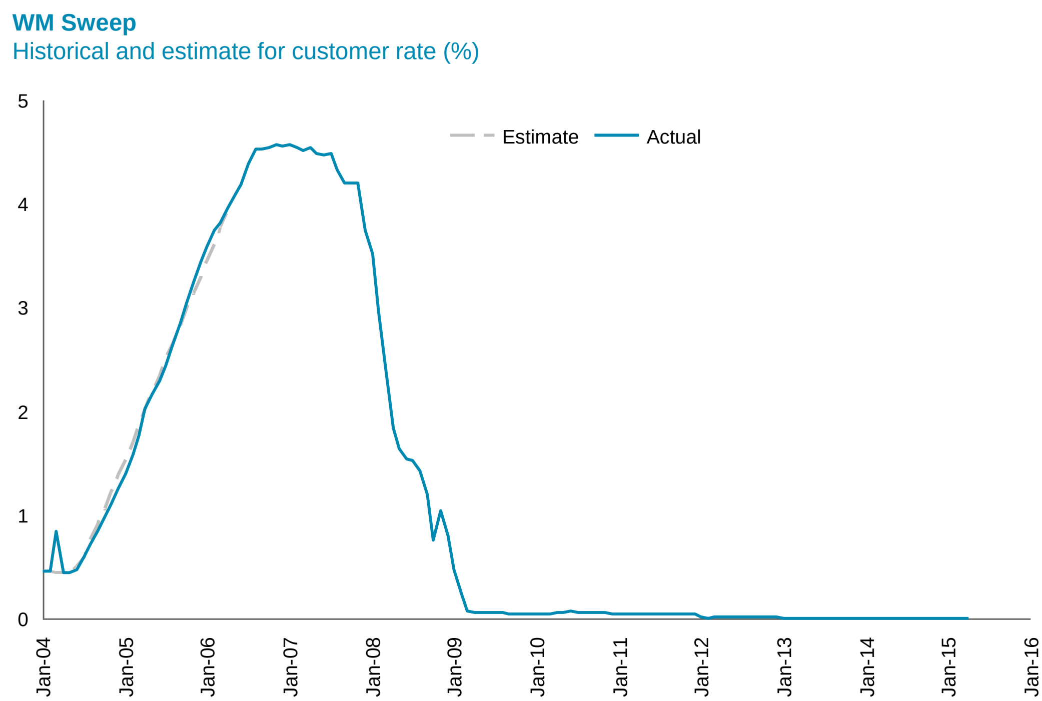
Table 162: Wealth Management Sweep Rate Model Diagnostics

WM Sweep Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	59%	-	-
	Adjusted R-squared	59%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	7%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.03	5	No multicollinearity
Linearity	RESET test	100%	10%	Linear specification appropriate

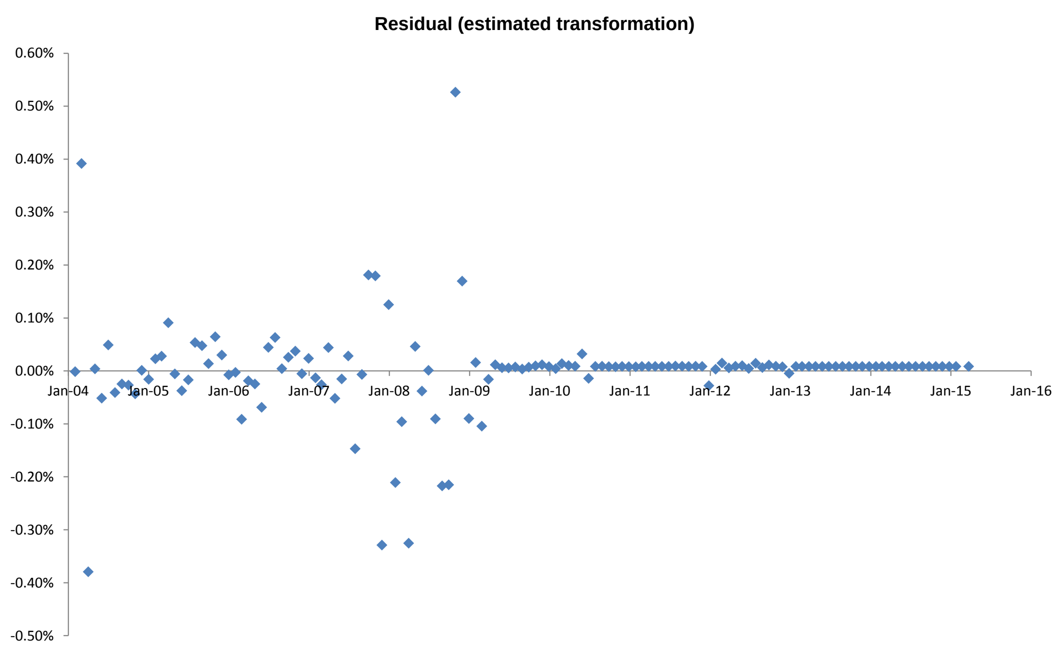
The diagnostic tests detected heteroskedasticity and serial correlation in the residuals of the Wealth Management Sweep rates model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Figure 164: Wealth Management Sweep Rate 9Q In-sample Prediction



In the select 9Q in-sample prediction, the model predicts the rise in rates experienced in form 2004–2006 closely.

Figure 165: Wealth Management Sweep Rate Residual Plot (%)



As seen on Figure 165, the residuals are generally randomly distributed across the x-axis over the estimated period. Starting 2009 the residuals become much closer to zero, as rates remain low and experience limited variation.

Figure 166: WM Sweep Rate Estimation Scatterplot

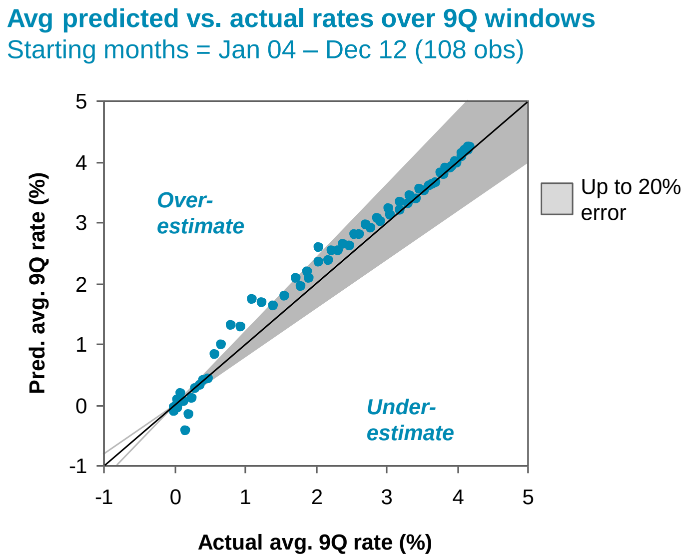
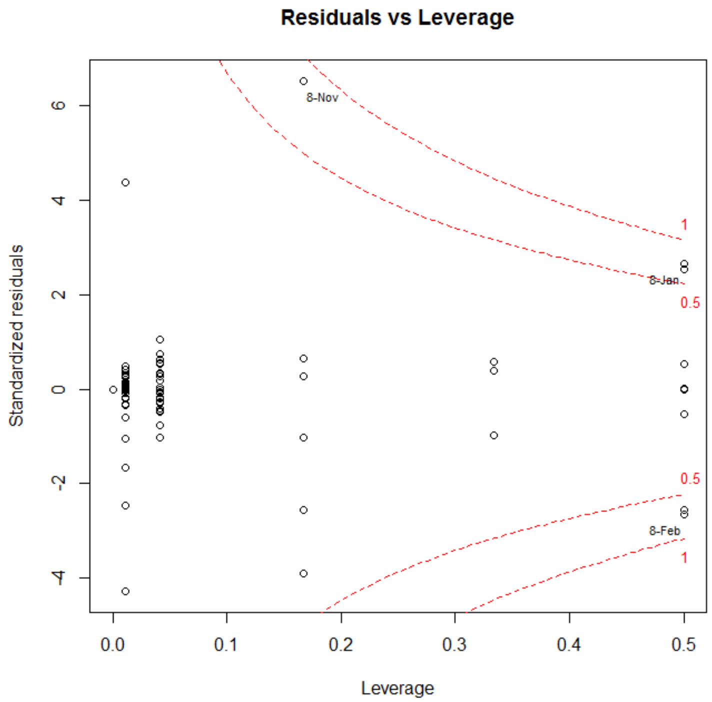


Figure 166 illustrates that the 9Q average estimated rates largely fall within a 20% error, especially when rates are higher.



The segment does not have a highly influential point.

6.7.6. Model sensitivity

6.7.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable (i.e. one or more transformations of the benchmark rate), the sensitivity can be directly interpreted from the coefficient estimates.

6.7.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

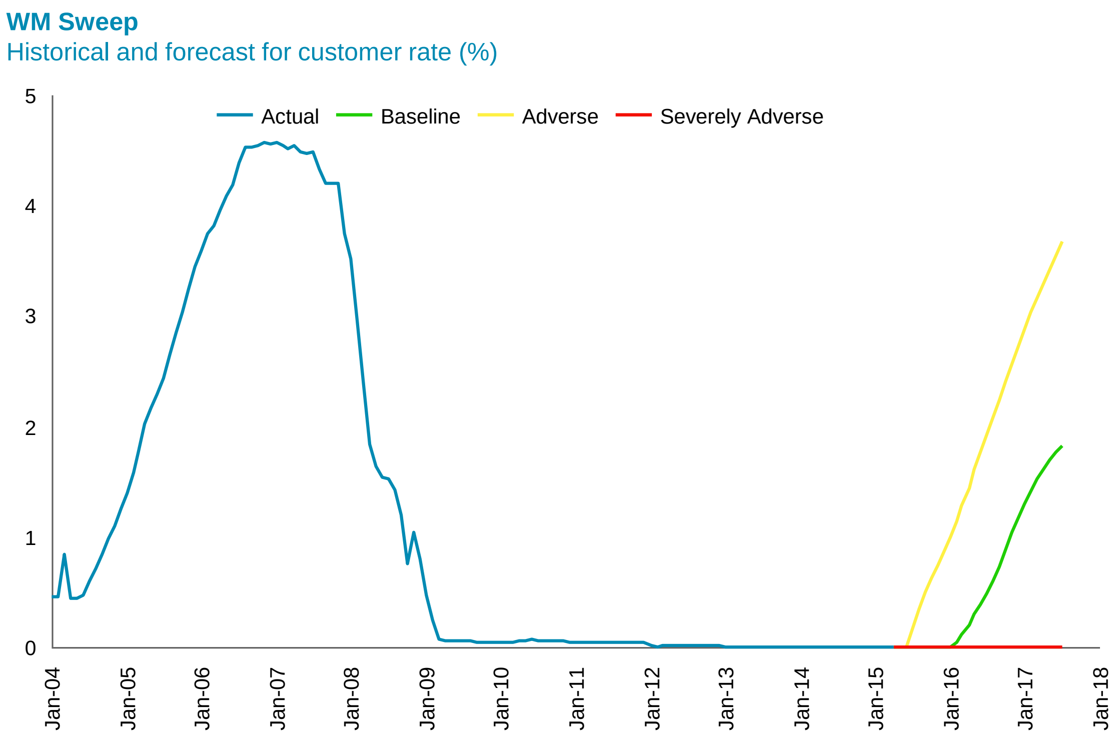
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

6.7.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 167.

Figure 167: Wealth Management Sweep Rates Model Forecast



The negative intercept in this model leads to some forecast observations going down to minus 30bps – this is unlikely to actual occur given the Fed Funds Rate in the forecast scenarios are positive. Hence, the model forecast is bounded to zero whenever the benchmark rate is not negative, as business intuition strongly suggests the deposit rate will not fall below zero unless the benchmark rate does.

The Working Group considered the forecast behavior for the selected WM Sweep model as requiring low scrutiny during management review, as the effective sensitivity of this model was considered to be intuitive.

6.7.7. Model limitations

One limitation of this model is that the data from the Pre-Merger Deposit Rates Database are product rates whose collection is managed outside the management accounting system. Despite this limitation, the Pre-Merger Deposit Rates Database was preferred over MAQ data whenever available in pursuit of developing statistical models utilizing all available data. Due to the merger between Bank of New York and Mellon Financial in July 2007, MAQ data is only available from 2008 onward which does not contain a raising rate environment for most of the segments, a limitation that was resolved by using the Pre-Merger Deposit Rates Database.

6.8. Asset Servicing/Treasury Services EU

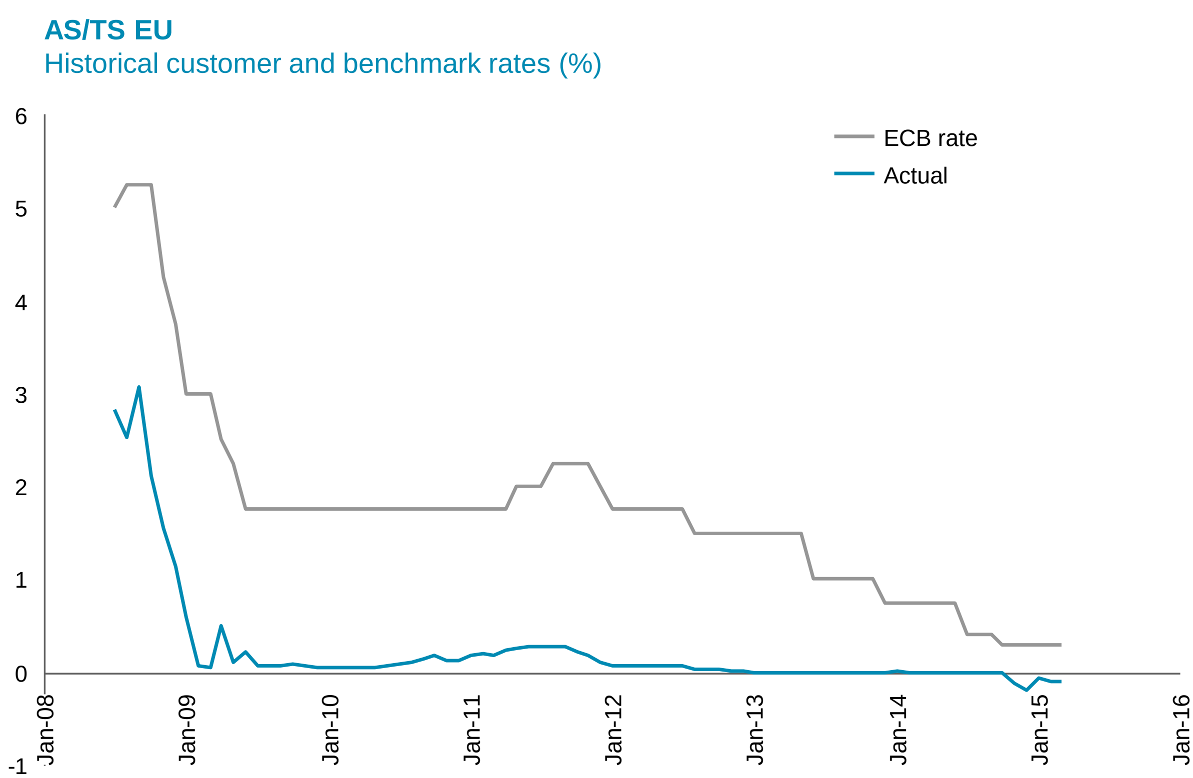
6.8.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Asset Servicing/Treasury Services EU (AS/TS EU) segment are modeled using the shorter Microstrategy data, which is only available from July 2008.

The historical rates data for the segment is shown on Figure 168.

- The historical AS/TS EU rate follows the directional movement of the ECB marginal rate, the segment's benchmark rate
- In 2015, the rate paid falls below zero for this segment
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 168: Historical rates for AS/TS EU



6.8.2. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.8.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 163 and Table 164.

Table 163: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Foreign Asset Servicing/Treasury Services EU – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	0	-5.6	<0.01	Reject unit root
Phillips-Perron	1	-5.7	<0.01	Reject unit root
KPSS	5	0.6	0.02	Reject stationarity

Table 164: Unit root tests and stationarity tests including a constant on first differences

Foreign Asset Servicing/Treasury Services EU – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	3	-4.6	<0.01	Reject unit root
Phillips-Perron	1	-8.1	<0.01	Reject unit root
KPSS	3	0.45	0.05	Reject stationarity

Stationarity tests for AS/TS EU rate levels yield mixed results: The ADF and PP tests reject a unit root while the KPSS test reject stationarity. However, since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be stationary.

The monthly first difference series also yields the same results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity.

There is, however, a limitation to these tests. The AS/TS EU rates data only spans a small portion of one rate cycle and therefore does capture much variation in the rate environment. As a result, stationarity tests on this data may not be representative of the long-term behavior of the variable.

Given the limited data available for this segment, additional consideration was given to academic literature. There are numerous studies that argue untransformed real interest rates are non-stationary.[31]

Given these considerations, as well as manual review of the rate levels and the first difference series, the modeling team chose to model these rates on first differences.

6.8.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

[31] See, e.g. Christopher J. Neely and David E. Rapach, "Real Interest Rate Persistence: Evidence and Implications," *Federal Reserve Bank of St. Louis Review*, November/December 2008, pp. 609–41.

No adjustments to data were necessary for the final models selected for deposits rates. Adjustments made to the alternative data sources are described in Section 4.1.

6.8.3. Model summary

A statistically sound model that is consistent with business intuition was found for the AS/TS EU segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology. The in-sample fit, however, is relatively unstable. The instability is largely caused by the lack of observations in the data used for modeling

The coefficient estimates are displayed in Table 165.

Table 165: Coefficient estimates for the AS/TS EU Rates model

	AS/TS EU Rates (in %) – Selected model		
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
EUROMLR_DMoML1	First difference – MoM	%	0.449
Intercept	None (level)	%	-0.010

The AS/TS EU rates model is a single variable model containing a difference month-over-month transformation of the ECB marginal rate. According to the model, a 1.00% change in the ECB marginal rate results in a 0.45% change of the same direction in the AS/TS EU deposits rate.

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient sign and estimate.

The modeling team considered the selected AS/TS EU rate model as requiring high scrutiny during management review, given the limited historical data this model was developed on.

6.8.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold

- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 166 reports the results of the significance tests. The coefficient estimate in the AS/TS EU rates model is statistically significant. The intercept is found to be statistically insignificant.

Table 166: Statistical significance tests of model and variables for AS/TS EU rates

AS/TS EU Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
EUROMLR_DMoML1	0.449	<1%	10%	Statistically significant
Intercept	-0.010	60%	10%	Statistically not significant

6.8.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 167: AS/TS EU Rate Model Diagnostics

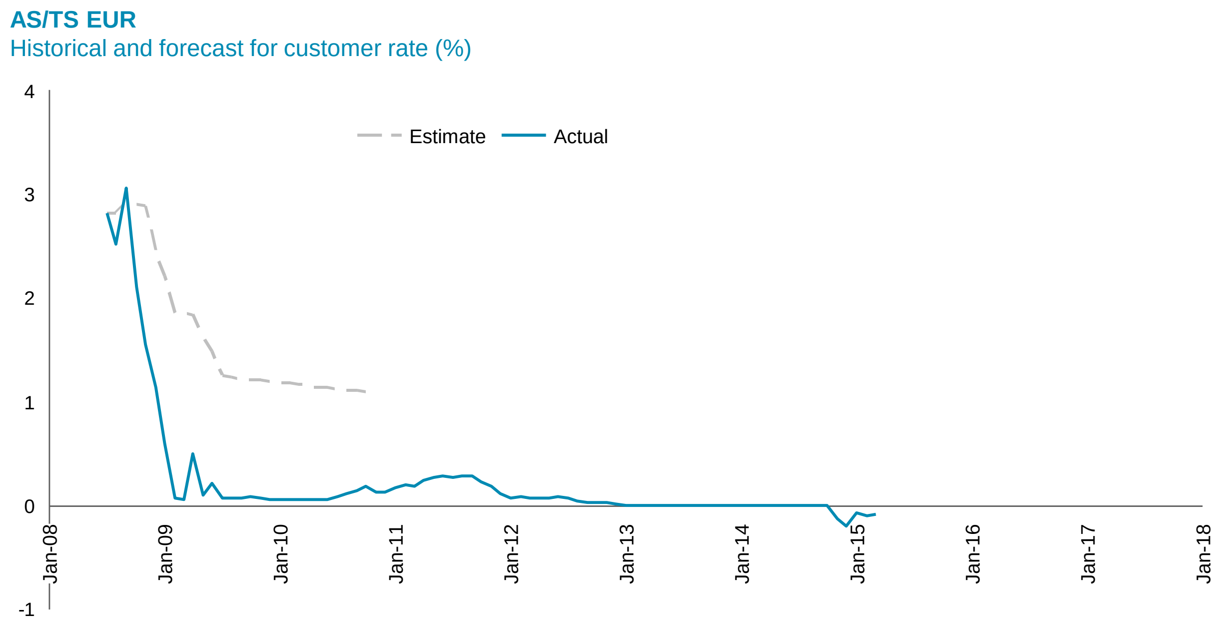
AS/TS EU Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	22%	-	-
	Adjusted R-squared	21%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	93%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	10%	10%	No serial correlation

Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	95%	10%	Linear specification appropriate

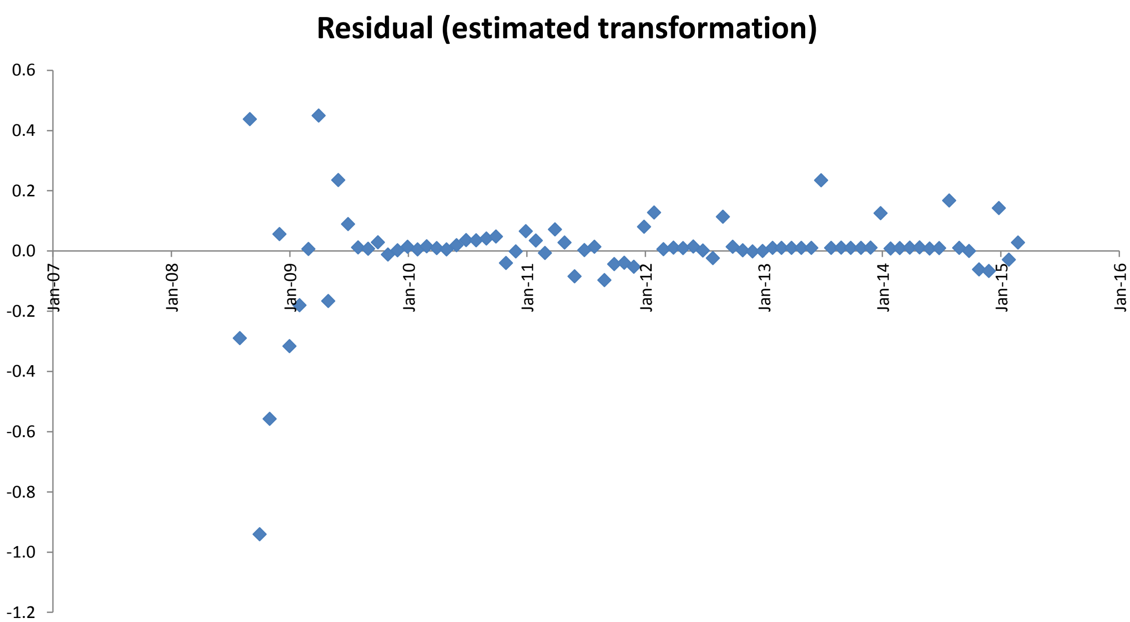
The AS/TS EU model passes all statistical tests.

Figure 169: AS/TS EU Rate 9Q In-sample Prediction



In the select 9Q in-sample prediction does not capture the full extent of the rate drop in 2008. This is noted as a weak back-test result that is caused largely by the limited availability of data.

Figure 170: AS/TS EU Rate Residual Plot (%)



As seen on Figure 170, the residuals are generally randomly distributed, though there is significant error in 2008 and 2009, when the variation in the deposits rates occur. Starting 2009 the residuals become much closer to zero, as rates remain low and experience limited variation.

Figure 171: AS/TS EU Rate Estimation Scatterplot

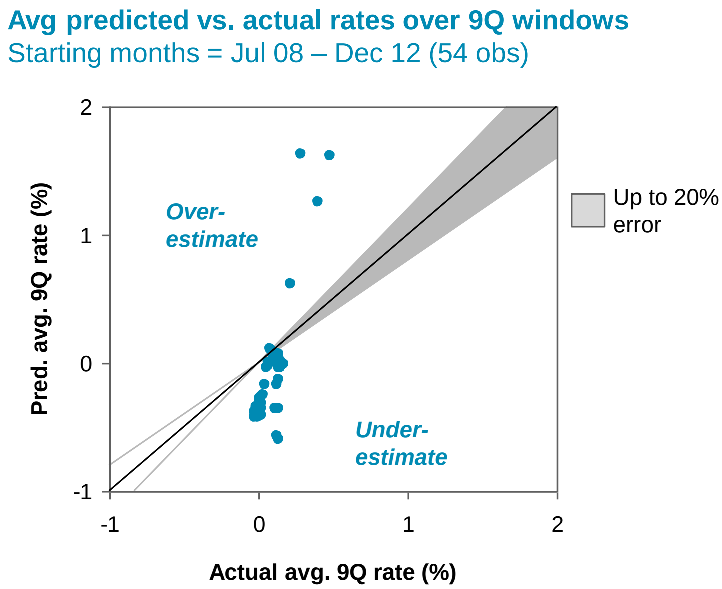
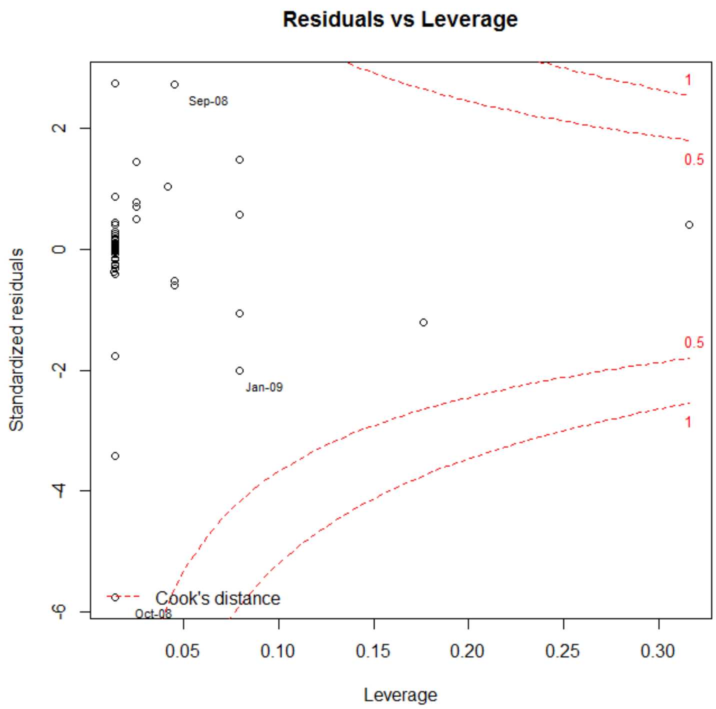


Figure 171 illustrates that most 9Q prediction averages underestimate the AS/TS EU rate.

These figures suggest this model does not perform well in in-sample back tests and therefore should be monitored closely, especially as more data becomes available.

Figure 172: Influential points for AS/TS EU Rate



The segment did not contain a highly influential point.

6.8.6. Model sensitivity

6.8.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable the sensitivity can be directly interpreted from the coefficient estimates.

6.8.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

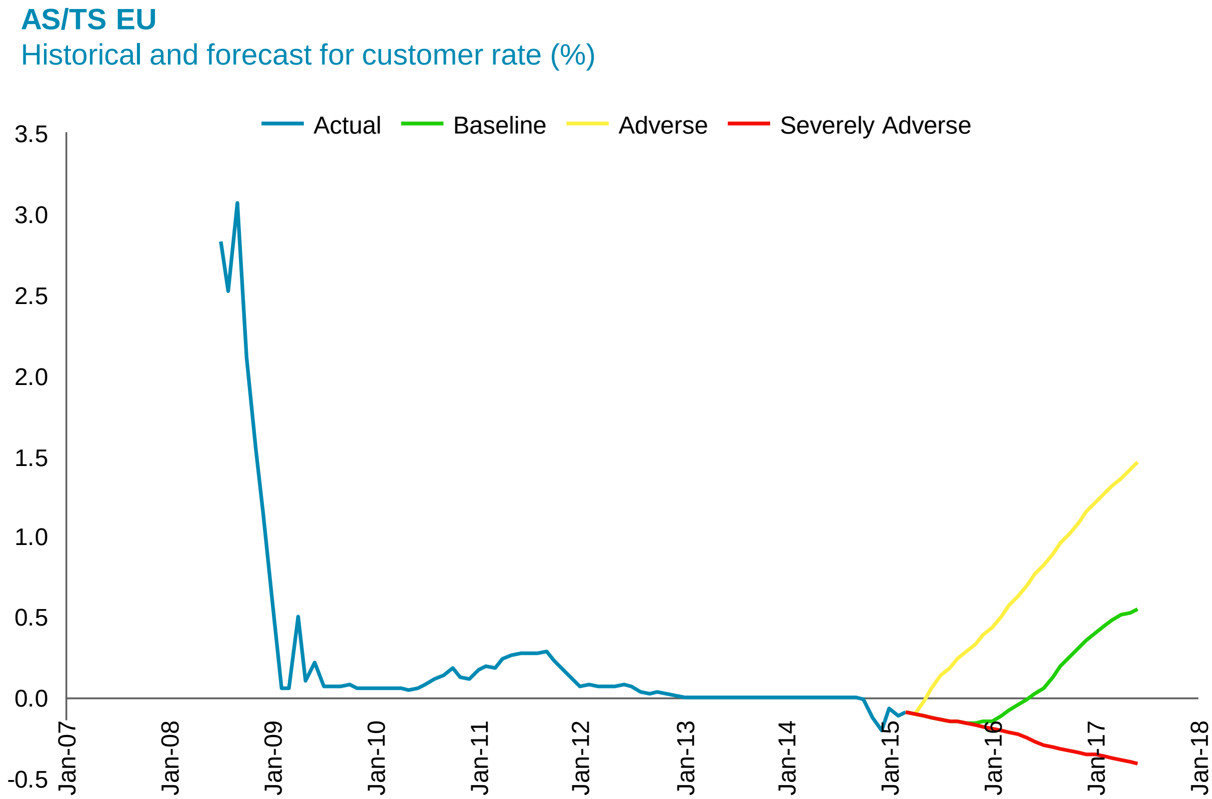
6.8.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 173. The negative intercept causes the forecasts to fall in the severe recession (Severely Adverse) scenario and the start of the Baseline scenario.

The Working Group considered the forecast behavior for the selected AS/TS EU model as requiring high scrutiny during management review, given the model was developed on such few observations.

Figure 173: AS/TS EU Rates Model Forecast



6.8.7. Model limitations

The main limitation of this model is the lack of observations in a higher rate environment, which limits the strength of models that can be generated. Therefore, it is critical that this model is revisited as soon as there are more data points available in a higher rate environment.

6.9. Asset Servicing/Treasury Services GB

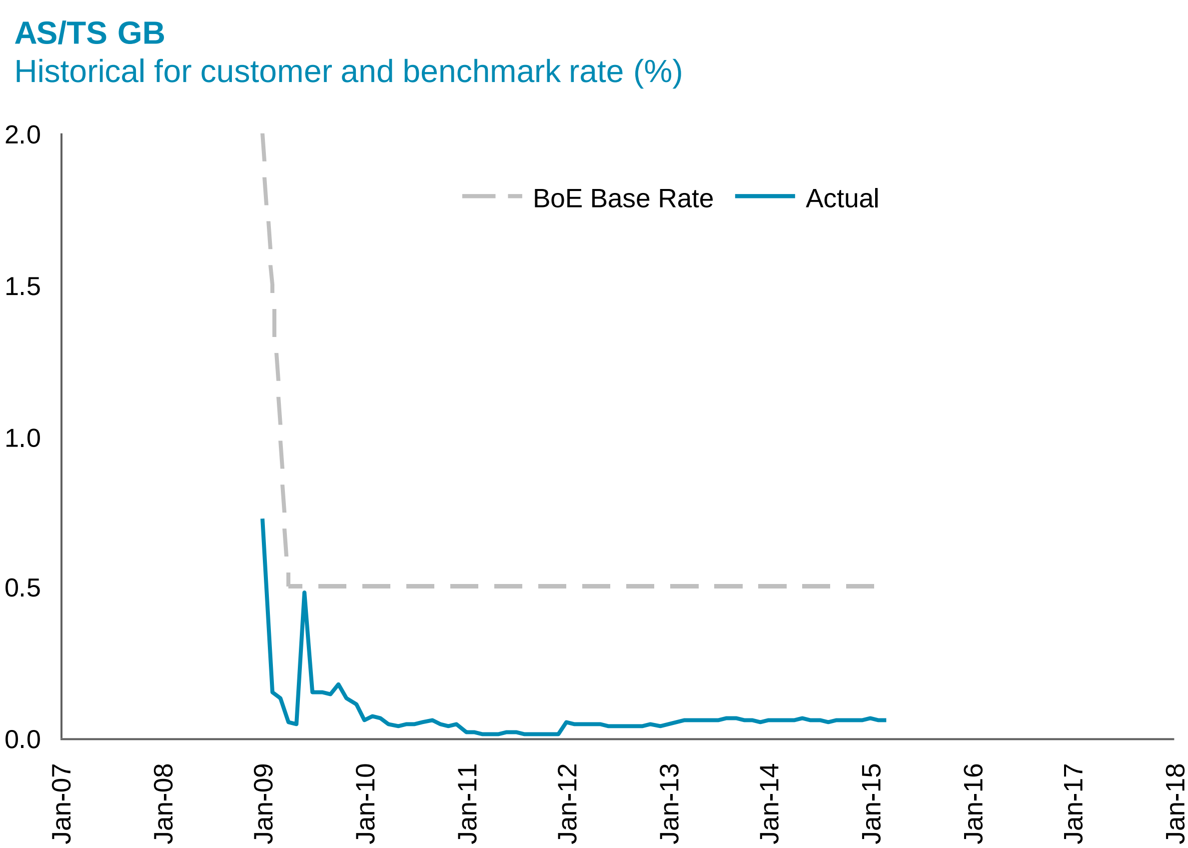
6.9.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Asset Servicing/Treasury Services GB (AS/TS GB) segment are modeled using the shorter Microstrategy data, which is only available from January 2009.

The historical rates data for the segment is shown on Figure 174.

- The historical AS/TS GB rate follows the directional movement of the Bank of England base rate, the segment's benchmark rate
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment
- On major exception is one point in June 2009, when the deposit rate increased for just one month despite a flat benchmark rate. The model estimate, however, is not materially affected by this single data point, so no adjustments were made to the data

Figure 174: Historical rates for AS/TS GB



6.9.2. Model summary

A statistically sound model that is consistent with business intuition was found for the AS/TS GB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology. The in-sample fit, however, is relatively unstable. The instability is largely caused by the lack of observations in the data used for modeling

The coefficient estimates are displayed in Table 168.

Table 168: Coefficient estimates for the AS/TS GB Rates model

AS/TS GB Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
LCBBASE_DMoM	First difference – MoM	%	0.447
Intercept	None (level)	%	0.0001

The AS/TS GB rates model is a single variable model containing a difference month-over-month transformation of the BoE base rate. According to the model, a 1.00% change in the BoE base rate results in a 0.45% change in the AS/TS GB deposits rate

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient sign and estimate.

Despite intuitiveness of this model, the modeling team recommends this model should be monitored as more data points become available.

The modeling team considered the selected AS/TS GB rate model as requiring high scrutiny during management review, given the limited historical data this model was developed on.

6.9.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.9.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 169 and Table 170.

Table 169: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Foreign Asset Servicing/Treasury Services GB – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	3	-2.5	0.12	Fail to Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	3	0.69	0.01	Reject stationarity

Table 170: Unit root tests and stationarity tests including a constant on first differences

Foreign Asset Servicing/Treasury Services GB – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	5	-2.1	0.24	Fail to Reject unit root
Phillips-Perron	1	-17	<0.01	Reject unit root
KPSS	3	0.31	0.13	Fail to Reject stationarity

Stationarity tests for AS/TS GB rate levels yield mixed results: The PP test rejects a unit root while the ADF test fails to reject the unit root and the KPSS test rejects stationarity. These results suggest the AS/ST GB rate levels may be non-stationary.

Similarly, the monthly first difference series also yields mixed results: The PP test rejects a unit root and the KPSS test fails to reject stationarity, while the ADF test fails to reject the unit root. Since the KPSS test is the primary test reviewed for first differences, the AS/TS GB rates on first differences is determined to be stationary.

Therefore, the modeling team uses first difference transformations for the model estimation.

6.9.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the final models selected for deposits rates. Adjustments made to the alternative data sources are described in Section 4.1.

6.9.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 171 reports the results of the significance tests. The coefficient estimate in the AS/TS GB rates model is statistically significant. The intercept is found to be statistically insignificant.

Table 171: Statistical significance tests of model and variables for AS/TS GB rates

AS/TS GB Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
LCBBASE_DMoM	0.447	<1%	10%	Statistically significant
Intercept	0.000	98%	10%	Statistically not significant

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

6.9.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 172: AS/TS GB Rate Model Diagnostics

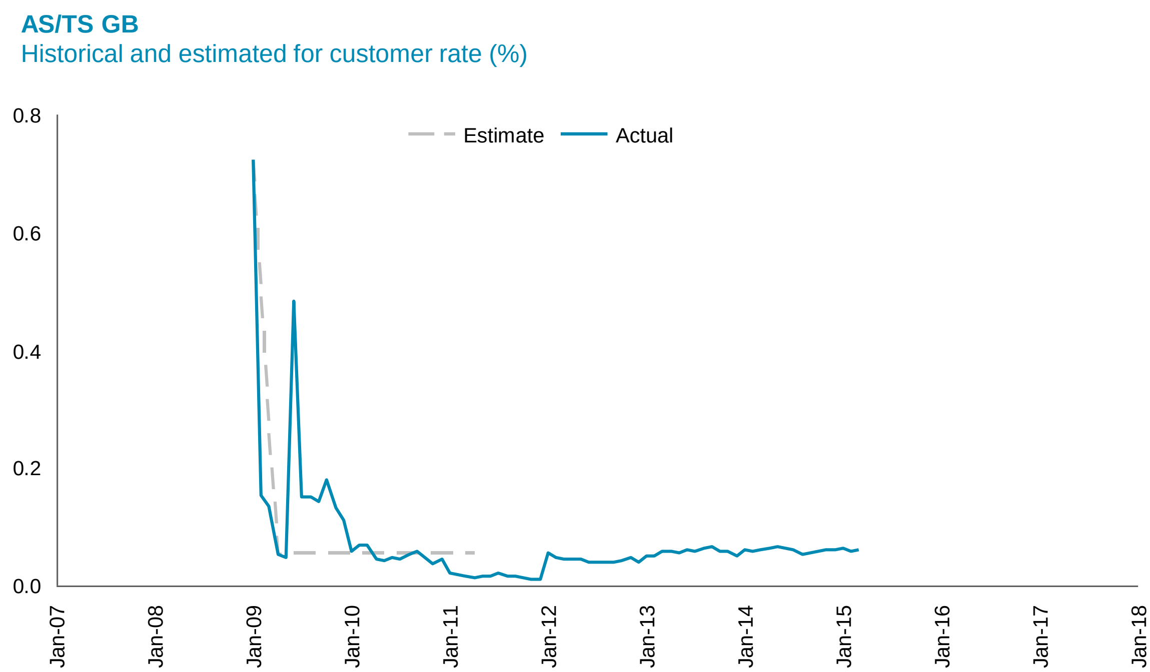
AS/TS GB Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	23%	-	-
	Adjusted R-squared	22%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	0%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity and serial correlation in the residuals of the AS/TS GB model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

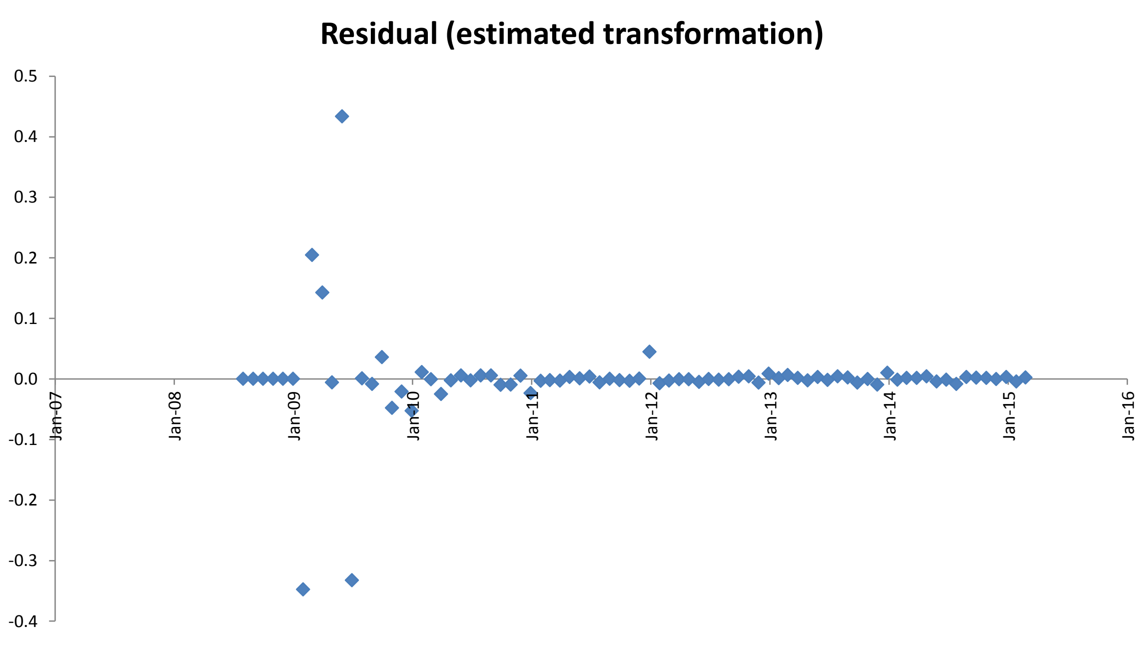
The model also suffers from model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 175: AS/TS GB Rate 9Q In-sample Prediction



In the select 9Q in-sample prediction captures the rate drop in the beginning of 2009, which is the vast majority of variation seen the AS/TS GB rate over the modeling period.

Figure 176: AS/TS GB Rate Residual Plot (%)



The residual plot on Figure 176 illustrates there is limited rate variation over the modeling period, as most residuals are close to zero during the period when rates remain flat starting mid-2009.

Figure 177: AS/TS GB Rate Estimation Scatterplot

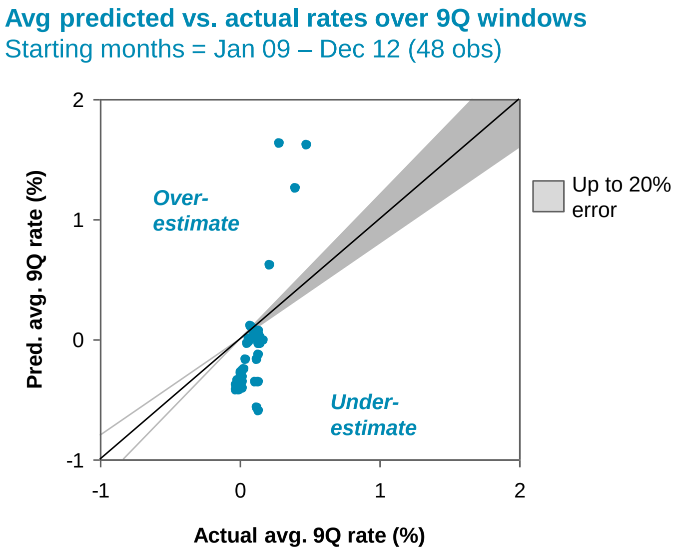
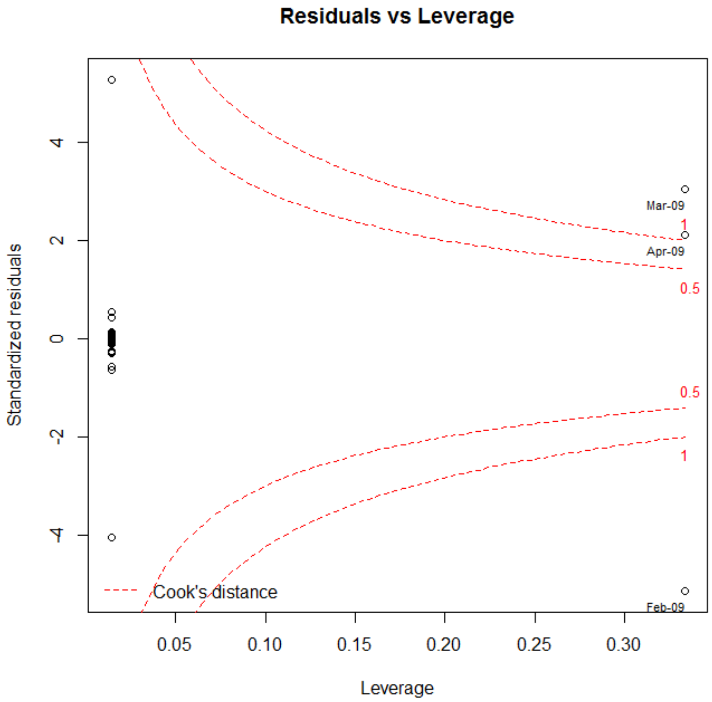


Figure 177 illustrates that most 9Q predictions underestimate the AS/TS GB rate.

These observations suggest this model is a weak model that should be monitored closely when applied to macroeconomic forecasts scenarios.

Figure 178: Influential points for AS/TS GB rate



For this segment Febuary, March and April 2009 are highly influential points. However, this is not surprising because rates rapidly increased and declined in this period and does not invalidate the model.

6.9.6. Model sensitivity

6.9.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable the sensitivity can be directly interpreted from the coefficient estimates.

6.9.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

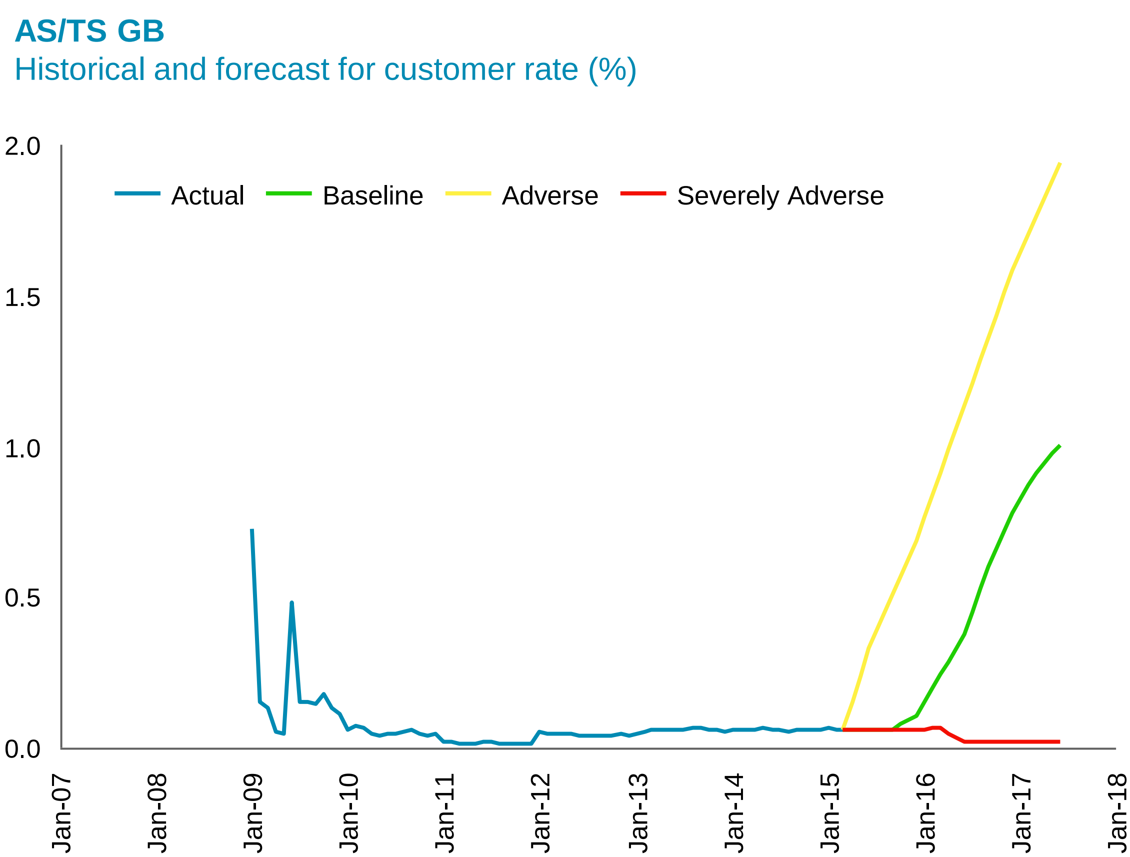
6.9.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 179.

The Working Group considered the forecast behavior for the selected AS/TS GB model as requiring high scrutiny during management review, given the model was developed on such few observations.

Figure 179: AS/TS GB Rates Model Forecast



6.9.7. Model limitations

The main limitation of this model is the lack of observations in a higher rate environment, which limits the strength of models that can be generated. Therefore, it is critical that this model is revisited as soon as there are more data points available in a higher rate environment.

6.10. Corporate Trust EU

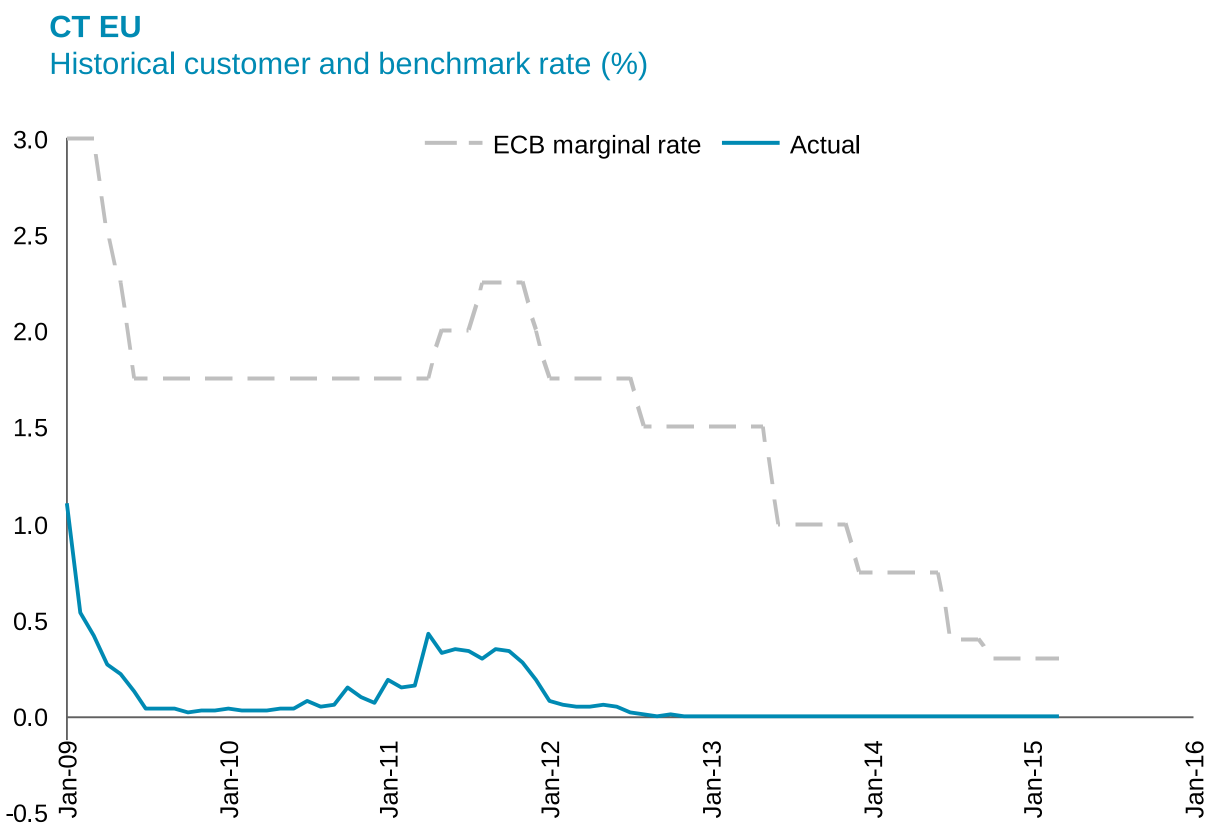
6.10.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Corporate Trust EU (CT EU) segment are modeled using the shorter Microstrategy data, which is only available from January 2009.

The historical rates data for the segment is shown in Figure 180.

- The historical CT EU rate follows the directional movement of the ECB's marginal rate, the segment's benchmark rate
- Movements of the deposit rate that occur when the benchmark rate remains flat are caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 180: Historical rates for CT EU



6.10.2. Model summary

A statistically sound model that is consistent with business intuition was found for the CT EU segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology. The in-sample fit, however, is relatively unstable. The instability is largely caused by the lack of observations in the data used for modeling

The coefficient estimates are displayed in Table 173.

Table 173: Coefficient estimates for the CT EU Rates model

CT EU Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
EUROMLR_DMoML1	First difference – MoM	%	0.222
EUROMLR_DMoML3	First difference – MoM	%	0.187
Intercept	None (level)	%	0.0078

The CT EU rates model is a two variable model containing a difference month-over-month transformation of the ECB marginal rate. According to the model, a 1.00% change in the ECB marginal rate results in a 0.41% change in the CT EU deposits rate.

In a review and challenge meeting, the line of business confirmed the intuitiveness of the coefficient signs and estimates.

Despite intuitiveness of this model, the modeling team recommends this model should be monitored as more data points become available.

The modeling team considered the selected CT EU rate model as requiring high scrutiny during management review, given the limited historical data this model was developed on.

6.10.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.10.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 174 and Table 175.

Table 174: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Foreign Corporate Trust EU – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	3	-1.8	0.37	Fail to Reject unit root
Phillips-Perron	1	-8.3	<0.01	Reject unit root
KPSS	4	0.61	0.02	Reject stationarity

Table 175: Unit root tests and stationarity tests including a constant on first differences

Foreign Corporate Trust EU – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-6.5	<0.01	Reject unit root
Phillips-Perron	1	-13	<0.01	Reject unit root
KPSS	3	0.38	0.08	Reject stationarity

Stationarity tests for CT EU rate levels yield mixed results: The PP test rejects a unit root while the ADF test fails to reject the unit root and the KPSS test rejects stationarity. These results suggest the CT EU rate levels may be non-stationary.

Similarly, the monthly first difference series also yields mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. The KPSS test is the primary test reviewed for first differences and by that preference the CT EU rates on first differences is determined to be non-stationary.

There is, however, a limitation to these tests. The CT EU rates data only spans a small portion of one rate cycle and therefore does capture much variation in the rate environment. As a result, stationarity tests on this data may not be representative of the long-term behavior of the variable.

Given the limited data available for this segment, additional consideration was given to academic literature. There are numerous studies that argue untransformed real interest rates are non-stationary.[32]

[32] See, e.g. Christopher J. Neely and David E. Rapach, "Real Interest Rate Persistence: Evidence and Implications," *Federal Reserve Bank of St. Louis Review*, November/December 2008, pp. 609–41.

Given these considerations, as well as manual review of the rate levels and the first difference series, the modeling team chose to model these rates on first differences.

6.10.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the final models selected for deposits rates. Adjustments made to the alternative data sources are described in Section 4.1.

6.10.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 176 reports the results of the significance tests. The coefficient estimates in the CT EU rates model are statistically significant individually and collectively. The intercept is found to be statistically insignificant.

Table 176: Statistical significance tests of model and variables for CT EU rates

CT EU Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
EUROMLR_DMoML1	0.222	<1%	10%	Statistically significant
EUROMLR_DMoML3	0.187	2%	10%	Statistically significant
Intercept	0.008	31%	10%	Statistically not significant

6.10.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 177: CT EU Rate Model Diagnostics

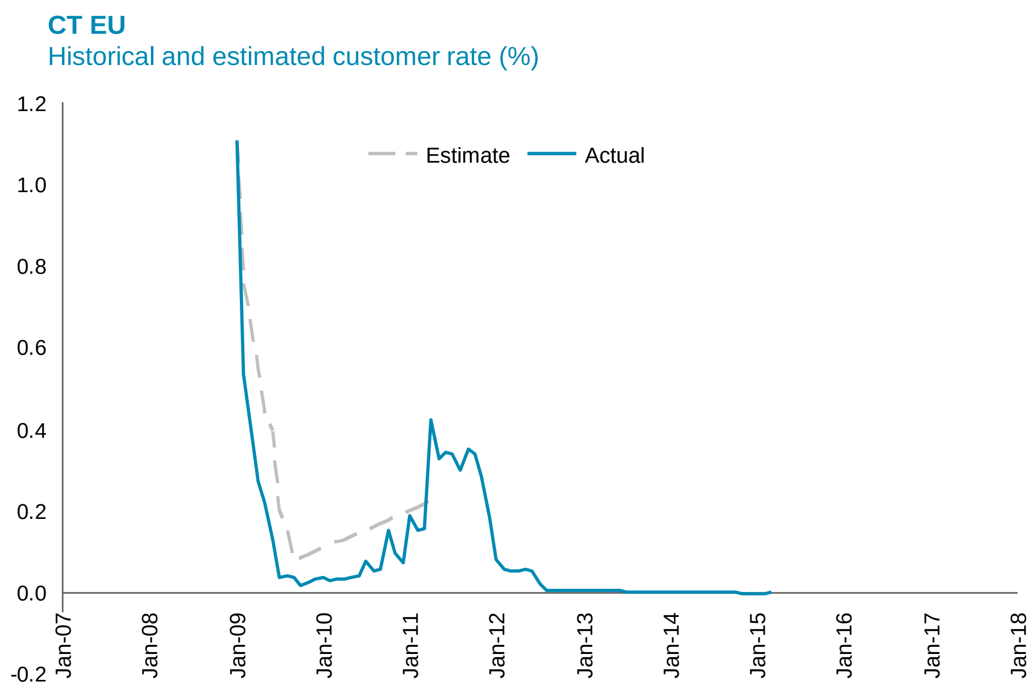
CT EU Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	48%	-	-
	Adjusted R-squared	47%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	56%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.14	5	No multicollinearity
Linearity	RESET test	0%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity in the residuals of the Corporate Trust Euro rates model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

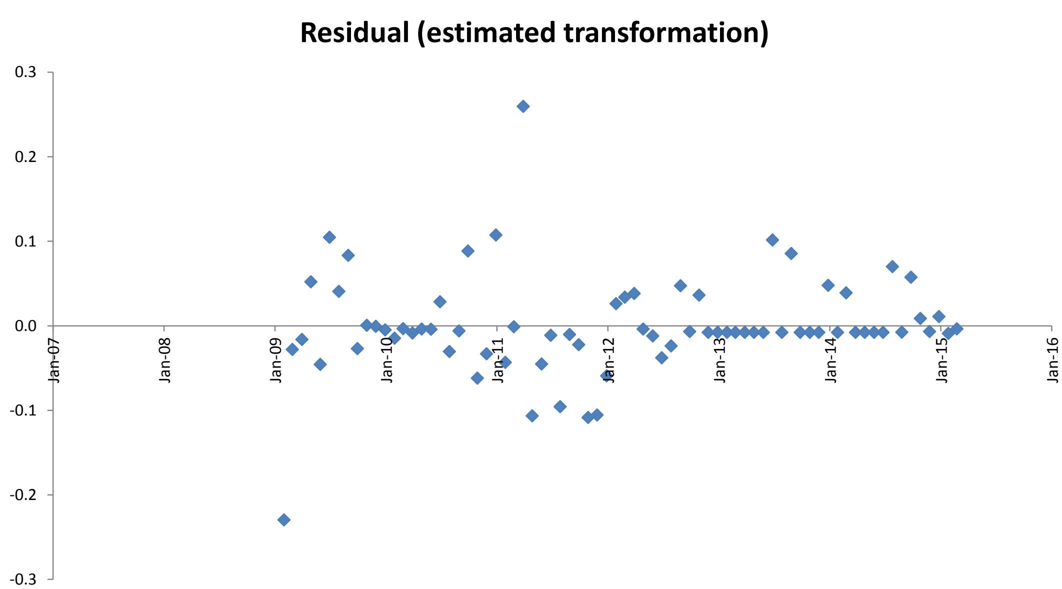
The CT EU model suffers from model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 181: CT EU Rate 9Q In-sample Prediction



In the select 9Q in-sample prediction captures the rate drop in the beginning of 2009, which is the vast majority of variation seen the CT EU rate over the modeling period.

Figure 182: CT EU Rate Residual Plot (%)



The residual plot on Figure 182 shows residuals that are randomly distributed around the x-axis.

Figure 183: CT EU Rate Estimation Scatterplot

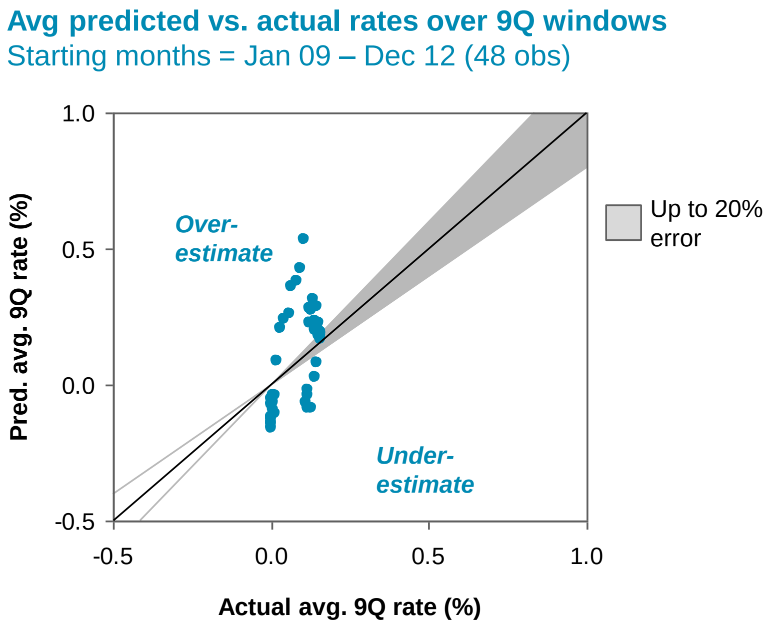
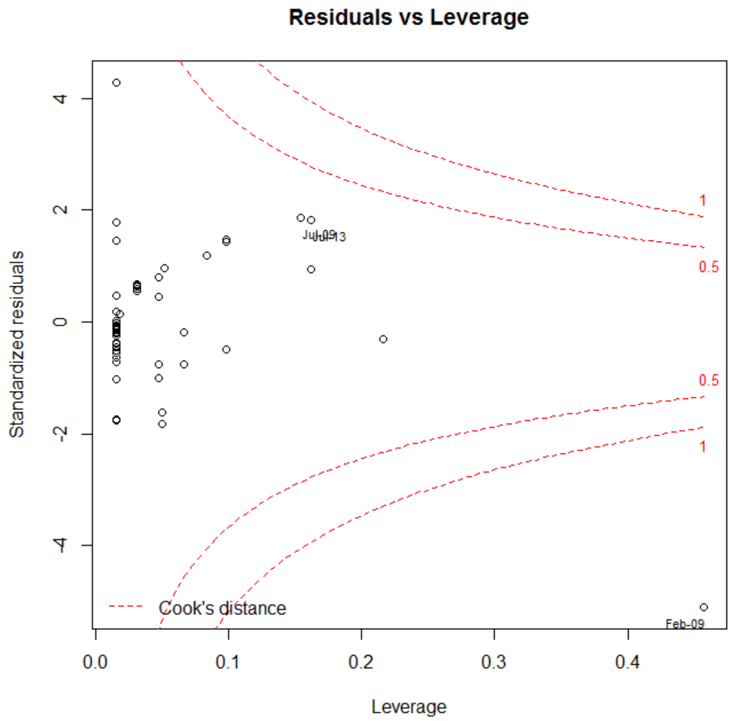


Figure 183 illustrates that most 9Q predictions have errors greater than 20%.

This given the poor performance in the back tests, the model outputs should be monitored closely when applied to macroeconomic forecasts scenarios.

Figure 184: Influential points for CT Euro Rates



For this segment February 2009 is a highly influential point. However, this is not surprising because of a large increase in the rate for this month and does not invalidate the model.

6.10.6. Model sensitivity

6.10.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable the sensitivity can be directly interpreted from the coefficient estimates.

6.10.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

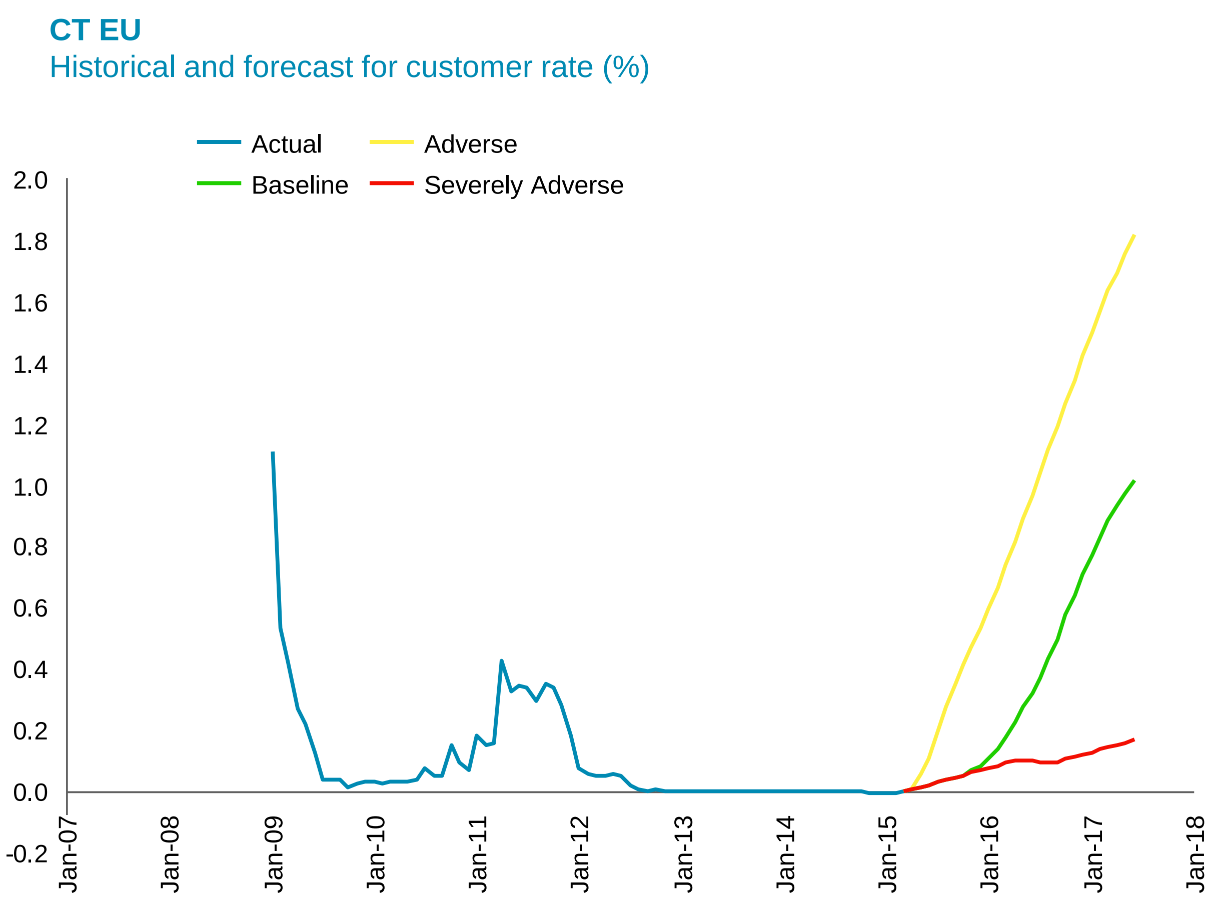
6.10.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 185.

The Working Group considered the forecast behavior for the selected CT EU model as requiring high scrutiny during management review, given the model was developed on such few observations.

Figure 185: CT EU Rates Model Forecast



6.10.7. Model limitations

The main limitation of this model is the lack of observations in a higher rate environment, which limits the strength of models that can be generated. Therefore, it is critical that this model is revisited as soon as there are more data points available in a higher rate environment.

6.11. Corporate Trust GB

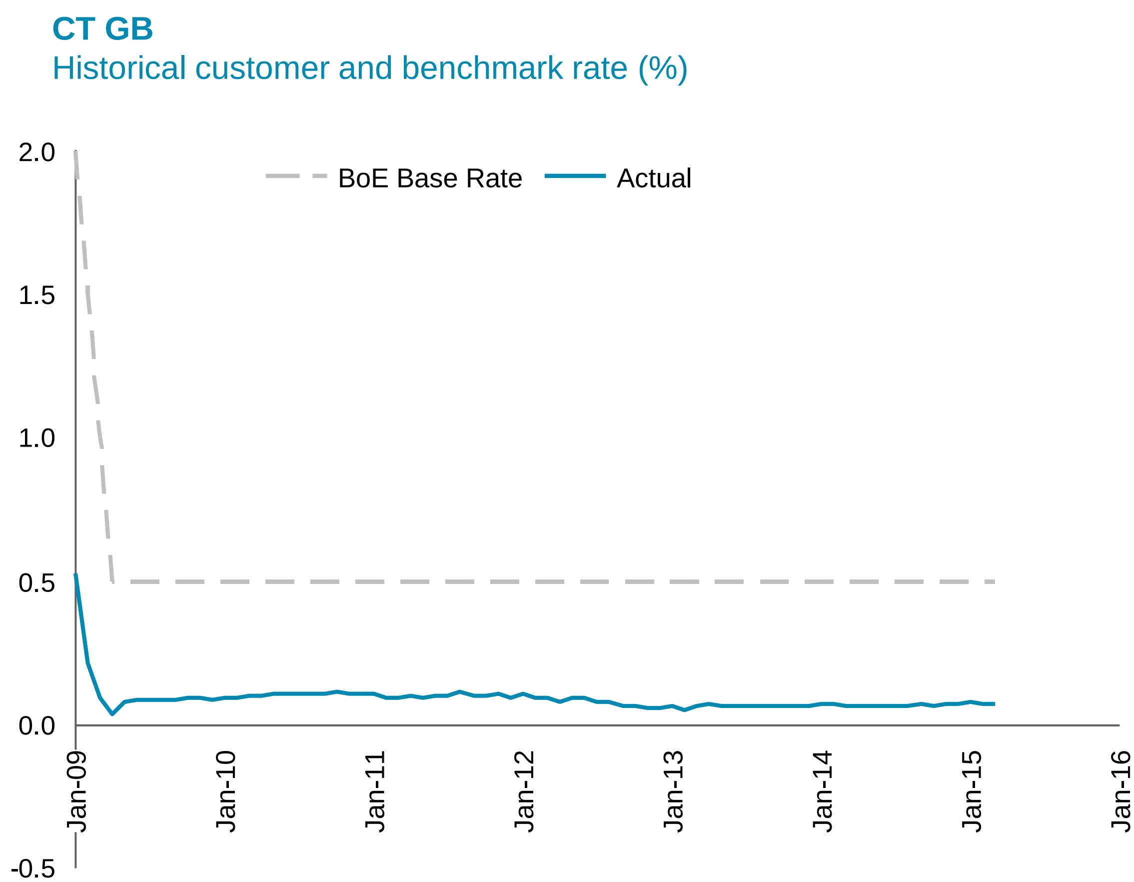
6.11.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Corporate Trust GB (CT GB) segment are modeled using the shorter Microstrategy data, which is only available from January 2009.

The historical rates data for the segment is shown in Figure 186.

- The historical CT GB rate follows the directional movement of the Bank of England's base rate, the segment's benchmark rate
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 186: Historical rates for CT GB



6.11.2. Model summary

A statistically sound model that is consistent with business intuition was found for the CT GB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology. The in-sample fit, however, is relatively unstable. The instability is largely caused by the lack of observations in the data used for modeling

The coefficient estimates are displayed in Table 178.

Table 178: Coefficient estimates for the CT GB Rates model

CT GB Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
LCBBASE_DMoML3	First difference – MoM, 3 lags	%	-0.085
LCBBASE_DQoQ	First difference – QoQ	%	0.109
Intercept	None (level)	%	0.0005

The CT GB rates model is a two variable model containing a difference month-over-month transformation with three lags and a difference quarter-over-quarter transformation of the Bank of England base rate. The two variables have opposite signs, which can be interpreted as an oversensitivity and correction of the captured relationship.

According to the model, a 1.00% change in the ECB marginal rate results in a 0.24% change in the CT GB deposits rate.

In a review and challenge meeting, the line of business suggested the sensitivity seems too low. Hence, the modeling team recommends this model should be monitored as more data points become available.

The modeling team considered the selected CT GB rate model as requiring high scrutiny during management review, given the limited historical data this model was developed on.

6.11.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.11.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 179 and Table 180.

Table 179: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Foreign Corporate Trust GB – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-4.1	<0.01	Reject unit root
Phillips-Perron	1	-18	<0.01	Reject unit root
KPSS	3	0.85	<0.01	Fail to Reject stationarity

Table 180: Unit root tests and stationarity tests including a constant on first differences

Foreign Corporate Trust GB – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	4	-5.2	<0.01	Reject unit root
Phillips-Perron	1	-27	<0.01	Reject unit root
KPSS	3	0.32	0.12	Fail to Reject stationarity

Stationarity tests for CT GB rate levels suggest the series is stationary: The ADF and PP tests reject a unit root while the KPSS test fails to reject stationarity.

Similarly, the monthly first difference series also yields the same results: The ADF and PP tests reject a unit root while the KPSS test fails to reject stationarity.

There is, however, a limitation to these tests. The CT GB rates data only spans a small portion of one rate cycle and therefore does capture much variation in the rate environment. As a result, stationarity tests on this data may not be representative of the long-term behavior of the variable.

Given the limited data available for this segment, additional consideration was given to academic literature. There are numerous studies that argue untransformed real interest rates are non-stationary.[33]

Given these considerations, as well as manual review of the rate levels and the first difference series, the modeling team chose to model these rates on first differences.

[33] See, e.g. Christopher J. Neely and David E. Rapach, “Real Interest Rate Persistence: Evidence and Implications,” *Federal Reserve Bank of St. Louis Review*, November/December 2008, pp. 609–41.

6.11.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the final models selected for deposits rates. Adjustments made to the alternative data sources are described in Section 4.1.

6.11.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 181 reports the results of the significance tests. The coefficient estimates in the CT GB rates model are statistically significant individually and collectively. The intercept is found to be statistically insignificant.

Table 181: Statistical significance tests of model and variables for CT GB rates

CT GB Rates (in %) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
LCBBASE_DMoML3	-0.085	<1%	10%	Statistically significant
LCBBASE_DQoQ	0.109	<1%	10%	Statistically significant
Intercept	0.000	61%	10%	Statistically not significant

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

6.11.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 182: CT GB Rate Model Diagnostics

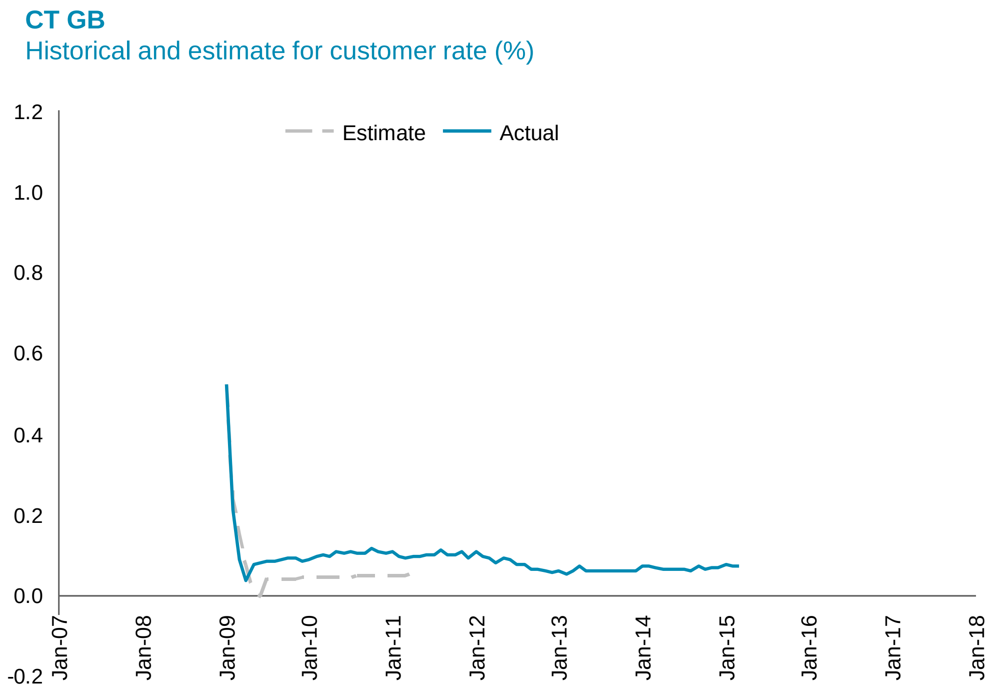
CT GB Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	84%	-	-
	Adjusted R-squared	83%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	2.71	5	No multicollinearity
Linearity	RESET test	0%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity and serial correlation in the residuals of the CT GB model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

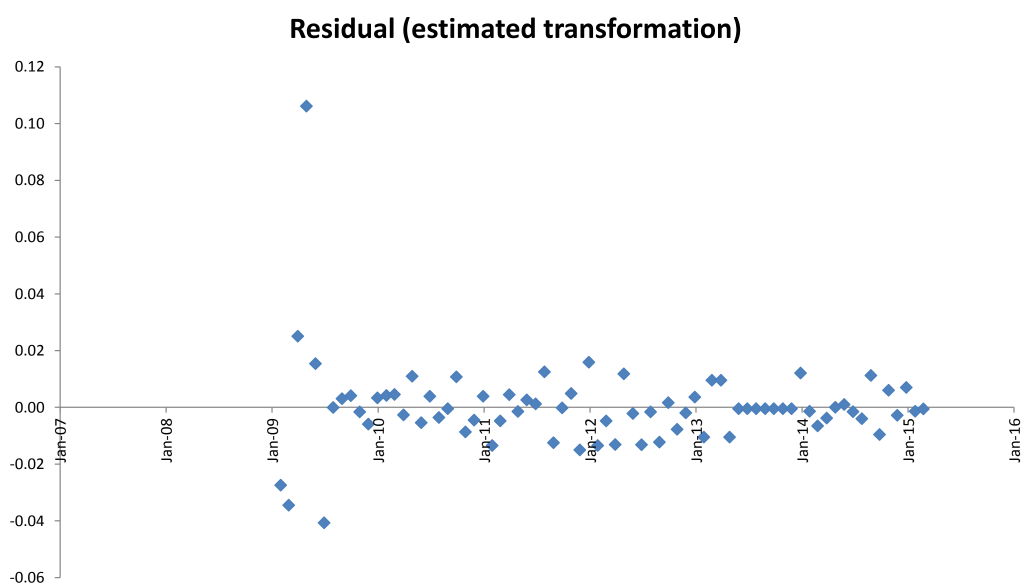
The model also suffers from model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 187: CT GB Rate 9Q In-sample Prediction



In the select 9Q in-sample prediction captures the rate drop in the beginning of 2009, which is the vast majority of variation seen the CT GB rate over the modeling period.

Figure 188: CT GB Rate Residual Plot (%)



The residual plot on Figure 188 shows residuals that are randomly distributed around the x-axis.

Figure 189: CT GB Rate Estimation Scatterplot

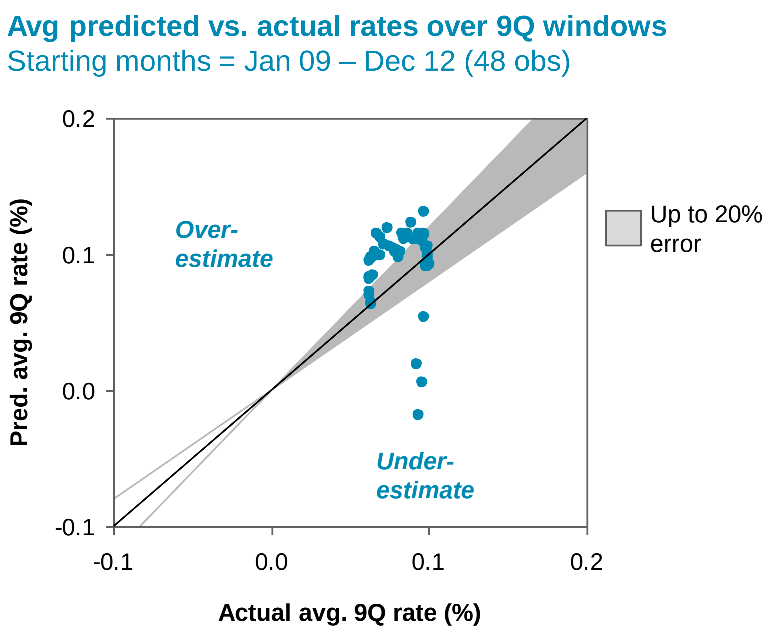
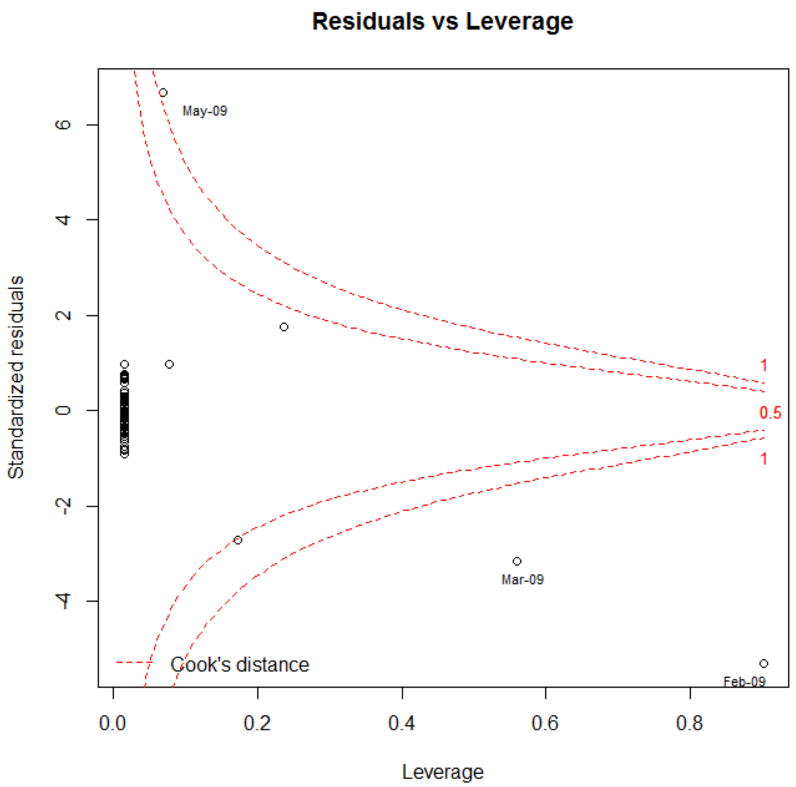


Figure 189 illustrates that most 9Q predictions have errors greater than 20%.

Given this performance in the back tests, the model outputs should be monitored closely when applied to macroeconomic forecasts scenarios.

Figure 190: Influential points for GT GB Rates



For this segment February March and May 2009 are highly influential points. However, this is not surprising because of the sharp decline in rates druing that period due to the recession and does not invalidate the model

6.11.6. Model sensitivity

6.11.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable the sensitivity can be directly interpreted from the coefficient estimates.

6.11.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

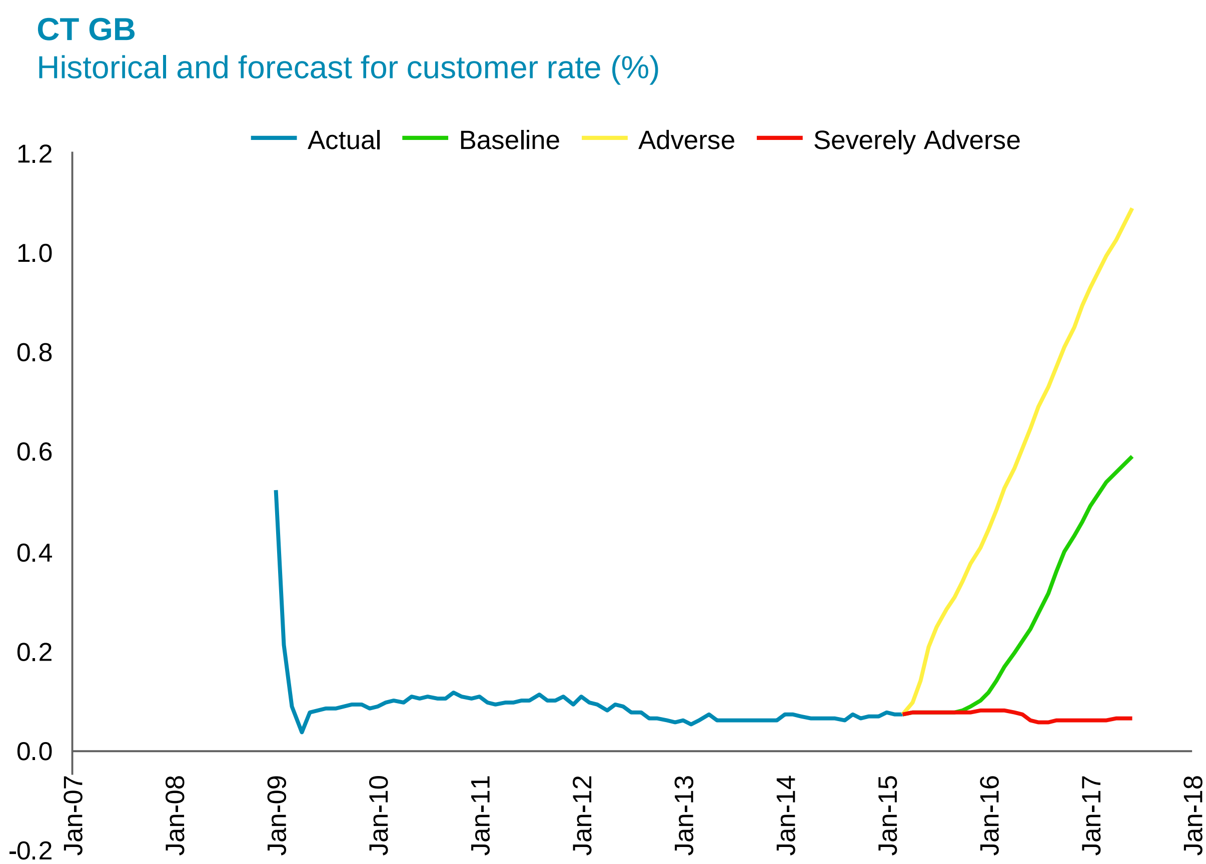
6.11.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 191.

As discussed earlier, the CT GB deposit rate's sensitivity to the benchmark interest rate was seen to be too low by the Working Group, and therefore this model should receive high scrutiny during management review.

Figure 191: CT GB Rates Model Forecast



6.11.7. Model limitations

The main limitation of this model is the lack of observations in a higher rate environment, which limits the strength of models that can be generated. Therefore, it is critical that this model is revisited as soon as there are more data points available in a higher rate environment.

6.12. Treasury Services IB

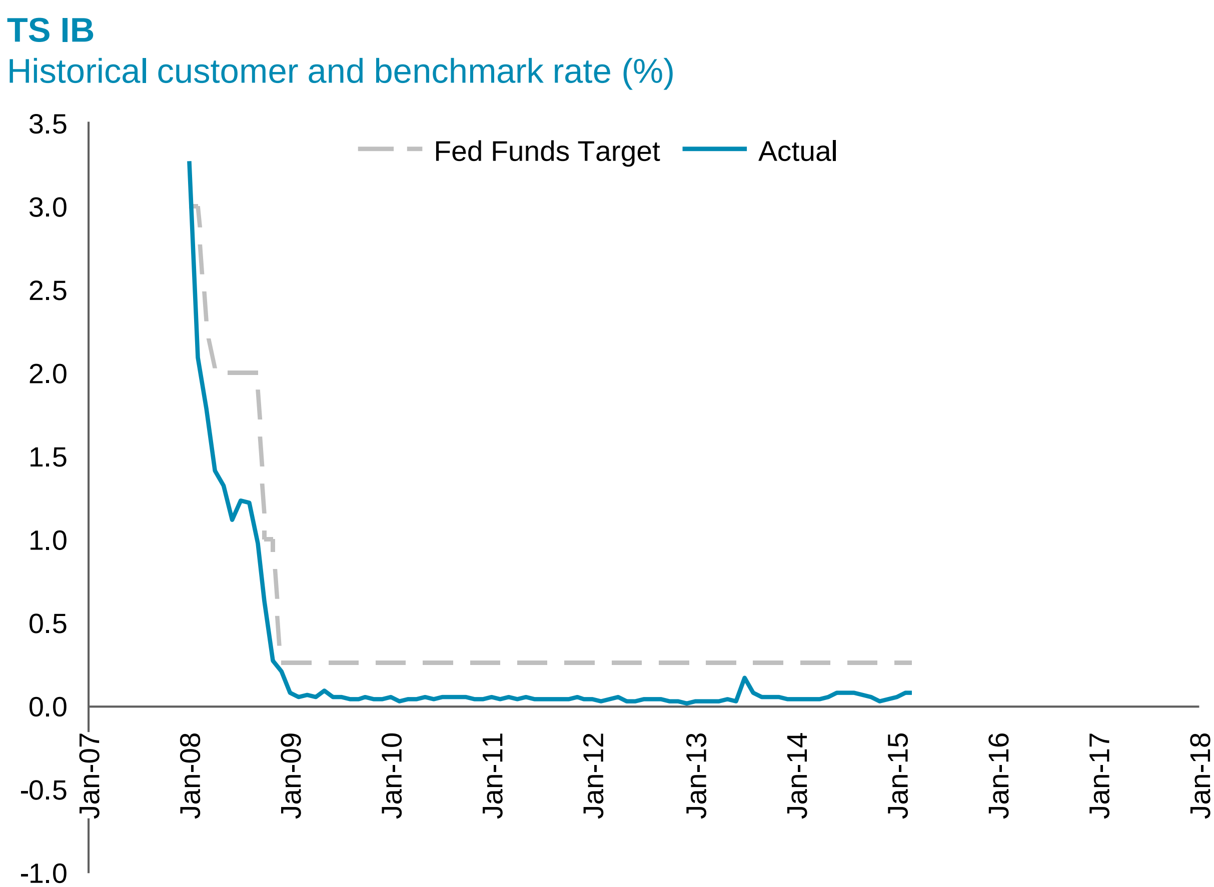
6.12.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Treasury Services IB (TS IB) segment are modeled using MAQ data, which is only available from January 2008.

The historical rates data for the segment is shown on Figure 192.

- The historical TS IB rate follows the directional movement of the Fed Funds Target rate, the segment's benchmark rate
- Movements of the deposit rate that occur when the benchmark rate remains flat is caused by changes in the mix of client balances, as not all customers are paid the same rate within this segment

Figure 192: Historical rates for TS IB



6.12.2. Model summary

A statistically sound model that is consistent with business intuition was found for the TS IB segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is tested to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology. The in-sample fit, however, is relatively unstable. The instability is largely caused by the lack of observations in the data used for modeling

The coefficient estimates are displayed in Table 183.

Table 183: Coefficient estimates for the TS IB rates

TS IB Rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**
Fed_Funds_t_DMoM	First difference – MoM	%	0.272
Fed_Funds_t_DMoML1	First difference – MoM	%	0.583
Intercept	None (level)	%	-0.0013

The TS IB rates model is a two variable model containing a difference month-over-month transformation and a difference month-over-month transformation with one lag of the Fed Funds Target rate.

The model suggests that a 1.00% change in the Fed Funds Target rate results in a 0.85% change in the TS IB deposits rate.

In a review and challenge meeting, suggested the sensitivity would be appropriate at higher rate environments (starting when Fed Funds Target is greater than ~50bps), but not lower at the lower interest environments. This suggests the model may overestimate the deposit rate paid, given that the rates are low currently. Hence, the modeling team recommends this model should be monitored closely as more data points become available.

The modeling team considered the selected TS IB rate model as requiring high scrutiny during management review, given the limited historical data this model was developed on.

6.12.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

6.12.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure.

The stationarity tests results for the deposit rates are shown in Table 184 and Table 185.

Table 184: Unit root tests and stationarity tests including a constant on untransformed deposit rate

Treasury Services IB – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	4	-5.3	<0.01	Reject unit root
Phillips-Perron	1	-13	<0.01	Reject unit root
KPSS	5	0.63	0.02	Reject stationarity

Table 185: Unit root tests and stationarity tests including a constant on first differences

Treasury Services IB – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	5	-2.2	0.19	Fail to Reject unit root
Phillips-Perron	1	-14	<0.01	Reject unit root
KPSS	4	0.7	0.01	Reject stationarity

Stationarity tests for TS IB rate levels yield mixed results: The ADF and PP tests reject a unit root while the KPSS test reject stationarity.

Similarly, the monthly first difference series also yields the same results: The ADF and PP tests reject a unit root while the KPSS test reject fails to reject stationarity.

There is, however, a limitation to these tests. The TS IB rates data only spans a small portion of one rate cycle and therefore does capture much variation in the rate environment. As a result, stationarity tests on this data may not be representative of the long-term behavior.

Given the limited data available for this segment, additional consideration was given to academic literature. There are numerous studies that argue untransformed real interest rates are non-stationary.[34]

Given these considerations, as well as manual review of the rate levels and the first difference series, the modeling team chose to model these rates on first differences.

[34] See, e.g. Christopher J. Neely and David E. Rapach, “Real Interest Rate Persistence: Evidence and Implications,” *Federal Reserve Bank of St. Louis Review*, November/December 2008, pp. 609–41.

6.12.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team and data experts to understand their cause.

No adjustments to data were necessary for the final models selected for deposits rates. Adjustments made to the alternative data sources are described in Section 4.1.

6.12.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

Table 186 reports the results of the significance tests. The coefficient estimates in the CT GB rates model are statistically significant individually and collectively. The intercept is found to be statistically insignificant.

Table 186: Statistical significance tests of model and variables for TS IB rates

TS IB Rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Fed_Funds_t_DMoM	0.272	<1%	10%	Statistically significant
Fed_Funds_t_DMoML1	0.583	<1%	10%	Statistically significant
Intercept	-0.001	74%	10%	Statistically not significant

6.12.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate level)
- Residual plot (on estimated first differences)
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

Table 187: TS IB Rate Model Diagnostics

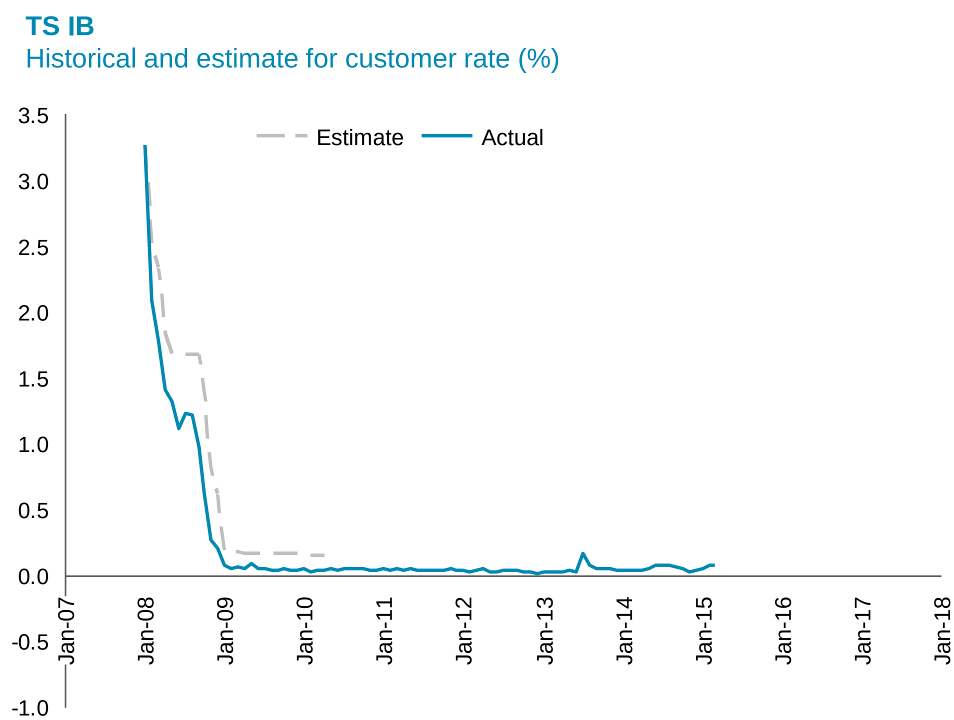
TS IB Rates – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	71%	-	-
	Adjusted R-squared	71%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	8%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	0%	10%	Linear specification inappropriate

The diagnostic tests detected heteroskedasticity and serial correlation in the residuals of the Wealth Management Personal rates model. The P-values considered when evaluating significance were therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

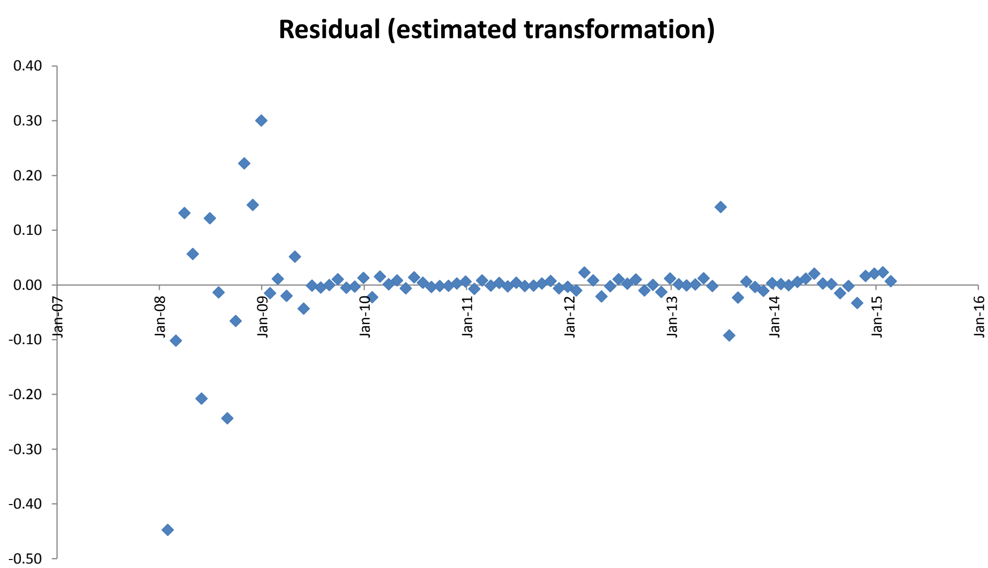
The model suffers from model misspecification. This result is tolerated for the deposit rates model since there is strong business intuition linking the benchmark rate and the deposit rate.

Figure 193: CT GB Rate 9Q In-sample Prediction



In the select 9Q in-sample prediction captures the rate drop in 2008, which is the vast majority of variation seen in the TS IB rate over the modeling period.

Figure 194: TS IB Rate Residual Plot (%)



The residual plot on Figure 188 shows residuals that are close to the x-axis for majority of the modeling period, as there is minimal variation of both the deposit rate and the benchmark rate. The larger residuals are mainly from 2008, when the majority of the variation of the rates coincides.

Figure 195: TS IB Rate Estimation Scatterplot

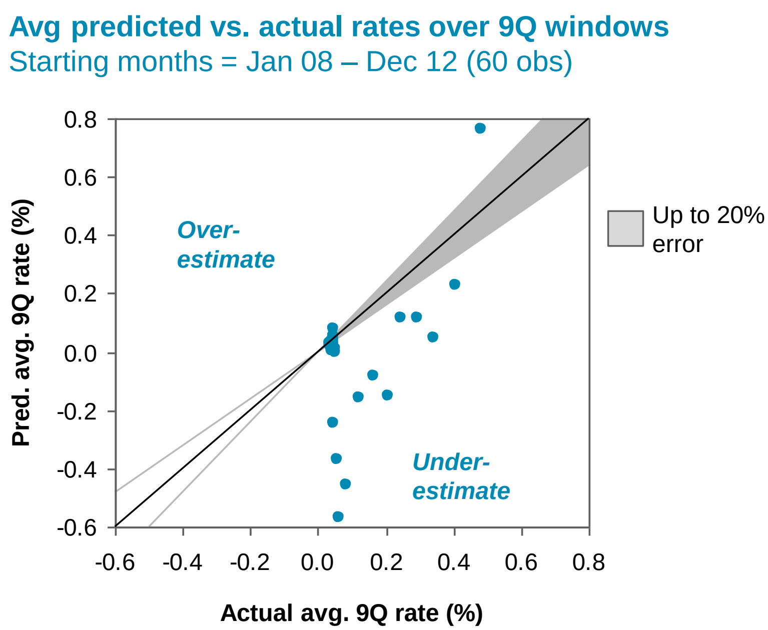
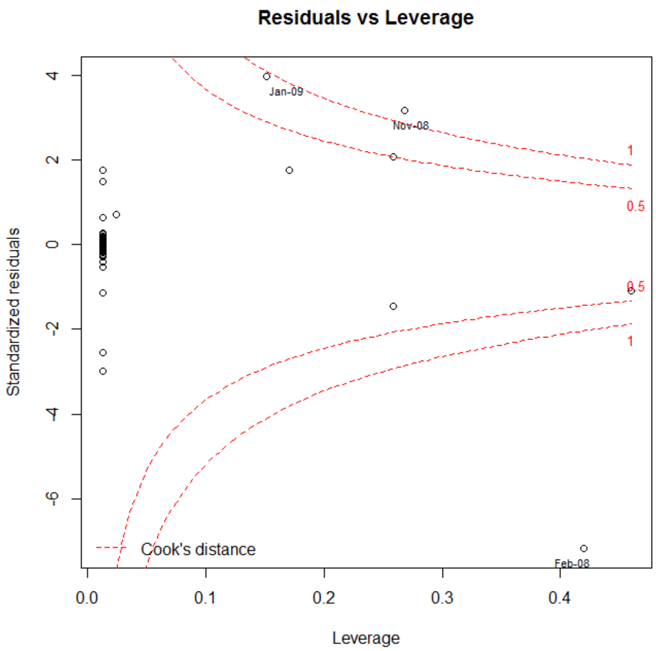


Figure 195 illustrates that most 9Q predictions have errors greater than 20%.

This given the poor performance in the back tests, the model outputs should be monitored closely when applied to macroeconomic forecasts scenarios.

Figure 196: Influential points for Treasury Services Rates



For this segment February and November 2008 are highly influential points. However, this is not surprising because these take place in the recession and does not invalidate the model

6.12.6. Model sensitivity

6.12.6.1. Sensitivity to changes in independent variables

Given the rates models only contain one type of independent variable the sensitivity can be directly interpreted from the coefficient estimates.

6.12.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

6.12.6.3. Sensitivity to stressed independent variable scenarios

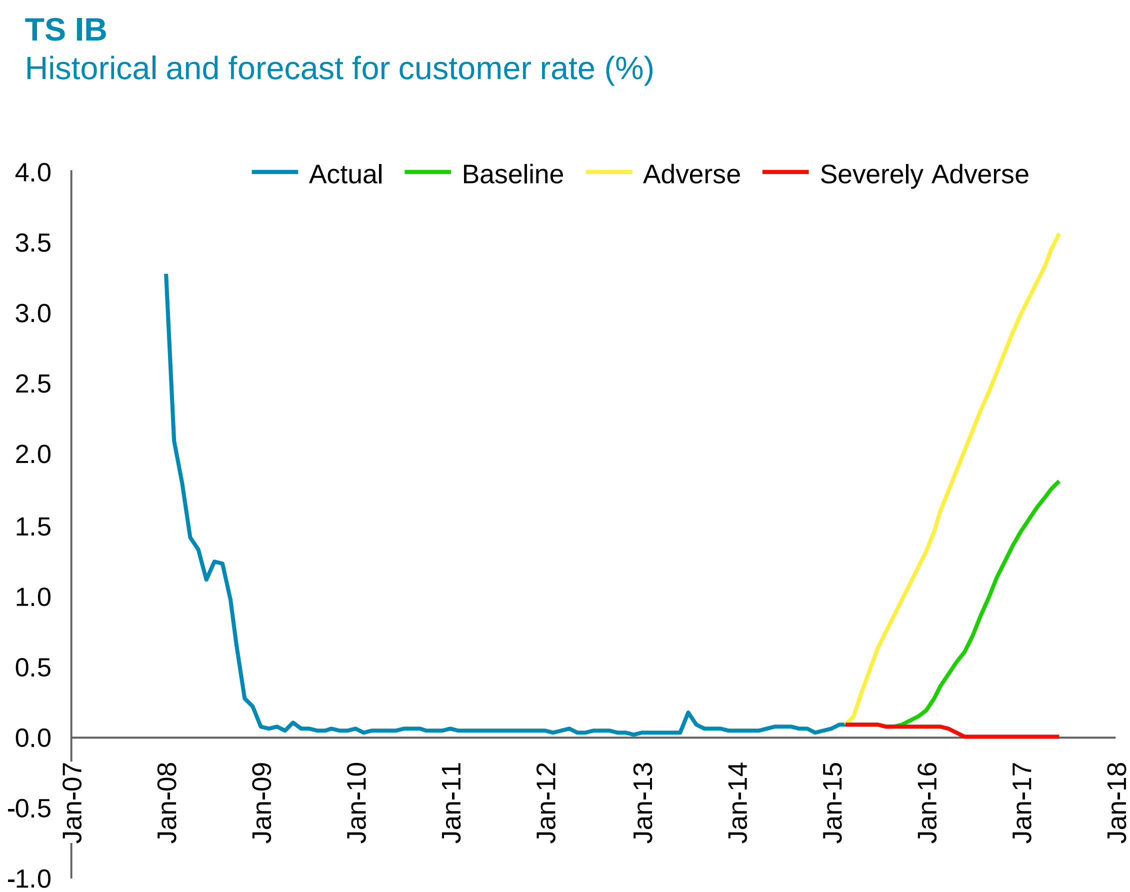
Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The forecasts output of the model is shown on Figure 197.

As discussed earlier, the TS IB deposit rate's sensitivity to the benchmark interest rate was seen to be too high by the Working Group, and therefore this model should receive high scrutiny during management review.

The negative intercept in this model leads to some forecast observations falling below zero – hence, the model forecast is bounded to zero whenever the benchmark rate is not negative, as business intuition strongly supports the deposit rate will not fall below zero unless the benchmark rate does.

Figure 197: TS IB Rates Model Forecast



6.12.7. Model limitations

The main limitation of this model is the lack of observations in a higher rate environment, which limits the strength of models that can be generated. Therefore, it is critical that this model is revisited as soon as there are more data points available in a higher rate environment.

6.13. Alternative Investment Services/Global Collateral Services IB

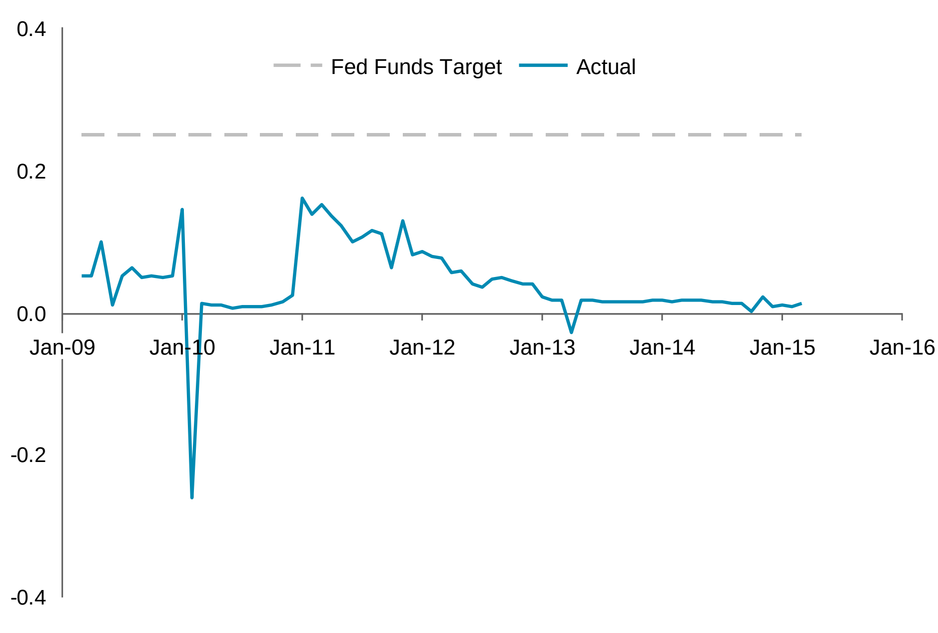
6.13.1. Deposit rates overview

As introduced in Section 3.5 (Methodology) and Section 4.1.3 (Deposit rates data), the rates for the Alternative Investment Services/Global Collateral Services Interest Bearing Deposits (AIS/GCS IB) segment are modeled using MAQ data.

The historical rates data for the segment is shown on Figure 198.

- The historical AIS/GCS IB rate is available starting March 2009, a period during which the Fed Funds Target rate is flat at 25 bps
- Given the AIS/GCS IB segment contains several products and businesses that started during this observation period, movements that occur to the deposit rate can be caused by:
  - Introductions and ramp up of new businesses
  - Changes in the mix of balances for each product within the segment, which pay out different rates
  - Accounting adjustments that cause volatility in the rate (i.e. January–February 2010)

Figure 198: Historical rates for AIS/GCS IB (%)



Given these factors, the rate model for this segment requires a qualitative framework.

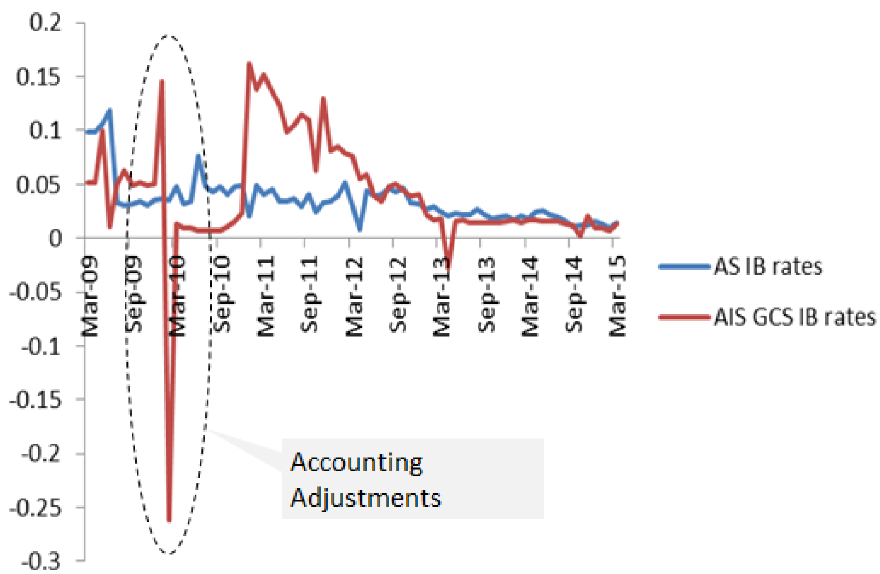
6.13.2. Qualitative framework

As discussed in Section 5.4.4, the AIS/GCS IB deposit balances are holding and processing of cash in connection with custody and related servicing activities for securities portfolios for hedge funds. Given the nature of the product is the similar to the Asset Servicing line of business, the most appropriate proxy was determined to be rates of the Asset Servicing IB segment.

Therefore, the qualitative framework decided is to apply the same rate forecasts of the AS IB rates model to the AIS/GCS IB segment. This qualitative framework was suggested by the business.

This approach relies on the assumption that the AS IB segment is an appropriate proxy for the AIS/GCS IB segment. The current rates are both around 1bp.

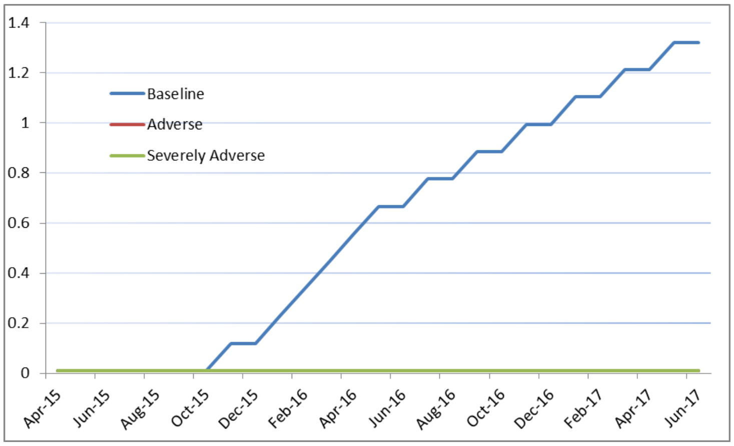
Figure 199: Comparison of AS IB and AIS/GCS IB Rates



BNY Mellon’s internal pricing strategy as currently in place is planning to price Asset Servicing interest bearing deposits at 5 to 15bps higher than deposits for AIS/GCS for Fed Target rates of 75bps or higher. The qualitative framework chosen does therefore maintain a conservative bias.

As of December 2015, the AIS/GCS IB segment had a rate of 0.013, and a balance of $10 BN.

Dry-Run results for AIS/GCS IB Rates



6.13.3. Approach limitations

All the limitations of the AS IB rates model are applicable to this AIS/GCS rate:

- One limitation of this approach is that the data from the Pre-Merger Deposit Rates Database are product rates whose collection is managed outside the management accounting system. Despite this limitation, the Pre-Merger Deposit Rates Database was preferred over MAQ data whenever available in pursuit of developing statistical models utilizing all available data. Due to the merger between Bank of New York and Mellon Financial in July 2007, MAQ data is only available from 2008 onward which does not contain a raising rate environment for most of the segments, a limitation that was resolved by using the Pre-Merger Deposit Rates Database.
- The developed approach assumes that the Asset Servicing Cash Reserves product is an appropriate proxy for the AS IB segment

In addition, this approach requires the assumption that the AS IB segment is an appropriate proxy for the AIS/GCS IB segment.

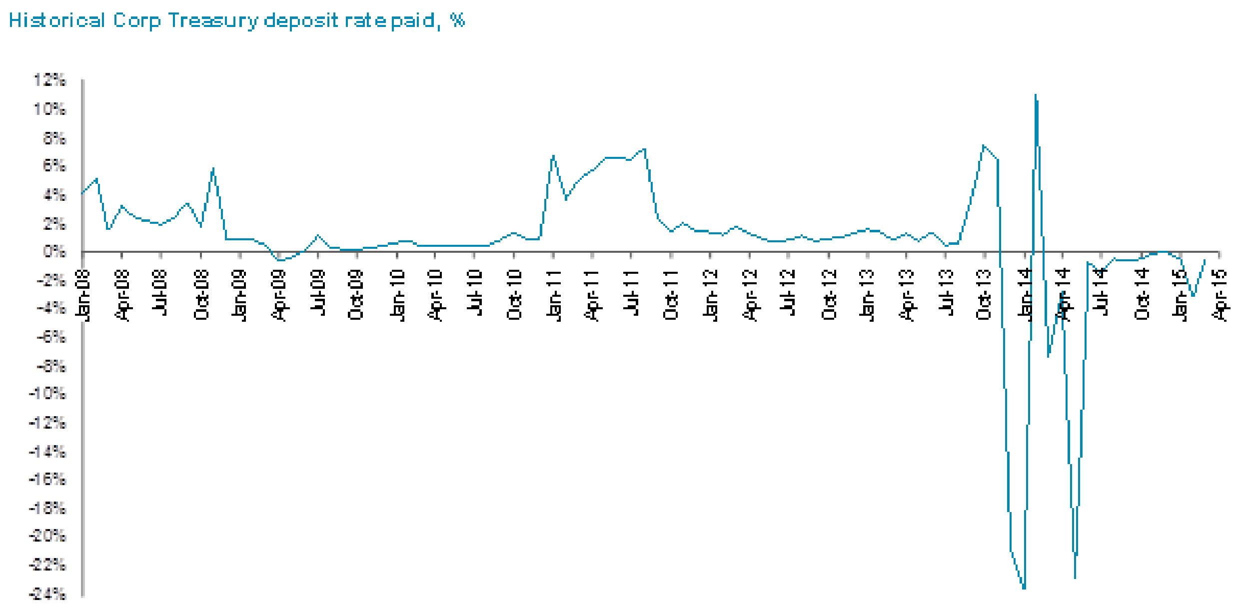
Given these limitations, the modeling team strongly recommends continual efforts to develop a rates model for AIS/GCS IB segment as more data for the AIS/GCS IB segment becomes available.

6.14. Corporate Treasury

6.14.1. Deposit rates overview

As discussed in Section 4.1.5.1, data for the Corporate Treasury segment suffers from significant volatility introduced by accounting adjustments resulting from the allocation process of Late Night Investment deposits to other lines of business. All models, based on data shown in the table below, had R^2 statistics of less than 1%. In order to develop a model with greater explanatory power, a thorough data cleaning exercise would be required to filter out the volatility introduced by accounting adjustments in the data.

Figure 200: Historical rates for Corporate Treasury (%)



Due to this challenge, a qualitative framework was developed for the segment.

6.14.2. Qualitative framework

The Corporate Treasury deposit balance consists of funds that are sourced at below the Interest on Excess Reserves rate. BNY Mellon deposits these funds at the Federal Reserve to earn the current Interest on Excess Reserves rate (IOER). The qualitative framework determined in a discussion with the business, is to price these deposits at a fixed 11.5 bps spread below the Interest on Excess Reserves rate. If the IOER is not available, the Fed Funds Target rate will be used as an approximation.. The spread is broken down to the following components:

- 5.5 bps for FDIC fees
- 1 bp for brokerage fees
- 5 bps as the minimum margin that BNY Mellon requires to accept funds for these transactions

As of December 2015, Corporate Treasury Interest Bearing Deposits had a size of $10.2 billion. However, given the approach for the Corporate Treasury balance model, any changes in the forecasting approaches for the Corporate Treasury Interest Bearing Deposits rates segment will have a minimal impact on the overall CCAR outcome. The reason is that Corporate Treasury expects less deposits as the adjustments for the new SLR regulation will reduce opportunities for such transactions over time and are expected to completely disappear by January 2018 with the implementation of the new SLR regulation.

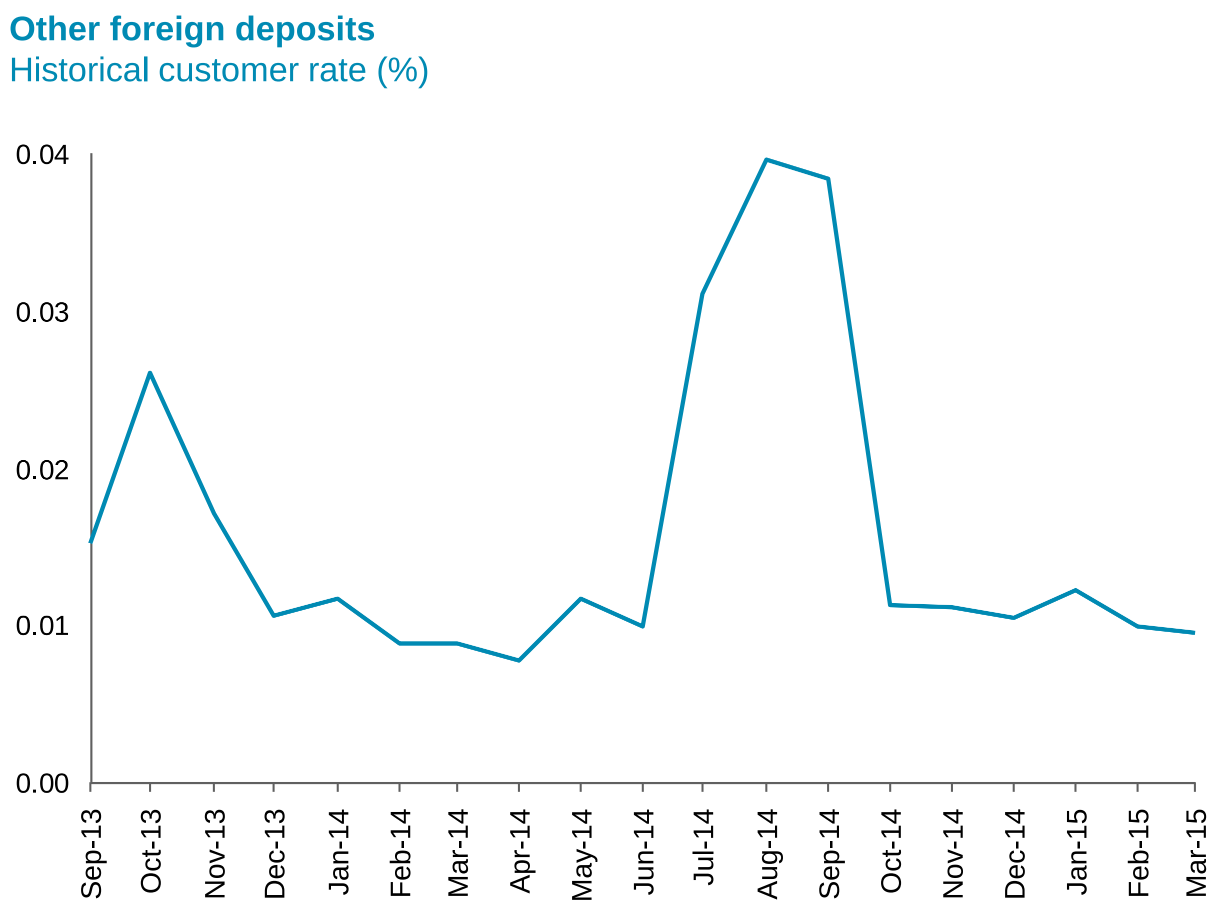
6.15. Rates model for foreign deposits in currencies other than USD, Euro and GBP

6.15.1. Deposit rates overview

As discussed in Section 4.1.5.2, data for the foreign deposits in non-USD, Euro and Sterling currencies (Foreign Other) is only available on MAQ starting from September 2013.

The historical rates data for the segment is shown on Figure 201.

Figure 201: Historical rates for Foreign Other (%)

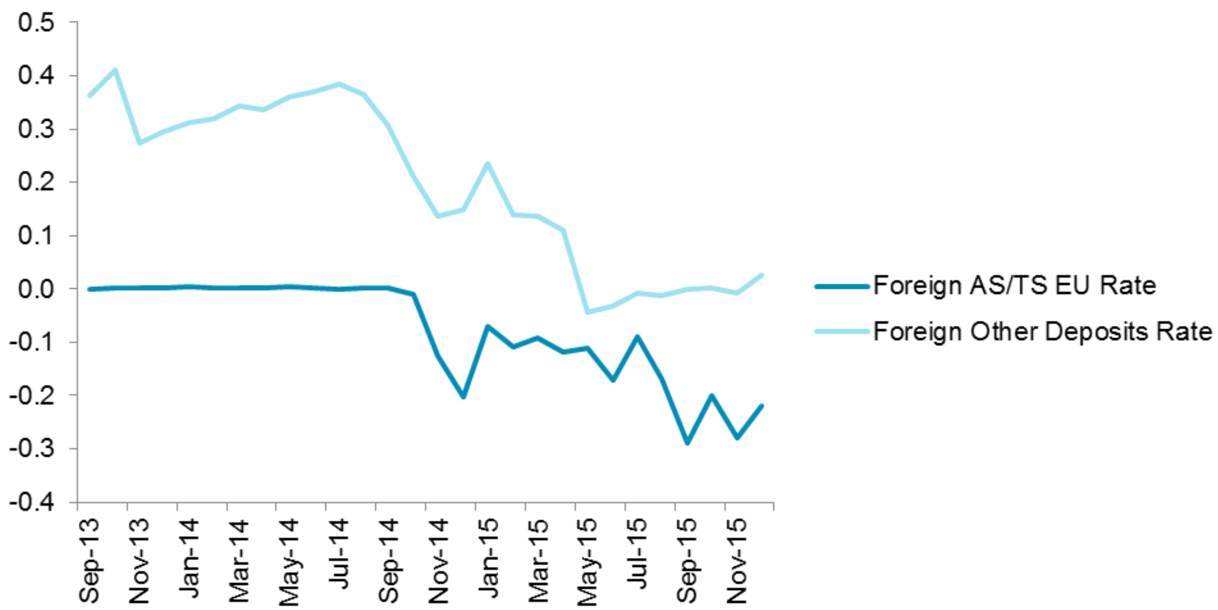


6.15.2. Qualitative framework

As discussed in Section 5.8, these deposit balances are largely for Asset Servicing activities. Given this, the qualitative framework developed is to apply the same rate forecasts of the Asset Servicing / Treasury Services Euro (AS /TS EU) segment rate model to this segment. In the case that the AS / TS EU rates are negative, the Foreign Other rates are floored at zero percent. This qualitative framework was suggested by the business.

Examination of the historical relationship between the two rates suggests that there is a relationship.

Figure 202 Relationship between AS/TS EU and foreign other rate



6.15.3. Approach limitations

All the limitations of the AS TS EU rates model are applicable.

In addition, this approach requires the assumption that the AS TS EU rate segment is an appropriate proxy for this segment.

6.16. Limitations to deposit rate models

The most significant limitation of the deposit rate models is the lack of historical data capturing variation in the rate environment. Since the rate environment has been largely static for the past ~5 years, many segments have few observations that capture effects of changing rate environments.

Also, for the segments that the extended data from the Pre-Merger Deposit Rates Database was used, assumptions of using the historical rates representing only part of the current balances were made. While business intuition supports the proxy assumptions made, this is acknowledged as a model limitation.

Therefore, all deposit rate models should be recalibrated when more observations are obtained in MAQ for all the balances on BNY Mellon's deposit book.

7. Loan and unfunded commitment balances

7.1. Overview

Section 7 provides details on the forecasting approaches for the loan balance segments. These forecasts align to the segmentation discussed in Section 3.1.3, following the methodology described in Section 3.4. The table below lists the segments covered in this section, and whether they used model-based versus qualitative frameworkes.

Table 188: Loan segments with forecasting approaches used for balances

Segment	Approaches used
FI loans	Model-based for all four components
Commercial loans	Model-based for all four components
CRE loans	Model-based for three components, qualitative for one component (Letter of Credit usage percentage)
Wealth Management loans (excluding mortgages)	Model-based for three components, qualitative for one component (Letter of Credit usage percentage)
Margin loans	Model-based for one component, qualitative for one component (unfunded commitment)
Overdrafts	Model-based
Wealth Management mortgages	Model-based
Lease financing	Qualitative framework
Other mortgages	Qualitative framework
HELOCs	Qualitative framework
Iron Hound loans	Qualitative framework
Reverse mortgages	Qualitative framework

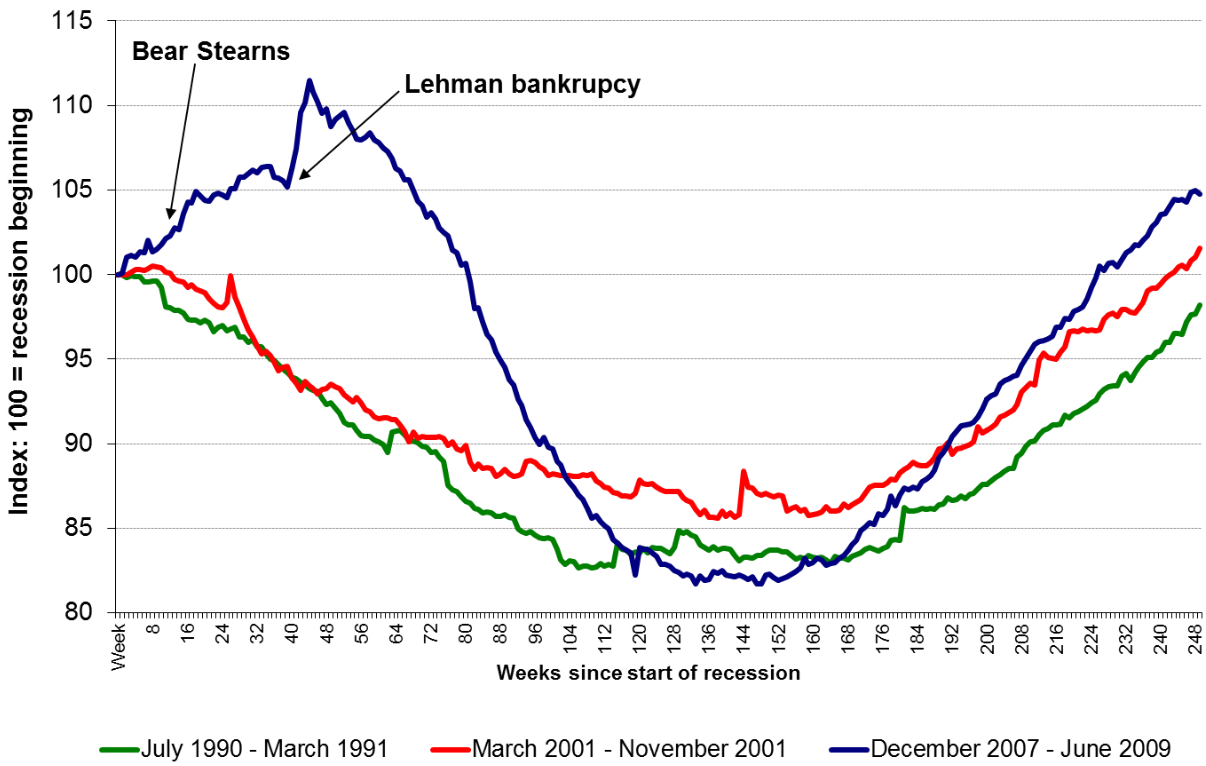
Section 7.2 discusses a period in the historical data when BNY Mellon underwent balance de-risking initiatives, and how this was considered during model development. The subsequent sections discuss the forecast approach and results for each loan balance segment.

7.2. Background on BNY Mellon historical de-risking initiatives

In July 2007, Bank of New York and Mellon Financial merged. Following the merger, the bank assessed the combined exposure to clients and client groups. As some of the clients between the former Bank of New York and former Mellon Financial overlapped, overexposures to certain clients were identified. BNY Mellon started the “tall trees program” to reduce this overexposure. The program was in effect in 2008–2010.

At the same time, the financial sector overall as well as BNY Mellon tightened lending following the global financial crisis in 2008 and 2009. Reduced lending is generally observed during recessions. For instance, the figure below shows outstanding C&I loans for large domestic banks through the last three recessions. The data used in in the figure below is collected by the Board of Governors of the Federal Reserve System.[35]

Figure 203: C&I lending by large domestic banks during recessions



This regular pattern of decreased lending by large financial institutions during recessions suggests that the lending behavior could be correlated with factors affecting the entire financial industry, such as macroeconomic variables. The BNY Mellon on-balance sheet loan balances decreased by about 40 percent from January 2008 to January 2010, while its unfunded commitments decreased by about 30 percent. The industry-wide observed decrease as shown in the figure above was approximately 19 percent over the same period.

[35] Information on the "Assets and Liabilities of Commercial Banks in the United States – H.8" collected by the Board of Governors of the Federal Reserve System can be found here: http://www.federalreserve.gov/releases/h8/about.htm (accessed on August 21, 2015). Large banks are defined as the top 25 domestically chartered commercial banks ranked by size.

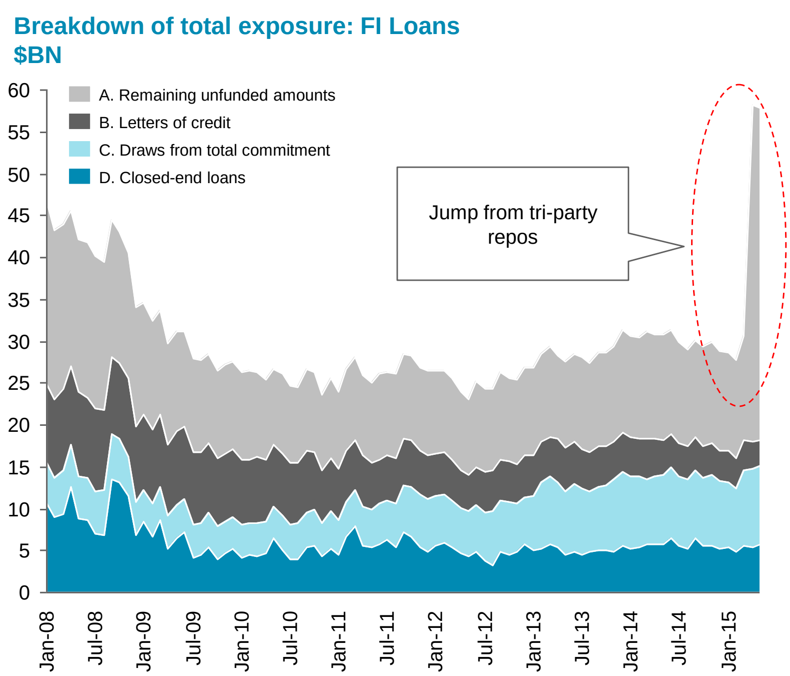
The effects of the industry-wide lending reduction and the tall trees program cannot be separated in BNY Mellon's loan data. The modeling team discussed the inclusion of indicator variables to account for the tall trees program with the Working Group. The inclusion of indicator variables would result in weaker models because the dummy variables would also absorb the impact of macroeconomic variables during the time period. As a result, the Working Group is decided not to use dummy variables for the loan models, even though the lending reduction was larger than observed in the industry.

7.3. Financial Institution loans

7.3.1. Business overview

BNY Mellon originates and purchases loans as part of its ongoing business. The Financial Institution (FI) loan segment comprises the largest loan type for BNY Mellon as measured by total commitment: as of April 30, 2015, BNY Mellon has $15 BN in funded FI loans plus $43 BN in unfunded commitments, including Letters of Credit. The figure below shows the breakdown over time for total exposure in this segment into the different unfunded and funded components described in Section 3.4.

Figure 204: Breakdown of total exposure for FI loans



Major borrowers in this segment include banks, asset managers, and the securities industry. Bank exposure is predominantly investment grade, short-term in nature, and primarily relates to the global trade finance and US dollar clearing businesses. Asset manager portfolio exposure tends to be in the form of high-quality, short-term liquidity facilities that are mainly provided to regulated mutual funds. A portion of the exposure in this segment is secured; for example, securities industry and asset managers often borrow against marketable securities held in custody. Overall, FI loans tend to be high quality with most meeting the investment grade equivalent criteria of BNY Mellon's internal credit rating classification, which uses criteria that are largely consistent with those of public rating agencies. As of March 31, 2015, 92% of the FI loan segment was investment grade. The table below shows the breakdown of funded and unfunded balances in this segment by borrower type, as of March 31, 2015.

Table 189: Funded and unfunded exposures for FI loans by borrower type

FI loan exposures as of March 31, 2015 (in USD MM)			
Borrower type	**Funded loans**	**Unfunded exposure (including Letters of Credit)**	**Total exposure**
Securities Industry	3,184	2,480	5,664
Asset Managers	1,139	4,663	5,801
Insurance	128	4,156	4,284
Banks	8,563	2,138	10,701
Government	343	3,115	3,458
Other	220	1,064	1,284
Total	13,576	17,615	31,191

At the onset of the 2008–2009 financial crisis, an increase in demand for loans was observed as borrowers turned to BNY Mellon as a source of funding under stress. Total exposures decreased in the several years following the 2008–2009 financial crisis, driven in part by management decisions to de-risk the bank's balance sheet and reduce redundant exposures across the legacy Bank of New York and legacy Mellon loan portfolios. In the more recent years, balances have stabilized and grown slowly as both of these strategic initiatives have expired. See Section 7.2 for further discussion on these initiatives.

On April 23, 2015, $28 BN in new tri-party committed facilities were booked. BNY Mellon extended these committed unfunded credit facilities to broker-dealer clients in line with the Federal Reserve's tri-party repo infrastructure reform. These facilities are fully secured and over-collateralized by the pledge of either US Treasury securities, GSE securities, or other similar high quality liquid assets (HQLA). They are extended to finance the clearance and settlement of tri-party repo transactions on an intraday basis, and therefore they are not expected to have end-of-day drawn balances. Furthermore, they are expected to roll off 18–24 months after they were booked in April 2015. They are still included in total unfunded commitments, but excluded from modeling as discussed below in Section 7.3.8.

7.3.2. Forecast quantities

In line with the methodology described in Section 3.4, the following quantities were forecasted for this segment, all using a statistical modeling approach:

1. Total commitment amount
2. Draw percentage, i.e. total drawn amount divided by total commitment amount (modeled as a percentage)
3. Letter of Credit usage percentage, i.e. total amount in unused Letters of Credit divided by total commitment amount (modeled as a percentage)
4. Closed-end loan balance

The forecasting approaches for these four quantities are documented separately in Sections 7.3.3-7.3.6. Section 7.3.8 discusses how these quantities are used to develop forecasts for unfunded commitments, Letters of Credit, and total funded loans, including any additional required qualitative components such as the tri-party repo commitments booked in April 2015.

7.3.3. Total commitment

7.3.3.1. Summary

A statistically sound model that is consistent with business intuition was found for FI loans – total commitment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for FI loans, which is found to be stationary upon manual review
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 190: Coefficient estimates for selected model for FI loans – total commitment

FI loans – total commitment (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
BNY Mellon AUC	% change – YoY	%	13.34	0.18
Corp Debt Outstanding	% change – MoM	%	379.46	0.25
3M Treasury	First difference – QoQ	%	700.71	0.30
Intercept	None (level)	$ MM	-222.26	N/A

The model contains the following drivers and variables:

- **Assets Under Custody –** BNY Mellon Assets Under Custody (AUC)
- **Debt issuances –** Corporate debt outstanding in the US, including bond issuances, loans, Commercial Paper, and other forms of debt
- **Short-term rates –** 3-month US Treasury rate

The intuition of these variables is as follows:

- BNY Mellon AUC has a positive coefficient, with the rationale that FI clients may borrow against their marketable securities that BNY Mellon holds under custody, and as AUC increases, borrowing capacity may similarly increase
- Corporate debt outstanding has a positive coefficient, with the rationale that higher corporate debt implies larger balance sheets for FI clients and greater demand for funding
- The 3-month Treasury rate has a positive coefficient, which is interpreted as a supply effect; as rates rise and the economics of these lines improves for the lender, BNY Mellon will have greater incentive to offer more commitments to increase earnings

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 205: Candidate models for FI loans – total commitment

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
Asset under custody	BNY AUC (% YoY)	BNY AUC (% YoY)		
Corporate credit				Baa to Treasury Spread (Diff YoY)
Debt issuances	Corp Debt Outstanding (% MoM)	Corp Debt Outstanding (% MoM)	Corp Debt Outstanding (% MoM)	Corp Debt Outstanding (% MoM)
General economic health			Real GDP growth (Level)	
Short-term rates	3M Treasury (Diff QoQ)			
Variation in balances explained through estimated first differences	**95%**	**87%**	**86%**	**84%**
R-squared (differences)	**24%**	**16%**	**16%**	**16%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.3.3.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.3.3.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The total commitment time series for the FI loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 191: Unit root tests and stationarity tests including a trend variable on balances

FI loans – total commitment – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	6	-0.8	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.6	0.29	Fail to reject unit root
KPSS	5	0.34	<0.01	Reject stationarity

Table 192: Unit root tests and stationarity tests including a constant on first differences

FI loans – total commitments – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-8.1	<0.01	Reject unit root
Phillips-Perron	1	-8.1	<0.01	Reject unit root
KPSS	3	1.01	<0.01	Reject stationarity

Stationarity tests for FI loan – total commitments balances yield mixed results: The ADF and PP tests fail to reject a unit root while the KPSS test fails to reject stationarity. These results suggest the FI loans – total commitments balances may be non-stationary. The monthly first difference series passes the ADF and PP tests at a high significance and only fails the KPSS test. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that a potential reason for the failure was the “Tall Trees” exposure reduction program which was executed over a limited period of the modeling period and hence should not impact the stationarity of the series going forward.

Based on these results, the FI loan – total commitments are modeled on their first differences, as manual review provided sufficient evidence of stationarity for the application of OLS.

7.3.3.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for FI loans – total commitments. The sharp increase in total commitments of $28 BN in April 2015 attributed to new tri-party repo facilities lies outside of the historical modeling period. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.3.3.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 206: Summary of drivers for FI loans – total commitment

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Total commitment increases when general economic health improves	US GDP growth, US unemployment rate
	Imports	• Increased foreign trade grows demand for trade financing loans, and therefore total commitment for FI loans	Volume of imports
	Exports		Volume of exports
Financial economy	**Assets under custody**	• With more AUC, BNY Mellon can offer more secured lending to FIs	BNY Mellon AUC
	Debt issuances	• Bank lending may increase as a component of total corporate debt • Bond issuance acts as a substitute for bank loans	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets lead to greater lending to FIs	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Hedge fund index	• Stronger hedge fund performance leads to greater lending to FIs	HFRX index, Eurekahedge HF index, Eurekahedge FoF index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates may lead to decreased appetite to offer commitments • Volatility and uncertainty may drive up demand if alternate sources of funding dry up	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to offer commitments	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.3.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for FI loans – total commitment are statistically significant. The intercept is found to be statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 193: Statistical significance tests of model and variables for FI loans – total commitment

FI loans – total commitment (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**HAC P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
BNY Mellon AUC	13.34	<1%	10%	Statistically significant
Corp Debt Outstanding	379.46	<1%	10%	Statistically significant
3M Treasury	700.71	<1%	10%	Statistically significant
Intercept	-222.26	3%	10%	Statistically significant

7.3.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

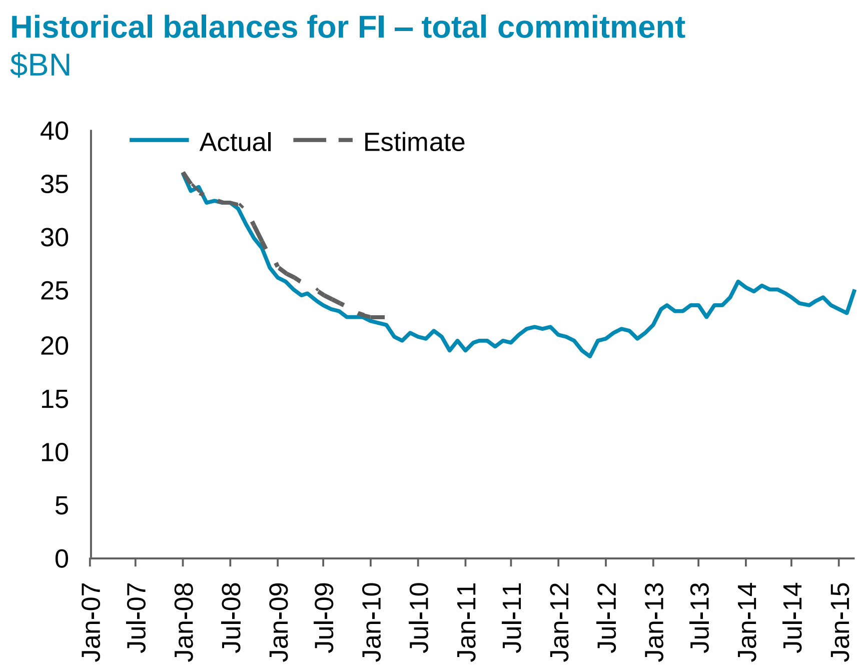
The diagnostic tests reviewed are exhibited below.

Table 194: Model Diagnostics for FI loans – total commitment

FI loans – total commitment (in USD MM) – Model diagnostics

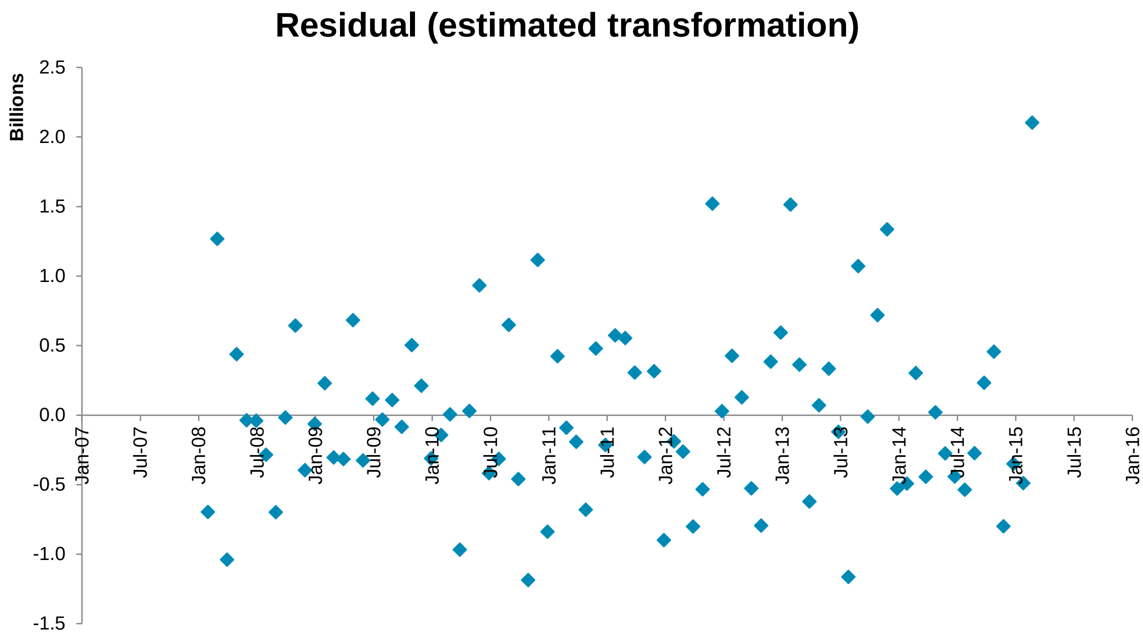
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	24%	-	-
	Adjusted R-squared	21%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.54	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	8%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.22	5	No multicollinearity
Linearity	RESET test	81%	10%	Linear specification appropriate

Figure 207: 9-quarter In-sample Prediction for FI loans – total commitment



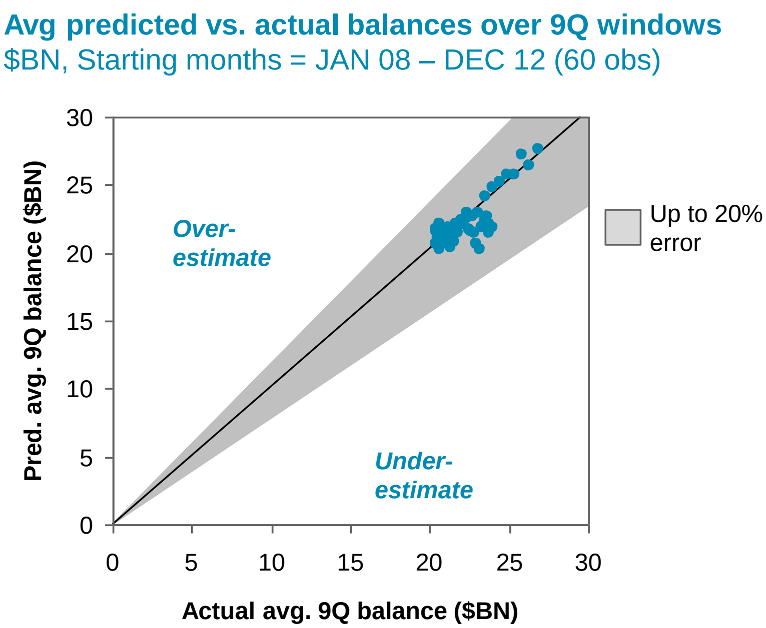
The in-sample back test of the model starting from January 2008 tracks very closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

Figure 208: Residual Plot for FI loans – total commitment ($ BN)



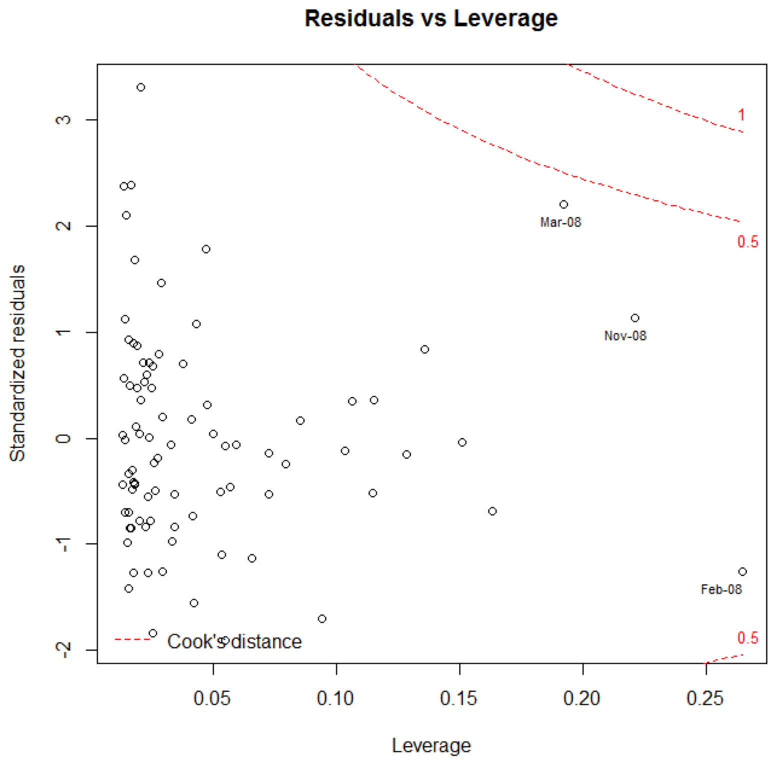
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 209: Estimation Scatterplot for FI loans – total commitment



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 210: Influential points for FI loans total commitment



The segment has no highly influential points.

7.3.3.6. Model sensitivity

7.3.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 195: Sensitivity to changes to independent variables for FI loans – total commitment

FI loans – total commitment – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
BNY Mellon AUC	% change – YoY	%	0.18	10.01	0.13
Corp Debt Outstanding	% change – MoM	%	0.25	0.50	0.18
3M Treasury	First difference –	%	0.30	0.36	0.22

	QoQ				
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the 3-month Treasury rate variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the 3-month Treasury rate variable results in a 0.30 standard deviation ($0.22 BN) increase in the predicted monthly change of the total commitment for the FI loan segment.

7.3.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. Only the coefficient on the 3-month Treasury rate variable was significant individually, which implies that component of the model may not remain stable over time.

Table 196: Statistical sensitivity tests for FI loans – total commitment

FI loans – total commitment (in USD MM) – Statistical significance tests of model and variables

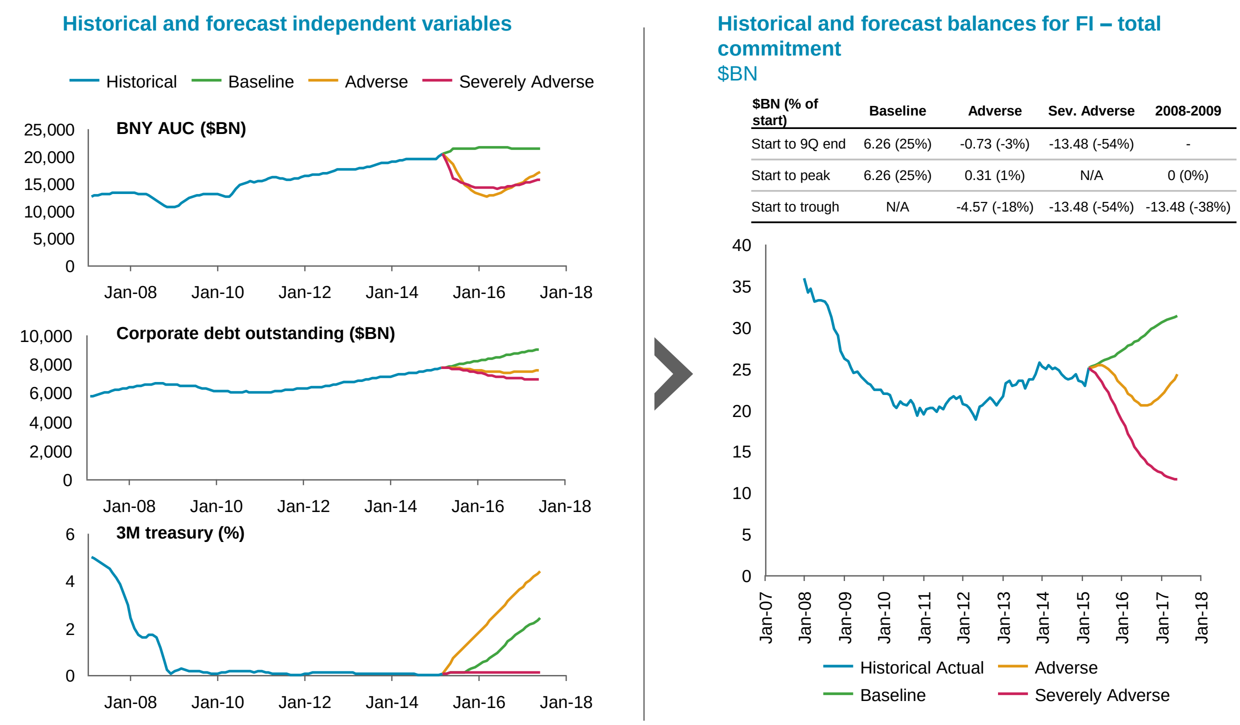
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
BNY Mellon AUC	13.343	13.491	0.34	Statistically insignificant
Corp Debt Outstanding	379.460	408.001	0.67	Statistically insignificant
3M Treasury	700.712	683.634	0.08	Statistically significant
Intercept	-222.259		0.54	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.19	Statistically insignificant

7.3.3.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 211: Final model forecast for FI loans – total commitment



$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	6.26 (25%)	-0.73 (-3%)	-13.48 (-54%)	-
Start to peak	6.26 (25%)	0.31 (1%)	N/A	0 (0%)
Start to trough	N/A	-4.57 (-18%)	-13.48 (-54%)	-13.48 (-38%)

The Working Group considered the forecast behavior for the selected FI loans – total commitment model as mostly reasonable, with a potentially overly steep decline in the severe recession scenario.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant decline in total commitments. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations that both supply and demand for committed lines would decline under macroeconomic stress. The ability to reduce lines significantly on a relatively short timescale is also consistent with the relatively shorter duration of commitments for FI borrowers. The line of business suggested that although the magnitude of the decline is consistent with historical experience, it may be overstated and should be monitored closely when the final outputs for submission are generated. In particular, the observed drop in the post-crisis historical period also coincided with a general period of de-risking for BNY Mellon, in addition to reduction of redundant exposures across the legacy Bank of New York and legacy Mellon banks
- **Interest rate shock (Adverse) scenario**: The model predicts a small decline followed by a recovery. This was judged to be consistent with business intuition
- **Baseline scenario**: The model predicts that total commitments will grow at a rate roughly consistent with observed historical growth over the most recent several years. This was judged to be consistent with business intuition

7.3.4. Draw percentage

7.3.4.1. Summary

A statistically sound model was found for FI loans – draw percentage. However, despite reasonable historical fit, this model was deemed by the Working Group and line of business as potentially over-aggressive in forecasting significant growth in draw percentage under various scenarios. Management scrutiny is therefore recommended for the outputs of this model.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the draw percentage time series for FI loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 197: Coefficient estimates for selected model for FI loans – draw percentage

FI loans – draw percentage (logit-transformed) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Dow Jones Industrial Average	% change – QoQ	%	-0.002222	-0.34
Nominal Imports	% change – MoM	%	0.010686	0.39
Real Disposable Income growth	None (level), 1-month lag	%	-0.004129	-0.44
Intercept	None (level)	None	0.021983	N/A

The model contains the following drivers and variables:

- **Equity markets** – Dow Jones Industrial Average
- **Imports** – Nominal US import of goods, seasonally adjusted
- **General economic health** – US Real Disposable Income growth

The intuition of these variables is as follows:

- The Dow Jones Industrial Average variable has a negative coefficient. This variable is interpreted as an indicator of macroeconomic strength or weakness; when overall macroeconomic conditions are weak or stressed, clients may increase their draws as access to regular alternate sources of funding is lost
- Nominal Imports has a positive coefficient and is interpreted as an indication of global trade finance activity. A significant portion of the FI loans segment consists of trade finance loans, and thus increase in trade finance activity is associated with increased draws
- The Real Disposable Income growth variable has a negative coefficient, and is interpreted similarly as the Dow Jones Industrial Average; as general economic health declines, clients have greater need to draw down from their committed lines

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 212: Candidate models for FI loans – draw percentage

Drivers Considered	Candidate models 1	2	3	4
Equity markets	DJI (% QoQ)	DJI (% MoM, 1M Lag)		
General economic health	Real Disposable Income (Level, 1M Lag)	Real Disposable Income (Level, 1M Lag)	Real Disposable Income (Level, 1M Lag)	Real Disposable Income (Level, 1M Lag)
Imports	Nominal Imports (% MoM)		Nominal Imports (% YoY)	Nominal Imports (% MoM)
Perceived credit risk				TED Spread (Diff YoY)
Short-term rates		Ovrnt LIBOR (Diff MoM)	Ovrnt Repo Rate (Diff MoM, 1M Lag)	
Variation in levels explained through estimated logit first differences	**96%**	**95%**	**96%**	**95%**
R-squared (differences)	**25%**	**21%**	**21%**	**21%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.3.4.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.3.4.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The logit-transformed draw percentage time series for the FI loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the logit-transformed levels are tested using unit root and stationarity tests including a time trend.

The first differences of the logit-transformed levels, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 198: Unit root tests and stationarity tests including a trend variable on levels

FI loans – draw percentage – Unit root test with trend on logit-transformed level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	4	-1.6	>0.10	Fail to reject unit root
Phillips-Perron	1	-3	0.13	Fail to reject unit root
KPSS	5	0.18	0.02	Reject stationarity

Table 199: Unit root tests and stationarity tests including a constant on first differences

FI loans – draw percentage – Single mean unit root test on logit-transformed first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-9.2	<0.01	Reject unit root
Phillips-Perron	1	-9.2	<0.01	Reject unit root
KPSS	4	0.08	0.67	Fail to reject stationarity

Stationarity tests for FI loans – draw percentage level series uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the FI loans – draw percentage deposit balances are modeled on their first differences.

7.3.4.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for FI loans – draw percentage. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.3.4.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 213: Summary of drivers for FI loans – draw percentage

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When the general economy is under stress, FI borrowers draw on committed lines more often to replace alternative sources of funding that are drying up	US GDP growth, US unemployment rate
Financial economy	**Equity markets**	• Weakening equity markets are correlated with stress in economic conditions, which leads to increased draws	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in market conditions may be a sign of stress in overall economic conditions, leading to increased draws	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• As systemic credit risk rises, draws may either increase as alternative funding options become less attractive, or decrease as overall lending slows down	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Borrowers may be more willing to draw from commitments at lower rates	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit	• Increasing corporate yields and spreads makes borrowing more expensive, leading to lower draws	Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.3.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for FI loans – draw percentage are statistically significant. The intercept is found to be statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 200: Statistical significance tests of model and variables for FI loans – draw percentage

FI loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**HAC P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Dow Jones Industrial Average	-0.002222	<1%	10%	Statistically significant
Nominal Imports	0.010686	<1%	10%	Statistically significant
Real Disposable Income growth	-0.004129	<1%	10%	Statistically significant
Intercept	0.021983	<1%	10%	Statistically significant

7.3.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

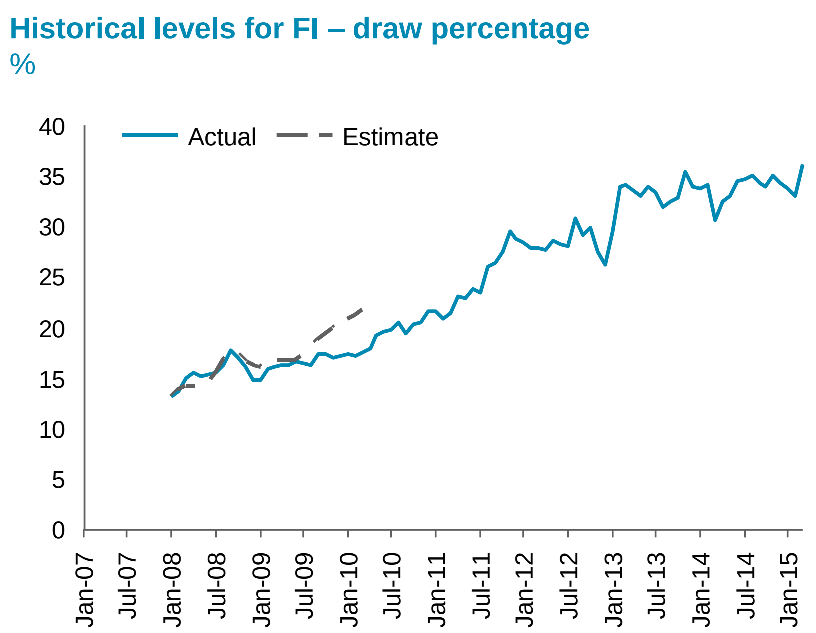
- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences of logit transform), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

Table 201: Model Diagnostics for FI loans – draw percentage

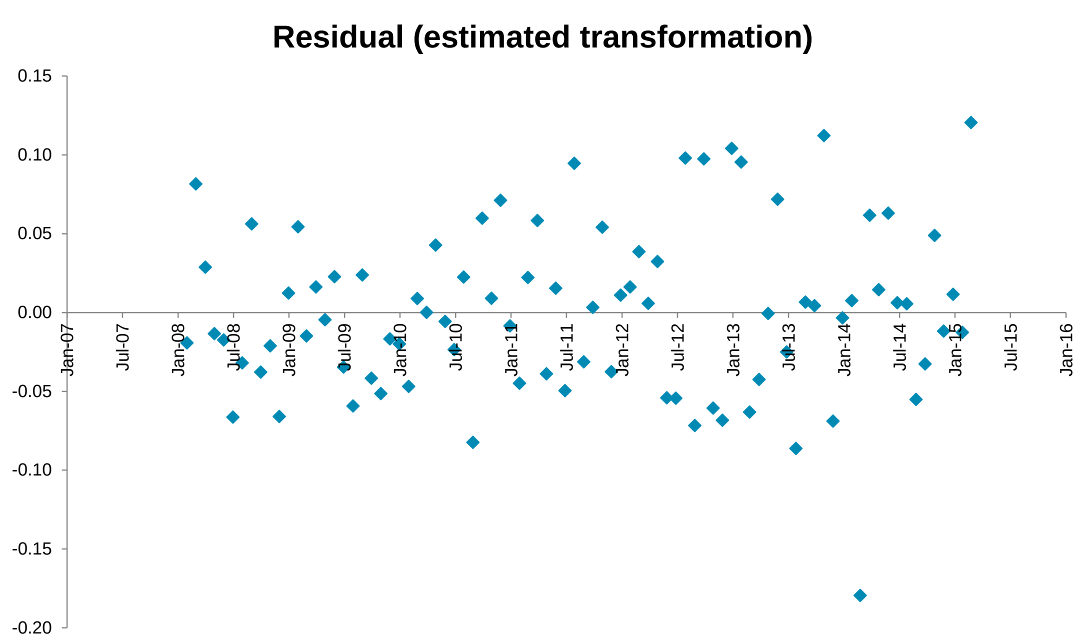
FI loans – draw percentage (logit-transformed) – Model diagnostics				
Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	25%	-	-
	Adjusted R-squared	22%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.82	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	2%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.81	5	No multicollinearity
Linearity	RESET test	49%	10%	Linear specification appropriate

Figure 214: 9-quarter In-sample Prediction for FI loans – draw percentage



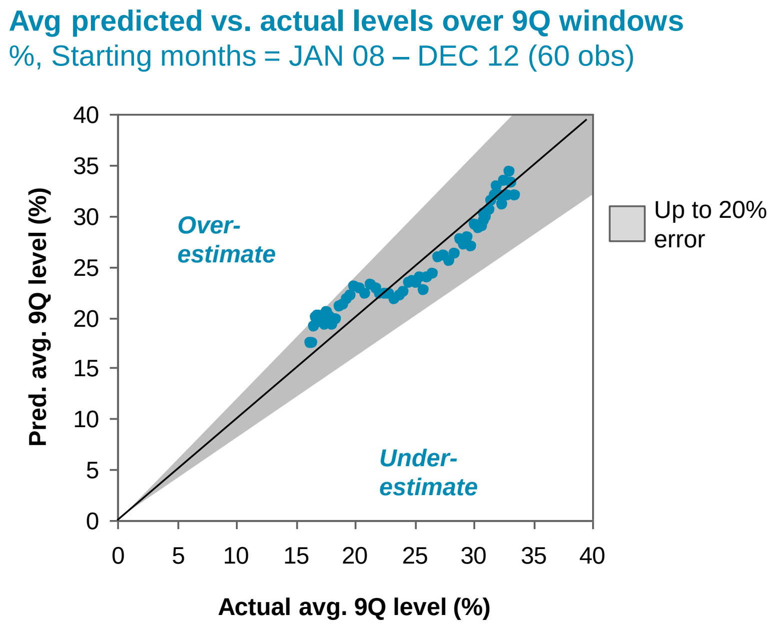
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, capturing the correct directional behavior along with a small bump in late 2008.

Figure 215: Residual Plot for FI loans – draw percentage



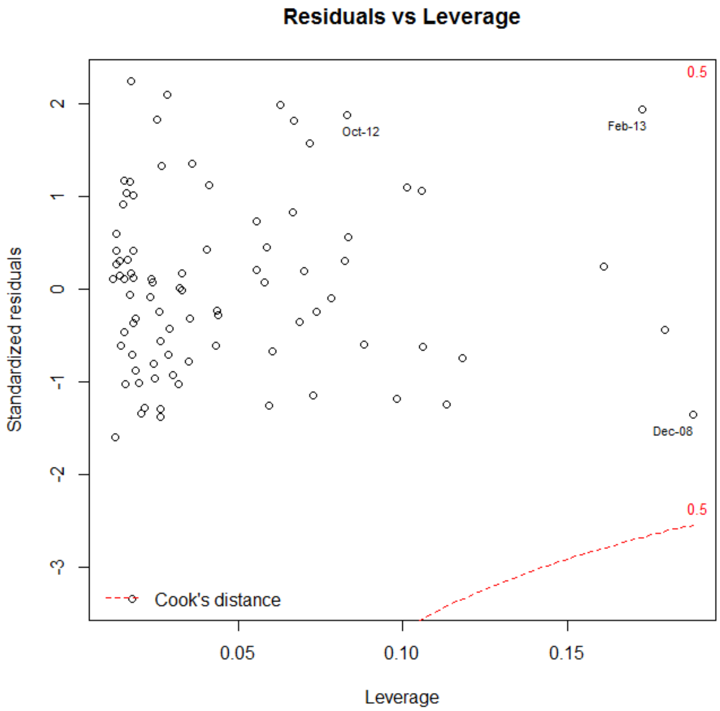
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 216: Estimation Scatterplot for FI loans – draw percentage



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 217: Influential points for FI Draws



The segment has no highly influential points.

7.3.4.6. Model sensitivity

7.3.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the dependent variable due to a one standard deviation increase in an independent variable.

Due to the usage of the logit transformation, the relationship between the independent variables and the level of the draw percentage is non-linear. Therefore, a one standard deviation shift in an independent variable will have different impacts on the actual draw percentage, depending on the level of the draw percentage. Sensitivity of the level to movements in independent variables will decrease as the level approaches 0% or 100%, since applying the inverse logit transformation to the dependent variable must produce a level that is bounded between 0% and 100%.

Table 202: Sensitivity to changes to independent variables for FI loans – draw percentage

FI loans – draw percentage (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
Dow Jones Industrial Average	% change – QoQ	%	-0.34	8.902
Nominal Imports	% change – MoM	%	0.39	2.10
Real Disposable Income growth	None (level), 1-month lag	%	-0.44	6.20
Intercept	None (level)	None	N/A	N/A

In the selected model for FI loans – draw percentage, the Real Disposable Income growth variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Real Disposable Income growth variable results in a 0.44 standard deviation decrease in the predicted monthly change of the logit-transformed draw percentage for the FI loan segment.

7.3.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. The coefficient of real disposable income growth, however, was statistically significant which implies the variable could become instable over time.

In addition, all of the coefficients are insignificant individually.

Table 203: Statistical sensitivity tests for FI loans – draw percentage

FI loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables

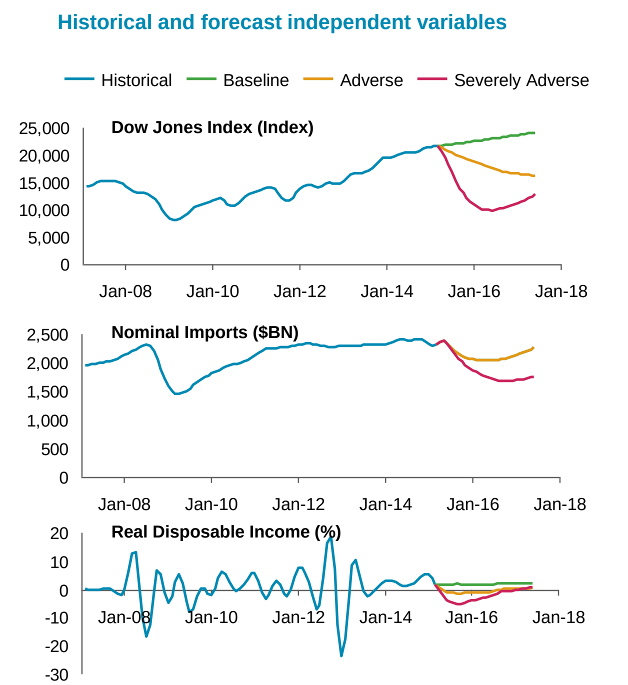
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
Dow Jones Industrial Average	-0.002222	-0.002	0.16	Statistically insignificant
Nominal Imports	0.010686	0.012	0.92	Statistically insignificant
Real Disposable Income growth	-0.004129	-0.004	0.02	Statistically significant
Intercept	0.021983		0.10	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.10	Statistically significant

7.3.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

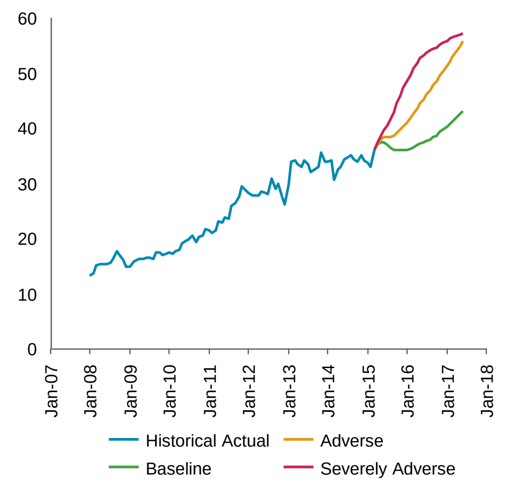
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 218: Final model forecast for FI loans – draw percentage



Historical and forecast levels for FI – draw percentage
%

%	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	7.08%	19.69%	21.08%	-
Start to peak	7.08%	19.69%	21.08%	4.58%
Start to trough	N/A	N/A	N/A	0.00%



The Working Group determined that the forecast behavior for the selected FI loans – draw percentage model requires higher scrutiny during management review.

The forecasted draw percentages show a strong upward trend in all three scenarios, driven by the strong, steady upward trend in the historical time series, despite leveling off in more recent years. The stress scenarios show higher draw percentages, which is consistent with the intuition that under stress, FI borrowers will draw more from their committed lines to replace alternate sources of funding that are no longer available. In a review with the line of business, it was noted that the scenario forecasts should be monitored closely when the final outputs for submission are generated. Management review is recommended to ensure that the forecasts are not overly aggressive, and are consistent with expectations.

7.3.5. Letter of Credit usage percentage

7.3.5.1. Summary

A statistically sound model that is consistent with business intuition was found for FI loans – Letter of Credit usage percentage. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the Letter of Credit usage percentage time series for FI loans, which is found to be stationary upon manual review
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 204: Coefficient estimates for selected model for FI loans – Letter of Credit usage percentage

FI loans – Letter of Credit usage percentage (logit-transformed) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Unemployment rate	First difference – MoM	%	7.75	0.30
Market volatility index	% change – QoQ	%	0.02	0.15
Prime rate	First difference – MoM, 1-month lag	%	-6.61	-0.16
Intercept	None (level)	None	-1.35	N/A

The model contains the following drivers and variables:

- **General economic health** – US unemployment rate
- **Market volatility/uncertainty (equity)** – Market volatility index, constructed using maximum close-of-day values of VIX in each period
- **Short-term rates** – Prime rate

The intuition of these variables is as follows:

- The unemployment rate variable has a positive coefficient; as overall macroeconomic conditions deteriorate, demand for Letters of Credit rises as greater credit enhancement is required
- The market volatility index variable has a positive coefficient; as market volatility rises, demand for Letters of Credit may increase as there is greater requirement for credit enhancement

- The prime rate variable has a negative coefficient and can be interpreted as a proxy for overall short-term interest rates. Rising interest rates are associated with economic recovery, which may reduce the need for credit enhancements

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 219: Candidate models for FI loans – Letter of Credit usage percentage

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Equity markets			KBW Bank Index (% QoQ)		
Exports	Nominal Exports (% QoQ)				
General economic health	Nominal GDP growth (Level, 1M Lag)	Unemployment rate (Diff MoM)	Unemployment rate (Diff MoM)	Unemployment rate (Diff MoM)	Unemployment rate (Diff MoM)
Long-term rates	10Y US Swap (Diff QoQ)				
Market volatility / uncertainty (equity)		Market Vol (% QoQ)		Market Vol (% QoQ)	
Perceived credit risk					1 week LIBOR 1 week OIS spread (Diff MoM, 1M Lag)
Short-term rates		Prime rate (Diff MoM, 1M Lag)	Prime rate (Diff MoM)		
Variation in levels explained through estimated logit first differences	**92%**	**96%**	**98%**	**96%**	**97%**
R-squared (differences)	**22%**	**20%**	**20%**	**18%**	**17%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.3.5.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.3.5.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The logit-transformed Letter of Credit usage percentage time series for the FI loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the logit-transformed levels are tested using unit root and stationarity tests including a time trend.

The first differences of the logit-transformed levels, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 205: Unit root tests and stationarity tests including a trend variable on levels

FI loans – Letter of Credit usage percentage – Unit root test with trend on logit-transformed level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	6	-1.2	>0.10	Fail to reject unit root
Phillips-Perron	1	-3	0.15	Fail to reject unit root
KPSS	5	0.27	<0.01	Reject stationarity

Table 206: Unit root tests and stationarity tests including a constant on first differences

FI loans – Letter of Credit usage percentage – Single mean unit root test on logit-transformed first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-9.8	<0.01	Reject unit root
Phillips-Perron	1	-9.8	<0.01	Reject unit root
KPSS	2	0.81	<0.01	Reject stationarity

Stationarity tests for FI loan – Letter of Credit usage percentage yield mixed results: The ADF and PP tests fail to reject a unit root while the KPSS test fails to reject stationarity. These results suggest the FI loans – total commitments balances may be non-stationary. In contrast, the monthly first difference series passes the ADF and PP tests at a high significance and fails the KPSS test. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that a potential reason for the failure was the “Tall Trees” exposure reduction program which was executed over a limited period of the modeling period and hence should not impact the stationarity of the series going forward.

Based on these results, the FI loan – Letter of Credit usage percentage are modeled on their first differences, as manual review provided sufficient evidence of stationarity for the application of OLS.

7.3.5.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for FI loans – Letter of Credit usage percentage. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.3.5.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 220: Summary of drivers for FI loans – Letter of Credit usage percentage

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When general economic conditions deteriorate, demand for Letters of Credit increases to provide credit enhancement • Alternatively, stronger economic conditions may drive up demand for Letters of Credit as transactional activity increases	US GDP growth, US unemployment rate
	Imports	• As volume of foreign trade increases, more Letters of Credit will be taken out	Volume of imports
	Exports		Volume of exports
Financial economy	**Equity markets**	• When equity markets are weak or volatile, demand for Letters of Credit increases to provide credit enhancement	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)		VIX, market volatility index
	Market volatility/ uncertainty (rates)	• When rates are volatile, demand for Letters of Credit increases to provide credit enhancement	10-year US T-note volatility index
	Perceived credit risk	• When perceived credit risk increases, demand for Letters of Credit increases to provide credit enhancement	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates are associated with improving economy, which can either increase Letter of Credit usage by increasing transactional activity, or decrease it by reducing the need for credit enhancement	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit	• Widening corporate credit spreads may indicate increased credit risk, increasing demand for Letters of Credit to provide credit enhancement	Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.3.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for FI loans – Letter of Credit usage percentage are statistically significant. The intercept is found to be statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 207: Statistical significance tests of model and variables for FI loans – Letter of Credit usage percentage

FI loans – Letter of Credit usage percentage (logit-transformed) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market_Vol_PQoQ	0.000	<1%	10%	Statistically significant
Prime_Rate_DMoML1	-0.066	2%	10%	Statistically significant
UE_DMoM	0.078	<1%	10%	Statistically significant
Intercept	-0.014	2%	10%	Statistically significant

7.3.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences of logit transform), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

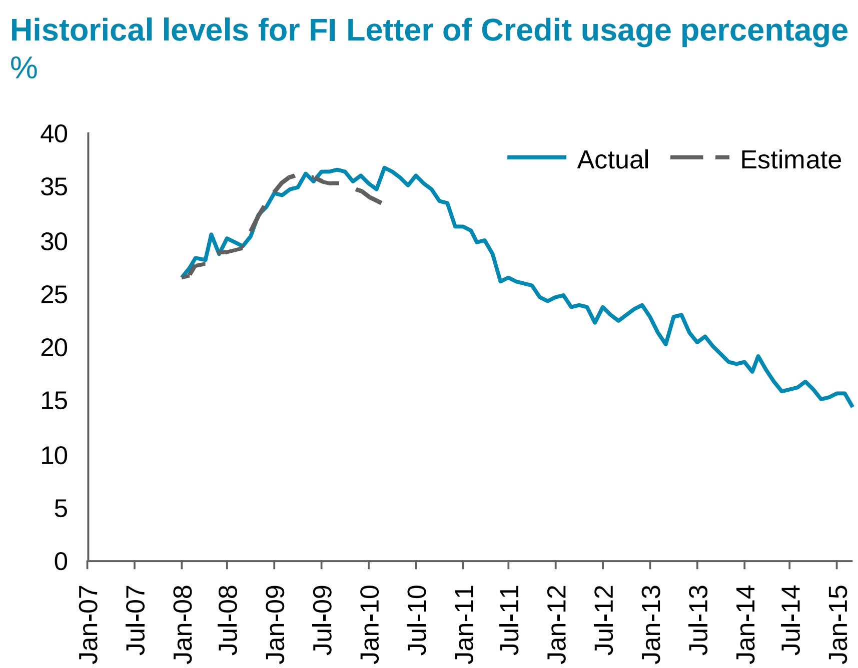
The diagnostic tests reviewed are exhibited below.

Table 208: Model Diagnostics for FI loans – Letter of Credit usage percentage

FI loans – Letter of Credit usage percentage (logit-transformed) – Model diagnostics

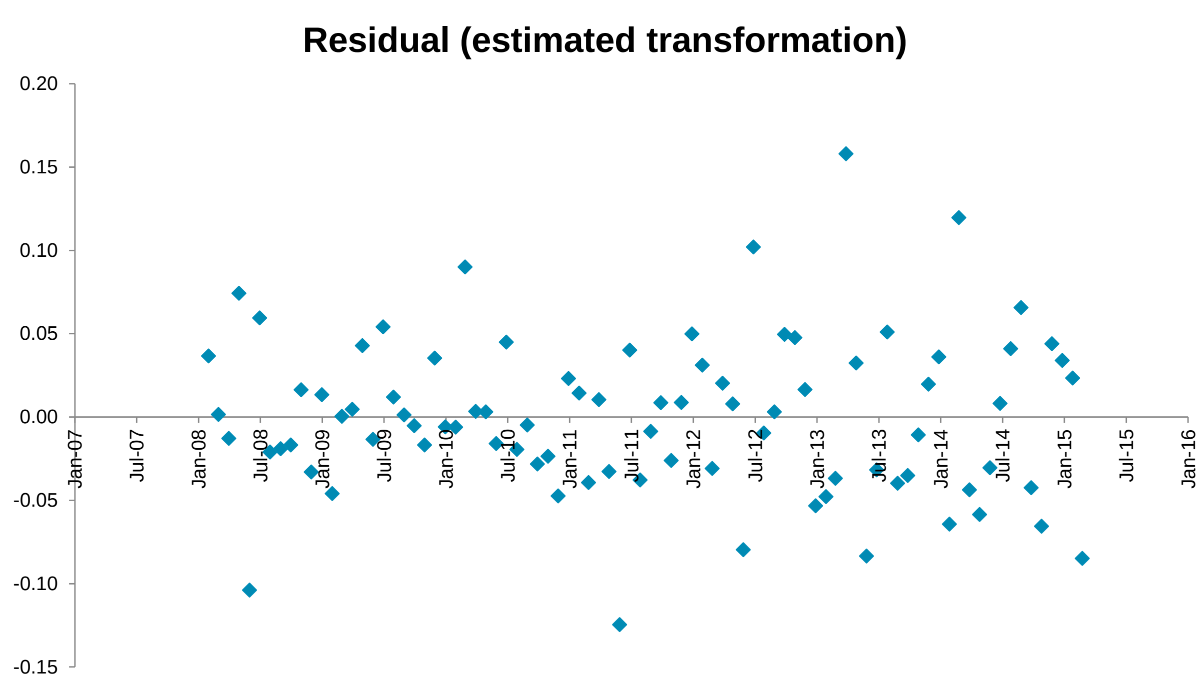
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	20%	-	-
	Adjusted R-squared	17%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.76	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	3%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.26	5	No multicollinearity
Linearity	RESET test	50%	10%	Linear specification appropriate

Figure 221: 9-quarter In-sample Prediction for FI loans – Letter of Credit usage percentage



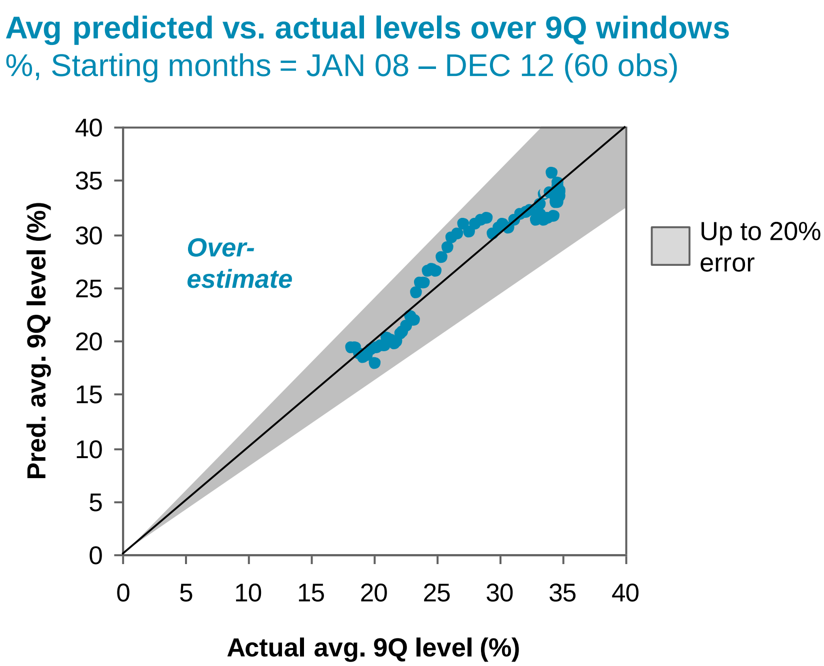
The in-sample back test of the model starting from January 2008 tracks very closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

Figure 222: Residual Plot for FI loans – Letter of Credit usage percentage



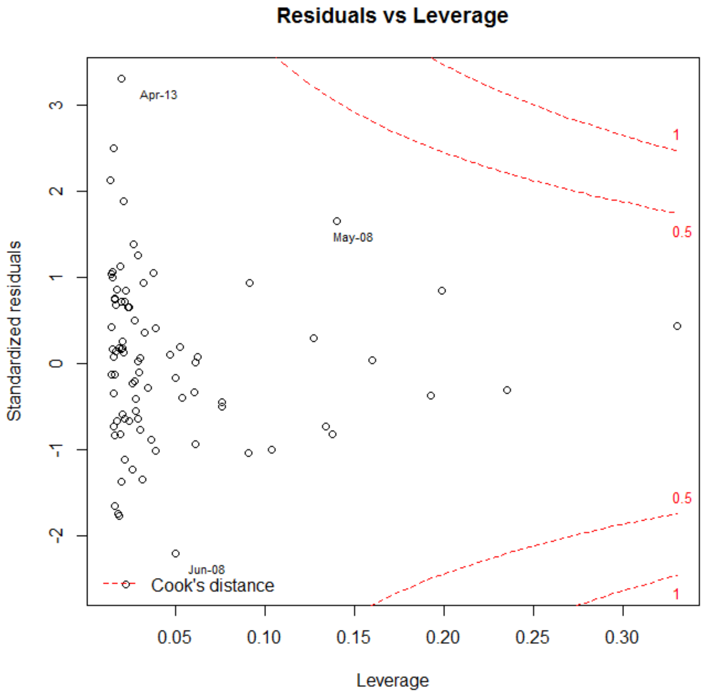
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 223: Estimation Scatterplot for FI loans – Letter of Credit usage percentage



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 224: Influential points for FI LoC usage



The segment has no highly influential points.

7.3.5.6. Model sensitivity

7.3.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the dependent variable due to a one standard deviation increase in an independent variable.

Due to the usage of the logit transformation, the relationship between the independent variables and the level of the draw percentage is non-linear. Therefore, a one standard deviation shift in an independent variable will have different impacts on the actual Letter of Credit usage percentage, depending on the level of the Letter of Credit usage percentage. Sensitivity of the level to movements in independent variables will decrease as the level approaches 0% or 100%, since applying the inverse logit transformation to the dependent variable must produce a level that is bounded between 0% and 100%.

Table 209: Sensitivity to changes to independent variables for FI loans – Letter of Credit usage percentage

FI loans – Letter of Credit usage percentage – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
Market_Vol_PQoQ	Percent change – QoQ	Index	0.15	48.56

Prime_Rate_DMoML1	First difference – MoM	%	-0.16	0.13
UE_DMoM	First difference – MoM	%	0.30	0.20
Intercept	None (level)	$ MM	N/A	N/A

In the selected model for FI loans – Letter of Credit usage percentage, the unemployment rate variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the unemployment rate variable results in a 0.30 standard deviation increase in the predicted monthly change of the logit-transformed Letter of Credit usage percentage for the FI loan segment.

7.3.5.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. The Prime Rate variable’s coefficient comes out significant which implies the variable might become unstable over time.

Table 210: Statistical sensitivity tests for FI loans – Letter of Credit usage percentage

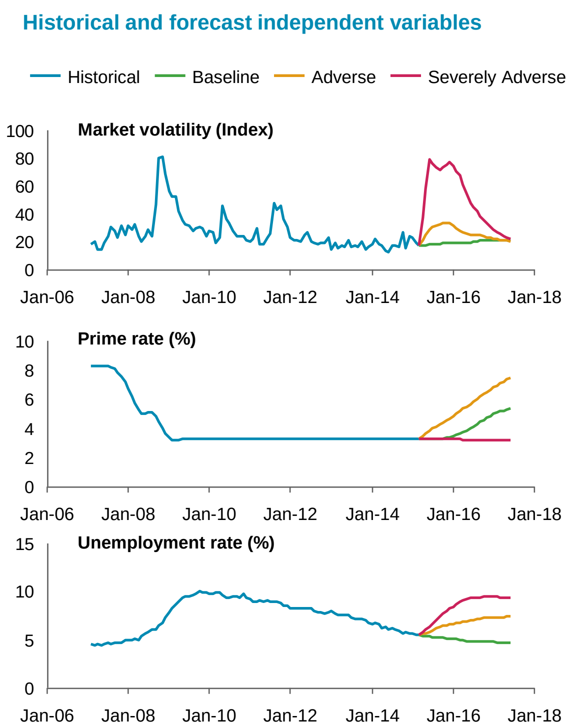
FI loans – Letter of Credit usage percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
Market_Vol_PQoQ	0.000	0.000	0.31	Statistically insignificant
Prime_Rate_DMoML1	-0.066	-0.065	0.00	Statistically significant
UE_DMoM	0.078	0.086	0.59	Statistically insignificant
Intercept	-0.014		0.81	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.00	Statistically significant

7.3.5.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

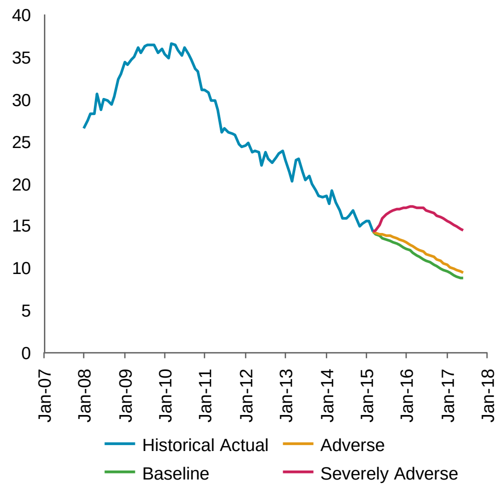
Figure 225: Final model forecast for FI loans – Letter of Credit usage percentage



Historical and forecast levels for FI Letter of Credit usage percentage

%

%	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-5.6%	-4.91%	0.12%	N/A
Start to peak	N/A	N/A	2.98%	9.91%
Start to trough	-5.56%	-4.91%	N/A	0.00%



The Working Group considered the forecast behavior for the selected FI loans – Letter of Credit usage percentage model as generally reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts a small rise in Letter of Credit usage, followed by a decline back to levels comparable to the start of the forecast horizon. This is consistent with business intuition that there could be a greater demand for Letters of Credit to provide credit enhancement as credit conditions worsen with overall deterioration of the macroeconomic environment
- **Interest rate shock (Adverse) scenario**: The model predicts a continued decline in Letter of Credit usage in line with the decreasing trend observed in recent years, similar to the forecast under the Baseline scenario
- **Baseline scenario**: The model predicts a continued decline in Letter of Credit usage in line with the decreasing trend observed in recent years

7.3.6. Closed-end loans

7.3.6.1. Summary

A statistically sound model was found for FI loans – closed-end loans. However, despite reasonable historical fit, this model was deemed by the Working Group and line of business as potentially over-aggressive in forecasting significant increases in closed-end loans under certain scenarios. Management scrutiny is therefore recommended for the outputs of this model.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the closed-end loan time series for FI loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 211: Coefficient estimates for selected model for FI loans – closed-end loans

FI loans – closed-end loans (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
5-year US swap rate	First difference – MoM	%	1,390.84	0.25
Market volatility index	First difference – MoM	Index	62.54	0.32
Intercept	None (level)	$ MM	-20.84	N/A

The model contains the following drivers and variables:

- **Long-term rates** – 5-year US swap rate
- **Market volatility/uncertainty (equity)** – Market volatility index, constructed using maximum close-of-day values of the VIX in each period

The intuition of these variables is as follows:

- The 5-year US swap rate variable has a positive coefficient, and is interpreted as an expectation of future interest rates. An increase suggests higher future interest rates, which could drive borrowers to take out loans while interest rates are still relatively lower. Supply could also be driven up as these loans would be expected to generate more income in the future
- The market volatility index variable has a positive coefficient and is interpreted as an indicator of market stress. When there is market stress, demand for loans may rise as access to alternate sources of funding may decline

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 226: Candidate models for FI loans – closed-end loans

	Candidate models		
Drivers Considered	**1**	**2**	**3**
Long-term rates	5Y US Swap (Diff MoM)	5Y US Swap (Diff MoM)	5Y US Swap (Diff MoM)
Market volatility / uncertainty (equity)	S&P Vol (30D MAVG) (Diff MoM)	Market Vol (Diff MoM)	
Perceived credit risk	1 week LIBOR 1 week OIS spread (Diff QoQ)		TED Spread (Diff MoM)
Variation in balances explained through estimated first differences	**43%**	**48%**	**61%**
R-squared (differences)	**23%**	**14%**	**14%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.3.6.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.3.6.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The closed-end loan time series for the FI loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 212: Unit root tests and stationarity tests including a trend variable on levels

FI loans – closed-end loans – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-1.2	>0.10	Fail to reject unit root
Phillips-Perron	1	-4.3	<0.01	Reject unit root
KPSS	4	0.26	<0.01	Reject stationarity

Table 213: Unit root tests and stationarity tests including a constant on first differences

FI loans – closed-end loans – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	5	-4.8	<0.01	Reject unit root
Phillips-Perron	1	-12	<0.01	Reject unit root
KPSS	16	0.23	0.21	Fail to reject stationarity

Stationarity tests for FI loans – closed-end loans balances yield mixed results: The ADF test fails to reject the unit root and the KPSS rejects stationarity while the PP test rejects a unit root. These results suggest the FI loans – closed-end loans balances may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the FI loans – closed-end loans deposit balances are modeled on their first differences.

7.3.6.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for FI loans – closed-end loans. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.3.6.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 227: Summary of drivers for FI loans – closed-end loans

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When the general economy is under stress, FI borrowers may take out bank loans to replace alternative sources of funding that are drying up	US GDP growth, US unemployment rate
	Imports	• Increased foreign trade grows demand for trade financing loans	Volume of imports
	Exports		Volume of exports
Financial economy	**Equity markets**	• Weakening equity markets are correlated with stress in economic conditions, which leads to increased demand • Alternatively, strong equity markets could also lead to increased demand driven by general economic growth	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Debt issuances	• Bank lending may increase as a component of total corporate debt • Bond issuance acts as a substitute for bank loans	Corporate debt outstanding, total bond issuance
	Hedge fund index	• Stronger hedge fund performance leads to greater lending to FIs	HFRX index, Eurekahedge HF index, Eurekahedge FoF index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in market conditions may be a sign of stress in overall economic conditions, leading to increased bank lending as access to alternative funding dries up	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• As systemic credit risk rises, lending may either increase driven by demand as alternative funding options become less attractive, or decrease driven by supply as overall lending slows down	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.3.6.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for FI loans – closed-end loans are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 214: Statistical significance tests of model and variables for FI loans – closed-end loans

FI loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market_Vol_DMoM	62.539	1%	10%	Statistically significant
US_5yr_swap_DMoM	1390.837	3%	10%	Statistically significant
Intercept	-20.844	89%	10%	Statistically not significant

7.3.6.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

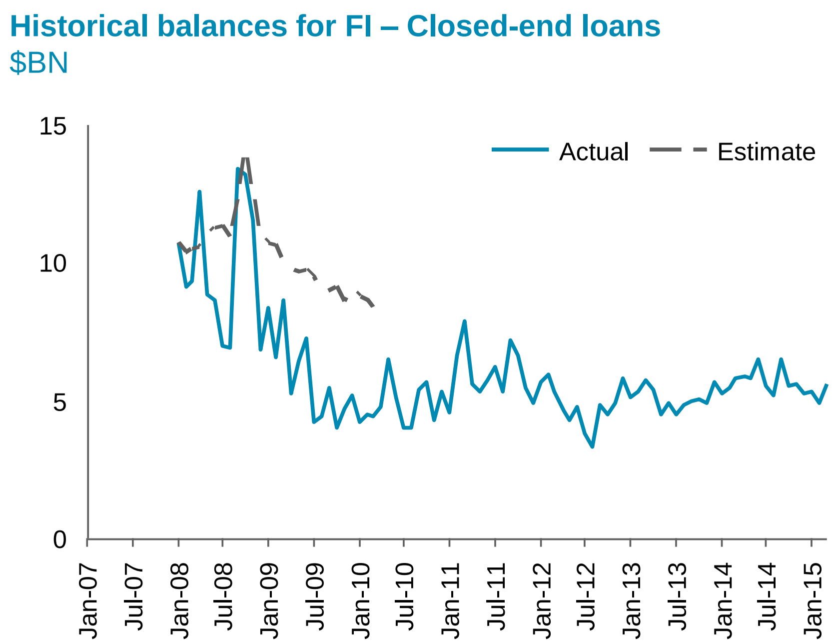
The diagnostic tests reviewed are exhibited below.

Table 215: Model Diagnostics for FI loans – closed-end loans

FI loans – closed-end loans (in USD MM) – Model diagnostics

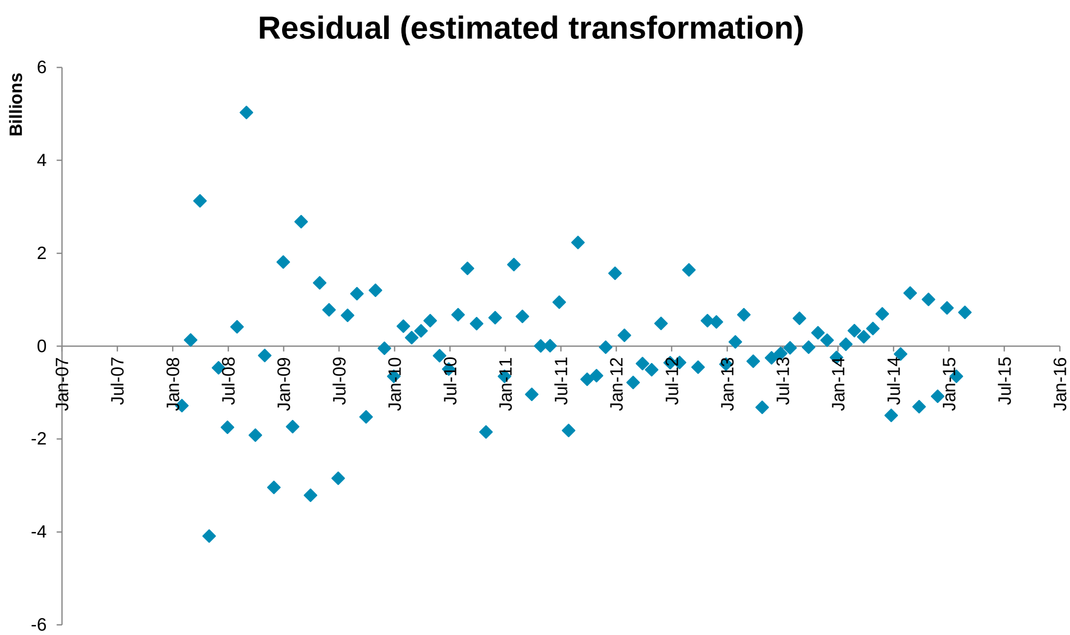
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	14%	-	-
	Adjusted R-squared	12%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.16	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.02	5	No multicollinearity
Linearity	RESET test	63%	10%	Linear specification appropriate

Figure 228: 9-quarter In-sample Prediction for FI loans – closed-end loans



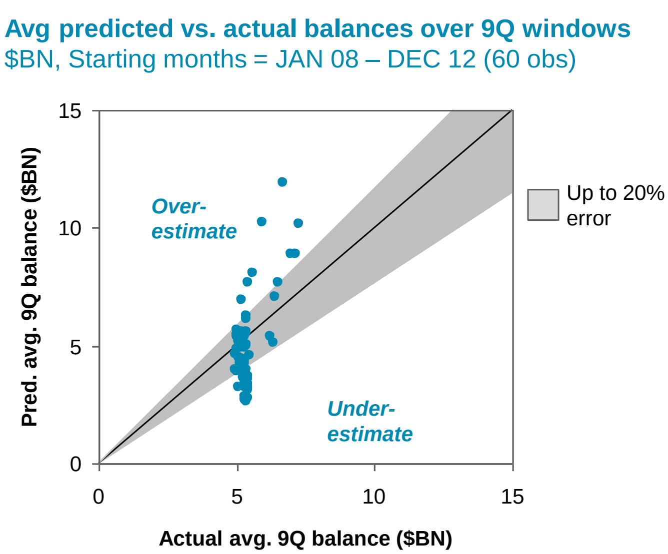
The in-sample back test of the model starting from January 2008 picks up the spike in late 2008, but is unable to capture the high observed volatility in balances. The decline from the peak of the spike is less pronounced in the estimate, which results in overestimates of the balance for the later part of the forecast.

Figure 229: Residual Plot for FI loans – closed-end loans ($ BN)



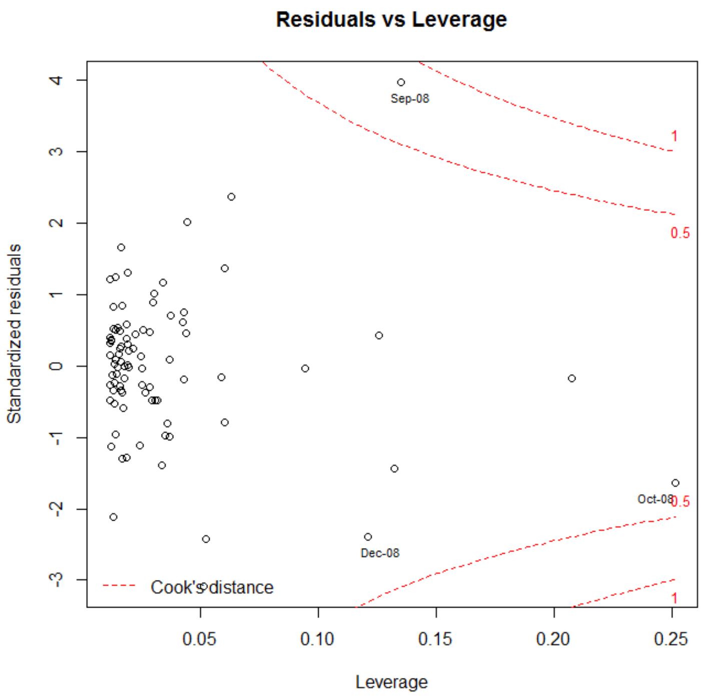
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 230: Estimation Scatterplot for FI loans – closed-end loans



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for some of the 9-quarter forecast windows. As noted above, the model does not capture the full magnitude of large changes, which leads to consistent overestimation or underestimation over 9-quarter forecast windows, depending on which month is taken as the starting month of the forecast.

Figure 231: Influential points for FI Closed-end loans



The segment has no highly influential points

7.3.6.6. Model sensitivity

7.3.6.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 216: Sensitivity to changes to independent variables for FI loans – closed-end loans

FI loans – closed-end loans – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Market_Vol_DMoM	First difference – MoM	Index	0.32	7.18	0.46

US_5yr_swap_DMoM	First difference – MoM	%	0.25	0.27	0.36
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model for FI loans – closed-end loans, the market volatility index variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the market volatility index variable results in a 0.32 standard deviation ($0.46 BN) increase in the predicted monthly change of the closed-end loans for the FI loan segment.

7.3.6.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically significant collectively. This suggests the model does not remain stable when removing observations from the development data and that the model might not remain stable over time.

Table 217: Statistical sensitivity tests for FI loans – closed-end loans

FI loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

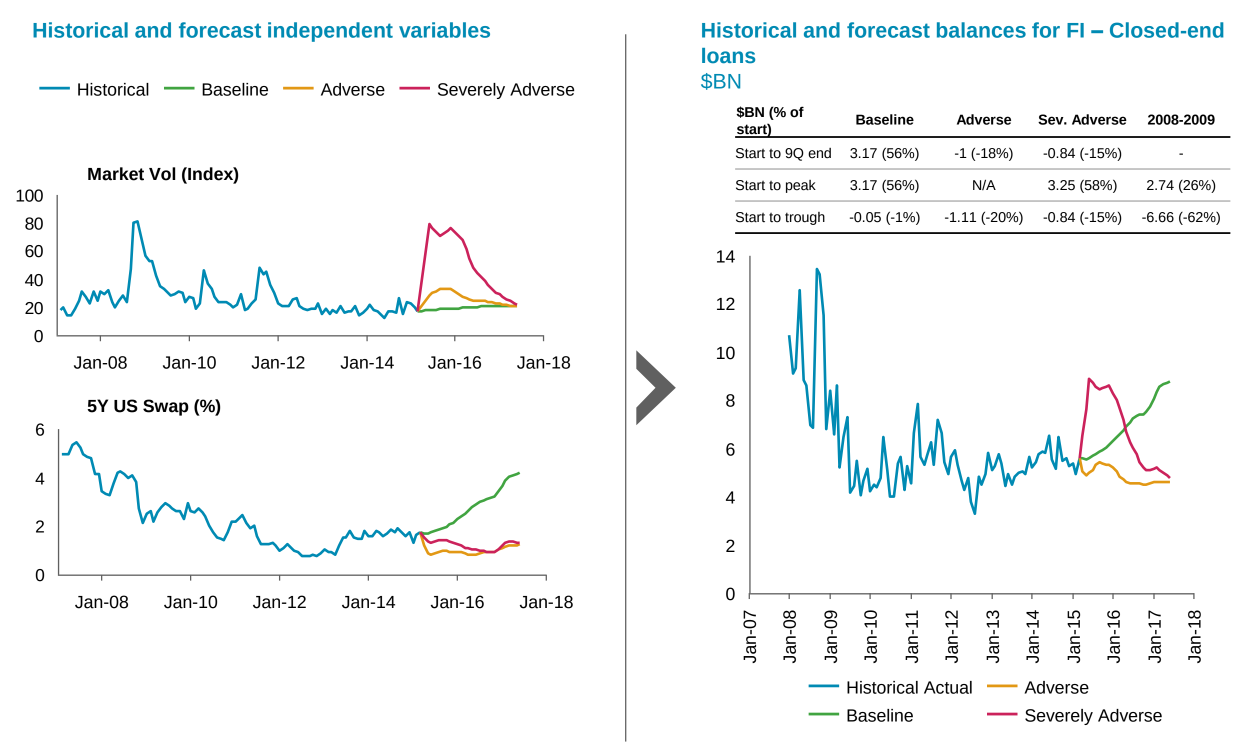
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
Market_Vol_DMoM	62.539	75.699	0.00	Statistically significant
US_5yr_swap_DMoM	1390.837	1718.363	0.14	Statistically insignificant
Intercept	-20.844		0.82	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.01	Statistically significant

7.3.6.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 232: Final model forecast for FI loans – closed-end loans



The Working Group determined that the forecast behavior for the selected FI loans – closed-end loans model requires higher scrutiny during management review.

- **Severe recession (Severely Adverse) scenario:** Closed-end loan balances grow rapidly before declining back to original levels by the end of the 9-quarter forecast horizon. This behavior is directionally consistent with the expectation that clients will require more funding through loans at the start of a severe macroeconomic downturn, which then moderates as alternative, more attractive sources of funding become more accessible. However, the Working Group and LOB indicated that the spike in balances under this scenario may be too strong
- **Interest rate shock (Adverse) scenario**: Closed-end loan balances remain relatively flat
- **Baseline scenario**: Closed-end loan balances grow fairly steeply, driven by rising interest rates. The Working Group and LOB indicated that this growth may be overly aggressive, especially given that balances have remained fairly stable in recent years. The increase mirrors the sharp post-crisis drop in balances, but this drop was partially driven by non-macroeconomic factors like BNY Mellon's reduction of redundant exposures across legacy Bank of New York and legacy Mellon

7.3.7. Model limitations

As discussed in Section 7.2, BNY Mellon underwent a period of balance sheet de-risking following the 2008–2009 financial crisis, concurrent with contraction in the overall lending market during this period. However, this period also coincides with the integration of the legacy Bank of New York and Mellon portfolios, which was characterized by active management decision to reduce redundant exposures shared across both legacy banks. As a result, the observed changes in forecast quantities reflect movements due to both the macroeconomic environment as well as factors idiosyncratic to BNY Mellon. As discussed in Section 4.2, the historical time series from the development data commingles both of these effects. Therefore, the developed models are potentially over-sensitive to changes in macroeconomic variables, and could produce more extreme forecasts than would be intuitively expected.

For total commitments, as mentioned in Section 7.3.1, $28 BN in new tri-party committed facilities were booked on April 23, 2015. These balances cannot be forecast by the model, as they are booked after the end of the historical period covered by the development data (March 2015). In addition, these unfunded commitments are expected to run off in 18–24 months according to a defined schedule, rather than changing in size based on movements in macroeconomic factors. Therefore, in the final forecast for total commitments and unfunded commitments, these unfunded commitments will be added to the model forecasts as an additional qualitative component, which is discussed further in Section 7.3.8.

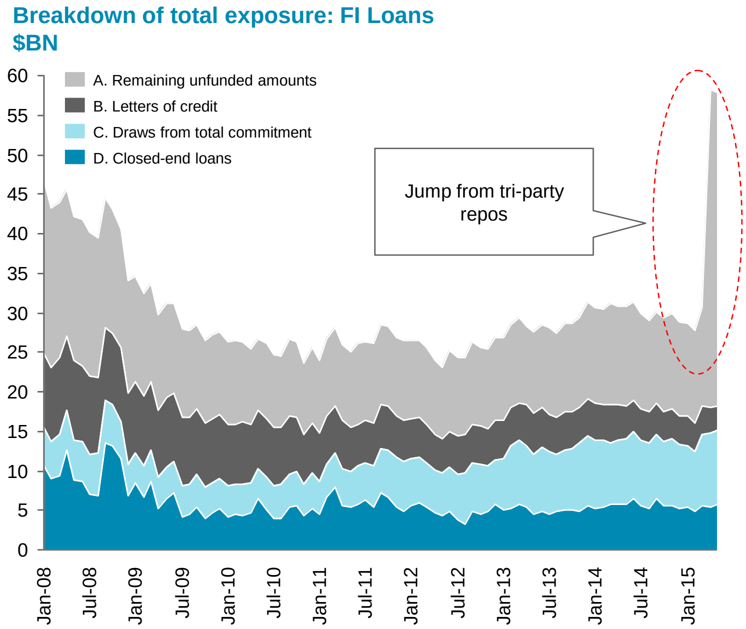
For draw percentage, the growth trend in the historical time series for the dependent variable has a strong impact on the forecasts that the models predict under a range of different scenarios, manifesting as a significant intercept that drives continuation of the growth trend. The model still incorporates sensitivity to macroeconomic factors, but their effect is relatively small compared to the growth trend. As the model is recalibrated in the future on longer historical time series, this effect could moderate, improving the quality of the model forecast.

7.3.8. Synthesis of forecast results

After forecasts have been generated from the models, a small set of additional calculations is required to obtain the desired balance forecasts shown in the figure below:

- Balances for funded draws from commitments (Quantity C in figure) can calculated as the product of total commitment and draw percentage
- Unfunded Letter of Credit amounts (Quantity B in figure) can be calculated as the product of total commitment and Letter of Credit usage percentage
- Unused unfunded commitments (Quantity A in figure) can be calculated as total commitments minus balances for funded draws minus unfunded Letter of Credit amounts. For the FI loan segment, an additional component needs to be added into the forecast for unfunded commitments to account for the tri-party repos discussed in Section 7.3.1. Credit Risk has developed projections for this additional component over the forecast horizon based on the facilities' expected run-off schedules
- Total funded loan balances can be calculated as the sum of balances for funded draws plus balances for closed-end loans (Quantity C + Quantity D in figure)

Figure 233: Breakdown of total exposure for FI loans

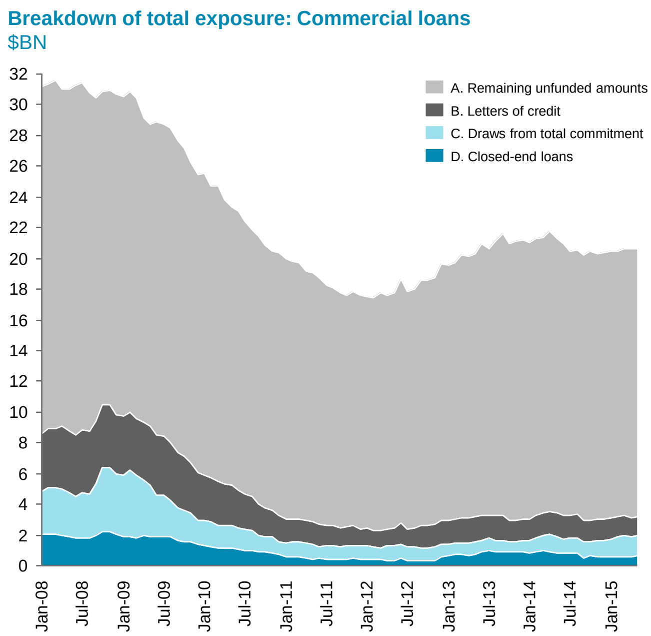


7.4. Commercial loans

7.4.1. Business overview

BNY Mellon originates and purchases loans as part of its ongoing business. The Commercial loan segment comprises the second largest loan type for BNY Mellon as measured by total exposure, after FI loans: as of April 30, 2015, BNY Mellon has $2 BN in funded Commercial loans plus $19 BN in unfunded commitments, including Letters of Credit. The figure below shows the breakdown over time for total exposure in this segment into the different unfunded and funded components described in Section 3.4.

Figure 234: Breakdown of total exposure for Commercial loans



Borrowers in this segment include companies in non-financial industries, namely Services, Manufacturing, Energy & Utilities, and Media & Telecom. BNY Mellon's credit strategy for this segment is to focus on investment grade names to support cross-selling opportunities, avoid single name/industry concentrations, and maintain a predominantly investment grade loan portfolio. As of March 31, 2015, 94% of the Commercial loan segment was investment grade, based on internal rating criteria that are largely consistent with those of public rating agencies. The table below shows the breakdown of funded and unfunded balances in this segment by borrower industry, as of March 31, 2015.

Table 218: Funded and unfunded exposures for Commercial loans by borrower industry

Commercial loan exposures as of March 31, 2015 (in USD MM)			
Borrower industry	**Funded loans**	**Unfunded exposure (including Letters of Credit)**	**Total exposure**
Services	783	6,189	6,971
Energy & Utilities	735	5,830	6,565
Manufacturing	290	5,689	5,979
Media & Telecom	152	1,663	1,815
Total	1,959	19,371	21,330

Commercial loans are used by borrowers for a range of purposes; the most common usages of these loans are for working capital, acquisitions, trade financing, and debt repayment and consolidation. Facilities with unfunded commitments are mostly used for working capital and as backup lines to support commercial paper and industrial revenue bonds.

Commercial loan facilities have historically experienced lower draws than facilities for other loan types, such as FI loans. At the onset of the 2008–2009 financial crisis, a small but noticeable increase in draws from committed facilities was observed. In the several years following the 2008–2009 financial crisis, both funded and unfunded exposures decreased, driven in part by management decisions to de-risk the bank's balance sheet and reduce redundant exposures across the legacy Bank of New York and legacy Mellon loan portfolios. In the more recent years, balances have stabilized as both of these strategic initiatives have expired. See Section 7.2 for further discussion on these initiatives.

7.4.2. Forecast quantities

In line with the methodology described in Section 3.4, the following quantities were forecasted for this segment, all using a statistical modeling approach:

1. Total commitment amount
2. Draw percentage, i.e. total drawn amount divided by total commitment amount (modeled as a percentage)
3. Letter of Credit usage percentage, i.e. total amount in unused Letters of Credit divided by total commitment amount (modeled as a percentage)
4. Closed-end loan balance

The forecasting approaches for these four quantities are documented separately in Sections 7.3.3–7.3.6. Section 7.3.8 discusses how these quantities are used to develop forecasts for unfunded commitments, Letters of Credit, and total funded loans.

7.4.3. Total commitment

7.4.3.1. Summary

A statistically sound model that is consistent with business intuition was found for Commercial loans – total commitment. Some management scrutiny may be needed for stress forecasts to ensure that the projected movements in balances are not overly extreme given management expectations.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for Commercial loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 219: Coefficient estimates for selected model for Commercial loans – total commitment

Commercial loans – total commitment (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Corp Debt Outstanding	% change – QoQ	%	127.54	0.46
S&P Volatility (30D MAVG)	% change – MoM	%	-5.12	-0.29
10-Year US T-Note Volatility Index	First difference – MoM, 1-month lag	Index	105.23	0.32
Intercept	None (level)	$ MM	-181.63	N/A

The model contains the following drivers and variables:

- **Debt issuances** – Corporate debt outstanding in the US, including bond issuances, loans, Commercial Paper, and other forms of debt
- **Market volatility/uncertainty (equity)** – 30-day moving average of VIX, which measures implied volatility of S&P 500 index options
- **Market volatility/uncertainty (rates)** – 10-year US T-Note Volatility Index, which measures a constant 30-day expected volatility of 10-year Treasury Note futures prices

The intuition of these variables is as follows:

- Corporate debt outstanding has a positive coefficient; the Commercial loans in this segment are a subset of total corporate debt outstanding, and this variable is interpreted to mean that BNY Mellon's total commitments have a positive correlation with the overall corporate debt market
- The S&P volatility variable has a negative coefficient; when equity markets are more volatile, BNY Mellon may have lower appetite for extending credit
- The 10-year US T-Note Volatility Index variable has a positive coefficient; when there is greater uncertainty in the longer-term rate environment, corporates may prefer to open or increase facilities to try to reduce uncertainty in borrowing rates

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs, noting also that the bank's risk appetite would be a constraint on the overall total commitments.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 235: Candidate models for Commercial loans – total commitment

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Corporate credit				Baa to Treasury Spread (Diff MoM)	
Debt issuances	Corporate Debt Outstanding (% QoQ)		Corporate Debt Outstanding (% MoM)	Corporate Debt Outstanding (% QoQ)	
Equity markets					MSCI World Index (% MoM)
Imports			Nominal Imports (% YoY)		
Market volatility / uncertainty (equity)	S&P Vol (30D MAVG) (% MoM)	S&P Vol (30D MAVG) (% MoM)			S&P Vol (30D MAVG) (% MoM)
Market volatility / uncertainty (rates)	10Y US T-Note Volatility Index (Diff MoM, 1M Lag)	10Y US T-Note Volatility Index (Diff MoM, 1M Lag)	10Y US T-Note Volatility Index (Diff MoM, 1M Lag)	10Y US T-Note Volatility Index (Diff MoM, 1M Lag)	
Yield spread		3M to 10Y T Spread (Level)			3M to 10Y T Spread (Level, 1M Lag)
Variation in balances explained through estimated first differences	**96%**	**95%**	**97%**	**96%**	**93%**
R-squared (differences)	**36%**	**33%**	**33%**	**32%**	**30%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.4.3.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.4.3.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The total commitment time series for the Commercial loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 220: Unit root tests and stationarity tests including a trend variable on balances

Commercial loans – total commitments – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	3	-0.9	>0.10	Fail to reject unit root
Phillips-Perron	1	-0.1	0.99	Fail to reject unit root
KPSS	5	0.37	<0.01	Reject stationarity

Table 221: Unit root tests and stationarity tests including a constant on first differences

Commercial loans – total commitments – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	7	-0.9	0.78	Fail to reject unit root
Phillips-Perron	1	-7.5	<0.01	Reject unit root
KPSS	2	0.94	<0.01	Reject stationarity

Stationarity tests for Commercial loans – total commitments yield mixed results: The ADF and PP tests fail to reject a unit root while the KPSS test fails to reject stationarity. These results suggest the levels may be non-stationary. The monthly first difference series passes the PP test but fails the KPSS and ADF tests. Because it failed the KPSS and ADF test, the modeling team reviewed the data manually. It was assessed that a potential reason for the failure was the "Tall Trees" exposure reduction program which was executed over a limited period of the modeling period and hence should not impact the stationarity of the series going forward.

Based on these results, the Commercial loans – total commitments are modeled on their first differences.

7.4.3.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Commercial loans – total commitments. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.4.3.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 236: Summary of drivers for Commercial loans – total commitment

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Total commitment increases when general economic health improves	US GDP growth, US unemployment rate
	Imports	• Increased foreign trade grows demand for trade financing loans, and therefore total commitment for Commercial loans	Volume of imports
	Exports		Volume of exports
Financial economy	**Debt issuances**	• Bank lending may increase as a component of total corporate debt • Bond issuance acts as a substitute for bank loans	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets lead to greater lending to corporates	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates may lead to decreased appetite to offer commitments • Volatility and uncertainty may drive up demand if alternate sources of funding dry up	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to offer commitments	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.4.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Commercial loans – total commitment are statistically significant. The intercept is found to be statistically significant.

Table 222: Statistical significance tests of model and variables for Commercial loans – total commitment

Commercial loans – total commitment (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Corp_debt_outst_PQoQ	127.539	<1%	10%	Statistically significant
SP_Vol_PMoM	-5.124	<1%	10%	Statistically significant
Tnote_Vol_10yr_DMoML1	105.235	<1%	10%	Statistically significant
Intercept	-181.628	<1%	10%	Statistically significant

7.4.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

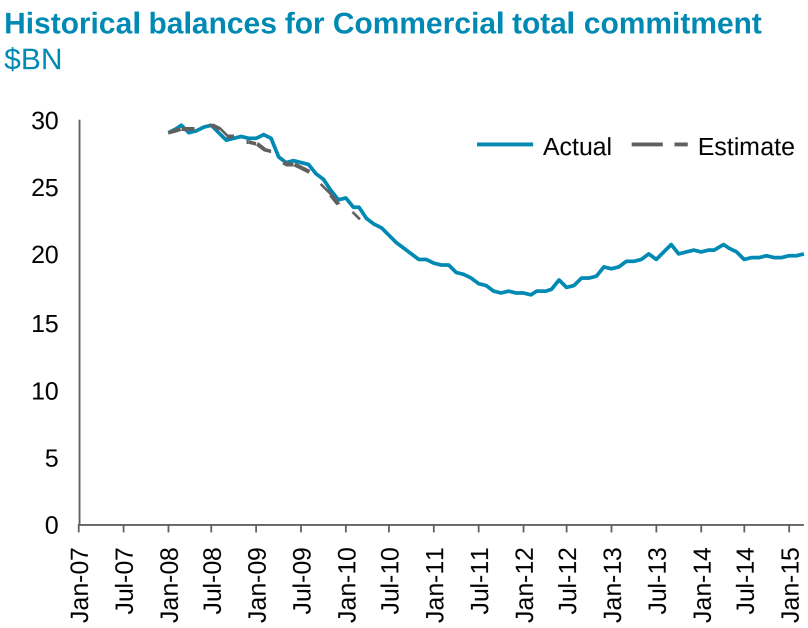
The diagnostic tests reviewed are exhibited below.

Table 223: Model Diagnostics for Commercial loans – total commitment

Commercial loans – total commitment (in USD MM) – Model diagnostics

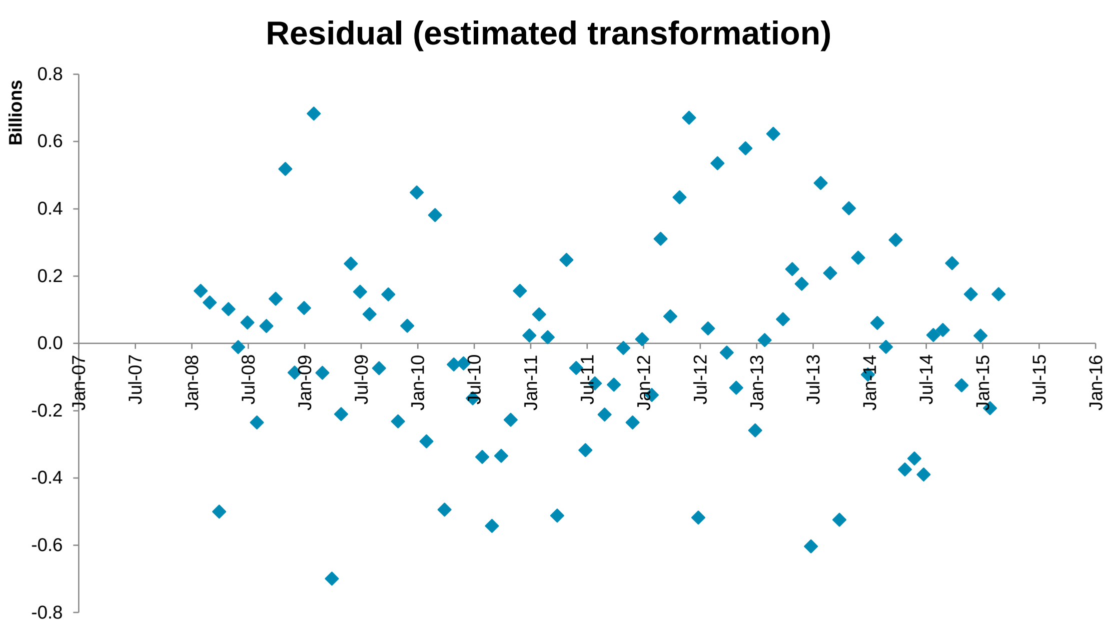
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	36%	-	-
	Adjusted R-squared	33%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.05	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	11%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.06	5	No multicollinearity
Linearity	RESET test	27%	10%	Linear specification appropriate

Figure 237: 9-quarter In-sample Prediction for Commercial loans – total commitment



The in-sample back test of the model starting from January 2008 tracks very closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

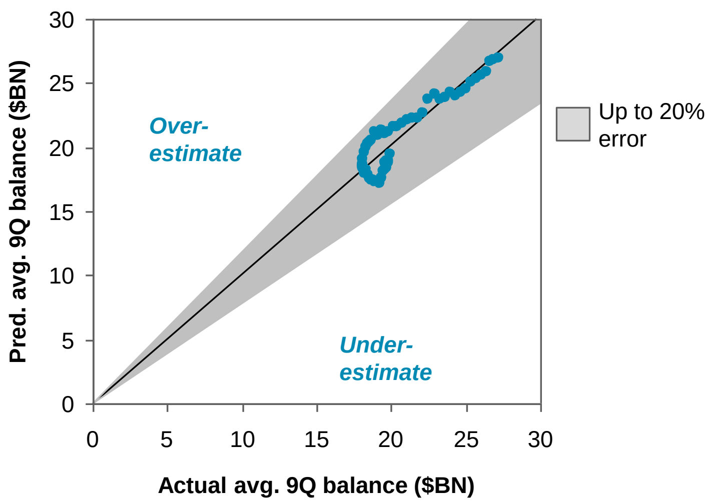
Figure 238: Residual Plot for Commercial loans – total commitment ($ BN)



As expected, the residuals appear to be randomly distributed around the horizontal axis.

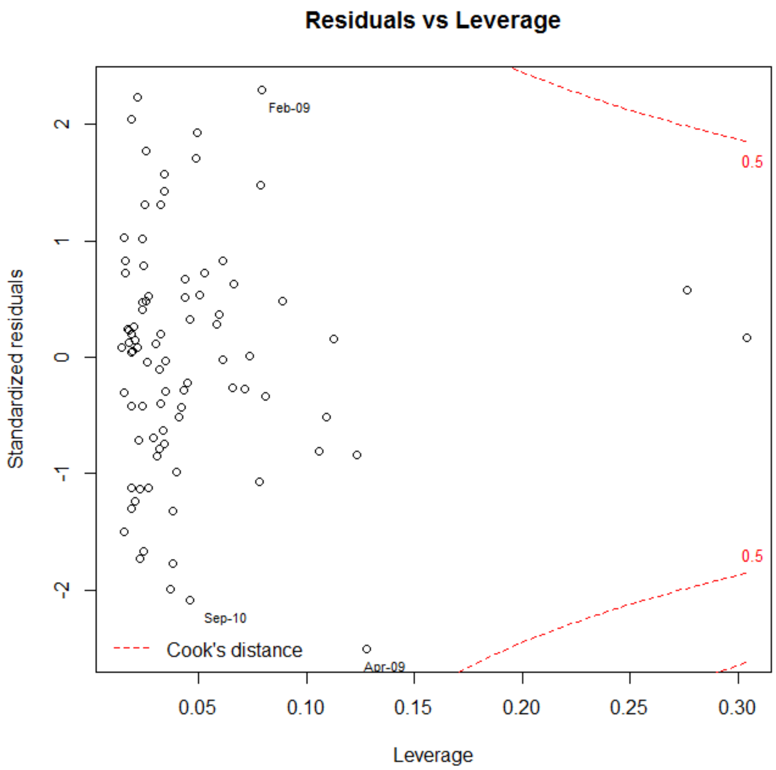
Figure 239: Estimation Scatterplot for Commercial loans – total commitment

Avg predicted vs. actual balances over 9Q windows
$BN, Starting months = JAN 08 – DEC 12 (60 obs)



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 240: Influential points Commercial loans total commitment



The segment has no highly influential points.

7.4.3.6. Model sensitivity

7.4.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 224: Sensitivity to changes to independent variables for Commercial loans – total commitment

Commercial loans – total commitment – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Corp_debt_outst_PQoQ	Percent change – QoQ	$ MM	0.46	1.47	0.17
SP_Vol_PMoM	Percent change – MoM	Index	-0.29	20.12	-0.11
Tnote_Vol_10yr_DMoML1	First difference – MoM	Index	0.32	1.13	0.12
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the corporate debt outstanding variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the corporate debt outstanding variable results in a 0.46 standard deviation ($0.17 BN) increase in the predicted monthly change of the total commitment for the Commercial loan segment.

7.4.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 225: Statistical sensitivity tests for Commercial loans – total commitment

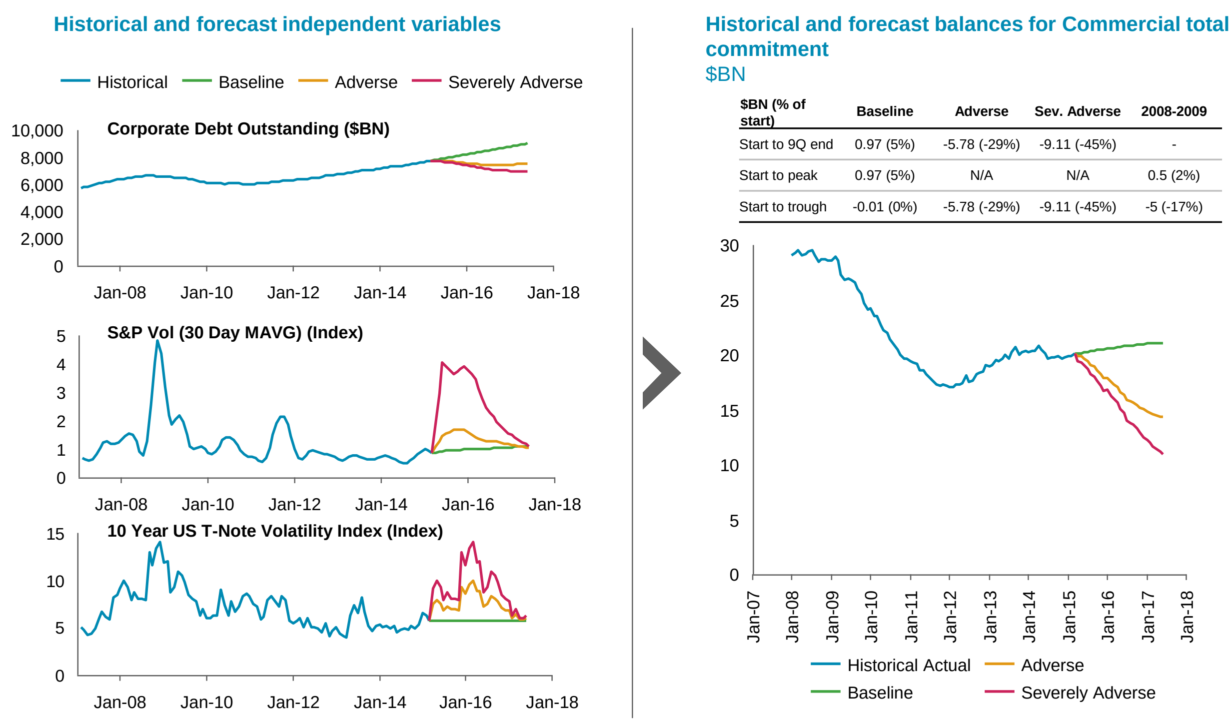
Commercial loans – total commitment (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Corp_debt_outst_PQoQ	127.539	125.596	0.43	Statistically insignificant
SP_Vol_PMoM	-5.124	-5.658	0.17	Statistically insignificant
Tnote_Vol_10yr_DMoML1	105.235	111.146	0.61	Statistically insignificant
Intercept	-181.628		0.43	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.69	Statistically insignificant

7.4.3.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 241: Final model forecast for Commercial loans – total commitment



The Working Group considered the forecast behavior for the selected Commercial loans – total commitment model as mostly reasonable; the decline under the severe recession scenario and the interest rate shock scenario were deemed to potentially be too steep.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant decline in total commitments. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations that both supply and demand for committed lines would decline under macroeconomic stress. The line of business suggested that although the magnitude of the decline is consistent with historical experience, it may be overstated and should be monitored closely when the final outputs for submission are generated. In particular, the observed drop in the post-crisis historical period also coincided with a general period of de-risking for BNY Mellon, in addition to reduction of redundant exposures across the legacy Bank of New York and legacy Mellon banks
- **Interest rate shock (Adverse) scenario**: The model predicts a significant decline, although not as large in magnitude as under the severe recession scenario. Similar to the decline under the severe recession scenario, the line of business suggested that this could potentially be too steep
- **Baseline scenario**: The model predicts that total commitments will grow at a slow rate roughly consistent with observed historical growth over the most recent several years. This was judged to be consistent with business intuition

7.4.4. Draw percentage

7.4.4.1. Summary

A statistically sound model was found for Commercial loans – draw percentage. Some management scrutiny may be needed for stress forecasts to ensure that the projected movements in balances are not overly extreme given management expectations.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the draw percentage time series for Commercial loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 226: Coefficient estimates for selected model for Commercial loans – draw percentage

Commercial loans – draw percentage (logit-transformed) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
S&P Volatility (30D MAVG)	% change – MoM	%	0.001034	0.23
Total Bond Issuance (ex MBS, gov)	% change – MoM, 1-month lag	%	-0.000366	-0.21
TED Spread	First difference – YoY	%	0.045760	-0.31
Intercept	None (level)	None	0.004405	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – 30-day moving average of VIX, which measures implied volatility of S&P 500 index options
- **Debt issuances –** Total US bond issuance volume, excluding MBS and government
- **Perceived credit risk** – TED spread, i.e. difference between 3-month LIBOR and 3-month T-bill interest rate

The intuition of these variables is as follows:

- The S&P volatility variable has a positive coefficient. When market conditions are uncertain, clients may increase their draws as alternate sources of funding may be less attractive or less available
- The total bond issuance variable has a negative coefficient. Bond issuance is an alternative source of funding and serves as a substitute for bank loans
- The TED spread variable has a positive coefficient. As perceived systemic credit risk and spreads increase, clients may increase their draws as alternate sources of funding may be less attractive or less available

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs. The line of business also noted that total commercial paper volumes may be a stronger explanatory variable than total bond issuance volumes, which is a potential future model enhancement.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 242: Candidate models for Commercial loans – draw percentage

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Corporate credit		Baa to Treasury Spread (Diff MoM)			Baa to Treasury Spread (Diff MoM)
Debt issuances	Total Bond Issuance (ex MBS, Gov) (% MoM, 1M Lag)	Total Bond Issuance (ex MBS, Gov) (% MoM, 1M Lag)	Corporate Debt Outstanding (% MoM)		Total Bond Issuance (ex MBS, Gov) (% MoM, 1M Lag)
Equity markets			DJI (% MoM)	DJI (% MoM)	
General economic health				Unemployment Rate (Diff MoM, 1M Lag)	
Market volatility / uncertainty (equity)	S&P Vol (30D MAVG) (%MoM)				Market Vol (Diff YoY)
Perceived credit risk	TED Spread (Diff YoY)	TED Spread (Diff YoY)	TED Spread (Diff MoM)	TED Spread (Diff MoM)	
Variation in levels explained through estimated logit first differences	**90%**	**90%**	**94%**	**88%**	**78%**
R-squared (differences)	**23%**	**23%**	**23%**	**22%**	**20%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.4.4.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.4.4.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The logit-transformed draw percentage time series for the Commercial loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the logit-transformed levels are tested using unit root and stationarity tests including a time trend.

The first differences of the logit-transformed levels, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 227: Unit root tests and stationarity tests including a trend variable on levels

Commercial loans – draw percentage – Unit root test with trend on logit-transformed level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	3	-1.8	>0.10	Fail to reject unit root
Phillips-Perron	1	-0.5	0.98	Fail to reject unit root
KPSS	5	0.26	<0.01	Reject stationarity

Table 228: Unit root tests and stationarity tests including a constant on first differences

Commercial loans – draw percentage – Single mean unit root test on logit-transformed first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	4	-3.3	0.02	Reject unit root
Phillips-Perron	1	-8.9	<0.01	Reject unit root
KPSS	1	0.29	0.14	Fail to reject stationarity

Stationarity tests for Commercial loans – draw percentage logit uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first difference is stationary.

Based on these results, Commercial loans – draw percentage segment is modeled on first differences.

7.4.4.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Commercial loans – draw percentage. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.4.4.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 243: Summary of drivers for Commercial loans – draw percentage

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When the general economy is under stress, borrowers draw on committed lines more often to replace alternative sources of funding that are drying up	US GDP growth, US unemployment rate
Financial economy	**Equity markets**	• Weakening equity markets are correlated with stress in economic conditions, which leads to increased draws	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in market conditions may be a sign of stress in overall economic conditions, leading to increased draws	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• As systemic credit risk rises, draws may either increase as alternative funding options become less attractive, or decrease as overall lending slows down	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Borrowers may be more willing to draw from commitments at lower rates	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit	• Increasing corporate yields and spreads makes borrowing more expensive, leading to lower draws	Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.4.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Commercial loans – draw percentage are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 229: Statistical significance tests of model and variables for Commercial loans – draw percentage

Commercial loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**HAC P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
S&P Volatility (30D MAVG)	0.001034	<1%	10%	Statistically significant
Total Bond Issuance (ex MBS, gov)	-0.000366	2%	10%	Statistically significant
TED Spread	0.045760	<1%	10%	Statistically significant
Intercept	0.004405	64%	10%	Statistically not significant

7.4.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

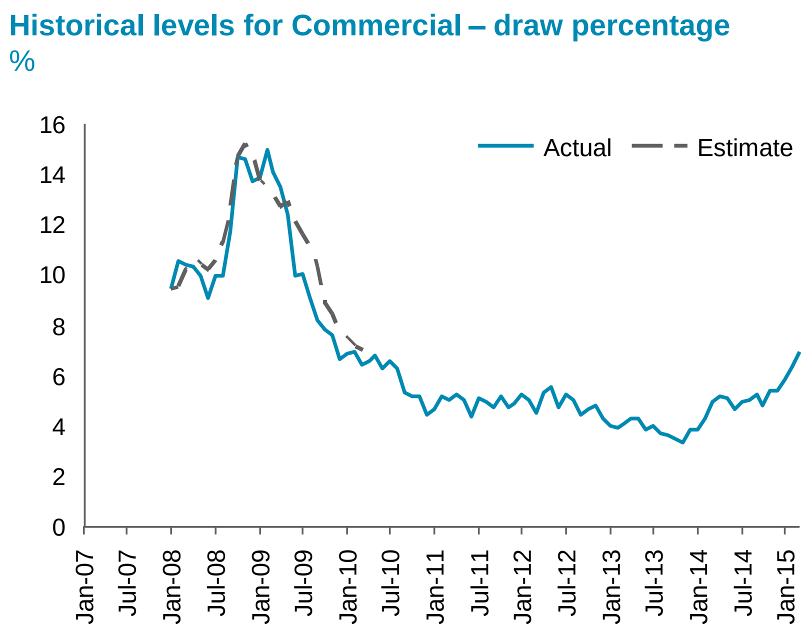
- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences of logit transform), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

Table 230: Model Diagnostics for Commercial loans – draw percentage

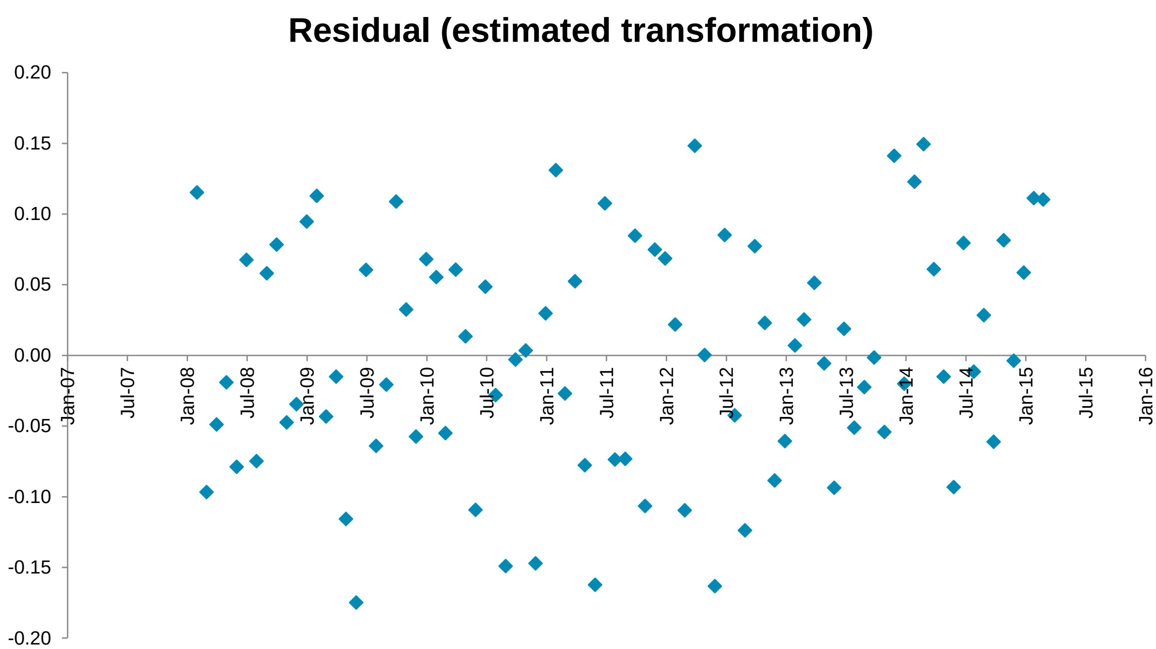
Commercial loans – draw percentage (logit-transformed) – Model diagnostics				
Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	23%	-	-
	Adjusted R-squared	20%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.05	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.04	5	No multicollinearity
Linearity	RESET test	13%	10%	Linear specification appropriate

Figure 244: 9-quarter In-sample Prediction for Commercial loans – draw percentage



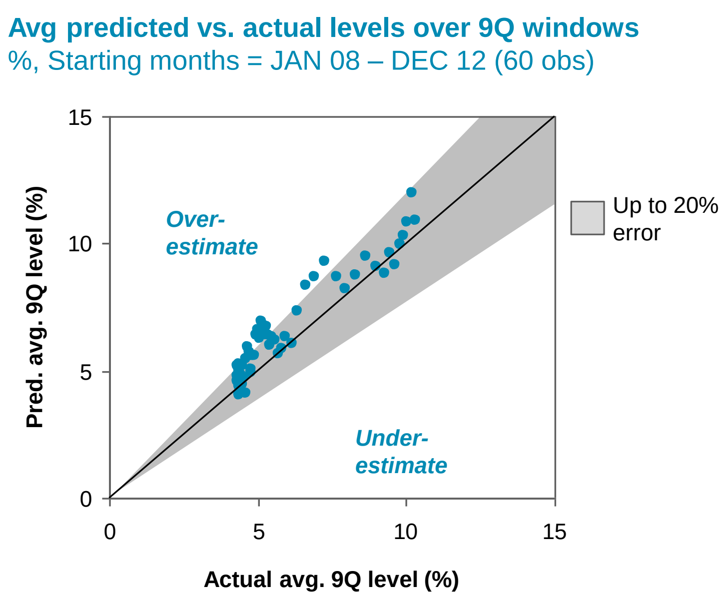
The in-sample back test of the model starting from January 2008 tracks very closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

Figure 245: Residual Plot for Commercial loans – draw percentage



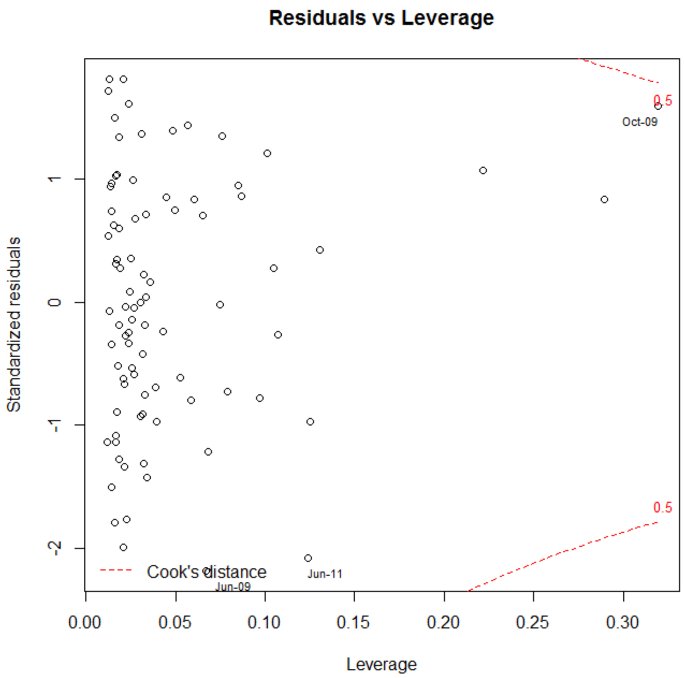
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 246: Estimation Scatterplot for Commercial loans – draw percentage



Estimated average 9-quarter levels generally tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with most estimated average values within or close to 20% of actual average values.

Figure 247: Influential points for Commercial loans draw %



The segment has no highly influential points.

7.4.4.6. Model sensitivity

7.4.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the dependent variable due to a one standard deviation increase in an independent variable.

Due to the usage of the logit transformation, the relationship between the independent variables and the level of the draw percentage is non-linear. Therefore, a one standard deviation shift in an independent variable will have different impacts on the actual draw percentage, depending on the level of the draw percentage. Sensitivity of the level to movements in independent variables will decrease as the level approaches 0% or 100%, since applying the inverse logit transformation to the dependent variable must produce a level that is bounded between 0% and 100%.

Table 231: Sensitivity to changes to independent variables for Commercial loans – draw percentage

Commercial loans – draw percentage (in USD MM) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
S&P Volatility (30D MAVG)	% change – MoM	%	0.23	20.12
Total Bond Issuance (ex MBS, gov)	% change – MoM, 1-month lag	%	-0.21	51.99
TED Spread	First difference – YoY	%	-0.31	0.62
Intercept	None (level)	None	N/A	N/A

In the selected model for Commercial loans – draw percentage, the TED spread variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the TED spread variable results in a 0.31 standard deviation decrease in the predicted monthly change of the logit-transformed draw percentage for the Commercial loan segment.

7.4.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. The TED spread variable is significant which may suggest the model might not remain stable when removing observations from the development data. This segment will be paid attention to in the on-going monitoring.

Table 232: Statistical sensitivity tests for Commercial loans – draw percentage

Commercial loans – draw percentage – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
SP_Vol_PMoM	0.001	0.001	0.91	Statistically insignificant
Tot_bond_exMBSgov_PMoML1	0.000	0.000	0.75	Statistically insignificant
TED_Spread_DYoY	0.046	0.043	0.01	Statistically significant
Intercept	0.004		0.00	Statistically significant
Chow-test on all shortened period coefficients	-	-	0.00	Statistically significant

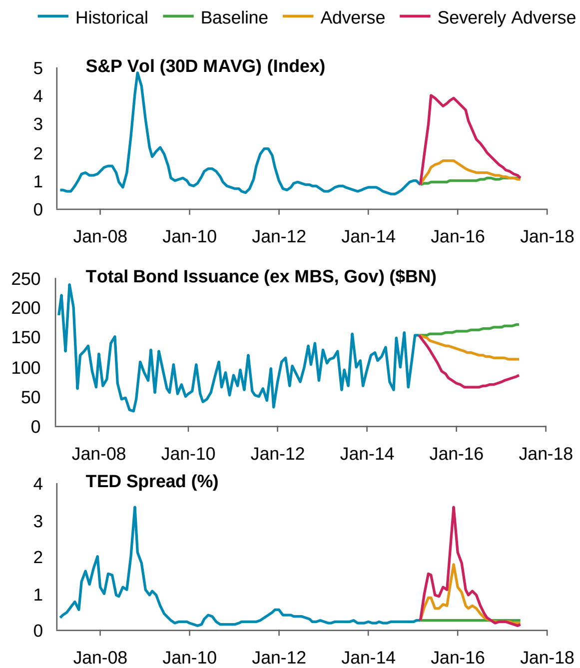
7.4.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 248: Final model forecast for Commercial loans – draw percentage

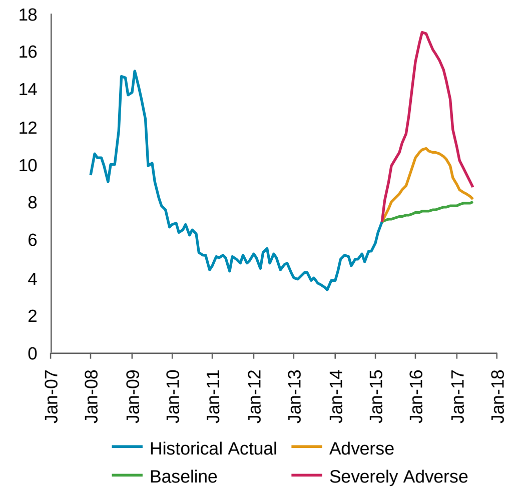
Historical and forecast independent variables



Historical and forecast levels for Commercial draw percentage

%

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	1.06%	1.22%	1.83%	-
Start to peak	1.06%	3.88%	10.08%	5.53%
Start to trough	N/A	N/A	N/A	-2.76%



The Working Group determined that the forecast behavior for the selected Commercial loans – draw percentage model is directionally intuitive, but may require scrutiny during management review to decrease the magnitude of observed spikes under stress scenarios.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant spike in draw percentage, followed by a reversion to levels closer to current levels. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations that under severe stress, borrowers will increase draws on their committed facilities for contingency funding. This is also consistent with observed behavior during the 2008–2009 financial crisis. However, the Working Group and line of business deemed the magnitude of the spike to be overly large, and thus this model's outputs should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario**: The model predicts a rise and decline in draw percentage, directionally similar to the severe recession scenario but lower in magnitude. Similar to severe recession scenario, the line of business suggested that the magnitude of the rise may be overstate
- **Baseline scenario**: The model predicts that draw percentage will rise slowly, ending in nine quarters at a level near the starting level. This was judged to be consistent with business intuition

7.4.5. Letter of Credit usage percentage

7.4.5.1. Summary

A statistically sound model that is consistent with business intuition was found for Commercial loans – Letters of Credit. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the Letter of Credit usage percentage time series for Commercial loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 233: Coefficient estimates for selected model for Commercial loans – Letter of Credit usage percentage

Commercial loans – Letter of Credit usage percentage (logit-transformed) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Baa to Treasury spread	First difference – YoY	%	0.006746	0.17
5-Year Treasury rate	First difference – MoM, 1-month lag	%	0.051275	0.15
Intercept	None (level)	None	-0.008247	N/A

The model contains the following drivers and variables:

- **Corporate credit** – Spread of Baa corporate bond yield to 10-year Treasury yield
- **Long-term rates** – 5-year US Treasury Note rate

The intuition of these variables is as follows:

- The Baa to Treasury spread variable has a positive coefficient. Widening spreads can indicate deterioration of corporate credit, which can lead to increased demand for Letters of Credit for credit enhancement
- The 5-year Treasury rate variable has a positive coefficient. This variable is interpreted as an indicator for economic recovery, and as expectations of future economic conditions improve, greater volume of transactional activity may increase the volume of Letters of Credit used

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 249: Candidate models for Commercial loans – Letter of Credit usage percentage

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Corporate credit		Baa to Treasury Spread (Diff YoY)	Baa to Treasury Spread (Diff QoQ)		Baa to Treasury Spread (Diff YoY)
Equity markets		KBW Bank Index (% MoM)		MSCI WORLD Index (% MoM)	
Long-term rates	5Y US Swap (Diff MoM)				5Y Treasury (Diff MoM, 1M Lag)
Market volatility/ uncertainty (equity)	S&P Vol (30D MAVG) (Diff MoM)			S&P Vol (30D MAVG) (% MoM)	
Short-term rates			3M Treasury (Diff MoM)		
Variation in levels explained through estimated logit first differences	**82%**	**86%**	**75%**	**78%**	**88%**
R-squared (differences)	**5%**	**4%**	**4%**	**4%**	**4%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.4.5.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.4.5.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The logit-transformed Letter of Credit usage percentage time series for the Commercial loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the logit-transformed levels are tested using unit root and stationarity tests including a time trend.

The first differences of the logit-transformed levels, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 234: Unit root tests and stationarity tests including a trend variable on levels

Commercial loans – Letter of Credit usage percentage – Unit root test with trend on logit-transformed level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-1.3	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.4	0.84	Fail to reject unit root
KPSS	5	0.25	<0.01	Reject stationarity

Table 235: Unit root tests and stationarity tests including a constant on first differences

Commercial loans – Letter of Credit usage percentage – Single mean unit root test on logit-transformed first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	0	-11	<0.01	Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	1	0.14	0.43	Fail to reject stationarity

Stationarity tests for Commercial loans – Letter of Credit usage percentage logit uniformly reject stationarity across all three tests. These results suggest these are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Commercial loans – Letter of Credit usage percentage logit are modeled on their first differences.

7.4.5.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Commercial loans – Letter of Credit usage percentage. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.4.5.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 250: Summary of drivers for Commercial loans – Letter of Credit usage percentage

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When general economic conditions deteriorate, demand for Letters of Credit increases to provide credit enhancement • Alternatively, stronger economic conditions may drive up demand for Letters of Credit as transactional activity increases	US GDP growth, US unemployment rate
	Imports	• As volume of foreign trade increases, more Letters of Credit will be taken out	Volume of imports
	Exports		Volume of exports
Financial economy	**Equity markets**	• When equity markets are weak or volatile, demand for Letters of Credit increases to provide credit enhancement	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)		VIX, market volatility index
	Market volatility/ uncertainty (rates)	• When rates are volatile, demand for Letters of Credit increases to provide credit enhancement	10-year US T-note volatility index
	Perceived credit risk	• When perceived credit risk increases, demand for Letters of Credit increases to provide credit enhancement	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates are associated with improving economy, which can either increase Letter of Credit usage by increasing transactional activity, or decrease it by reducing the need for credit enhancement	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit	• Widening corporate credit spreads may indicate increased credit risk, increasing demand for Letters of Credit to provide credit enhancement	Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.4.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Commercial loans – Letter of Credit usage percentage are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 236: Statistical significance tests of model and variables for Commercial loans – Letter of Credit usage percentage

Commercial loans – Letter of Credit usage percentage (logit-transformed) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Baa to Treasury spread	0.006746	<1%	10%	Statistically significant
5-Year Treasury rate	0.051275	10%	10%	Statistically significant
Intercept	-0.008247	16%	10%	Statistically not significant

7.4.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences of logit transform), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

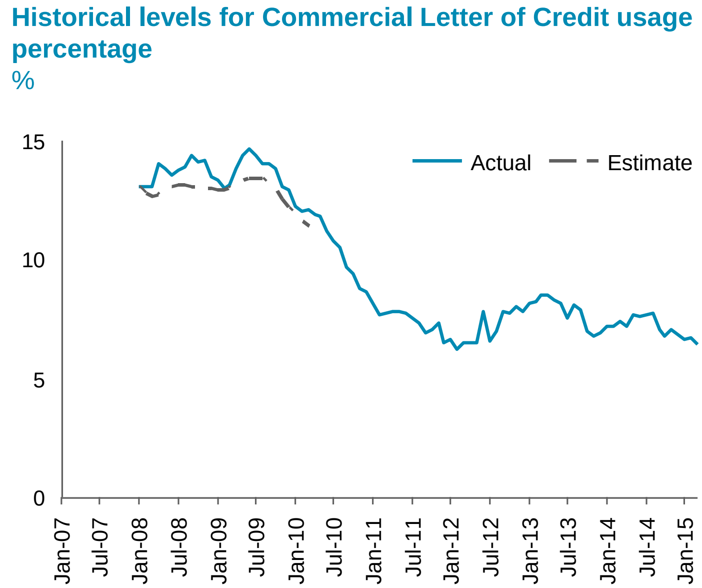
The diagnostic tests reviewed are exhibited below.

Table 237: Model Diagnostics for Commercial loans – Letter of Credit usage percentage

Commercial loans – Letter of Credit usage percentage (logit-transformed) – Model diagnostics

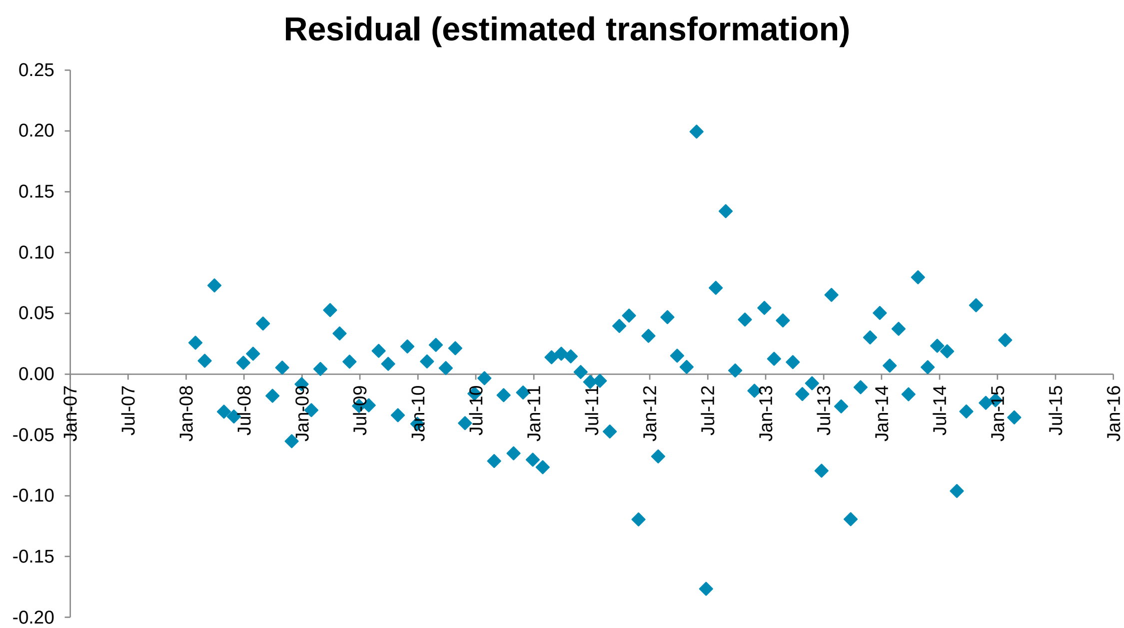
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	4%	-	-
	Adjusted R-squared	1%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.75	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	8%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.07	5	No multicollinearity
Linearity	RESET test	57%	10%	Linear specification appropriate

Figure 251: 9-quarter In-sample Prediction for Commercial loans – Letter of Credit usage percentage



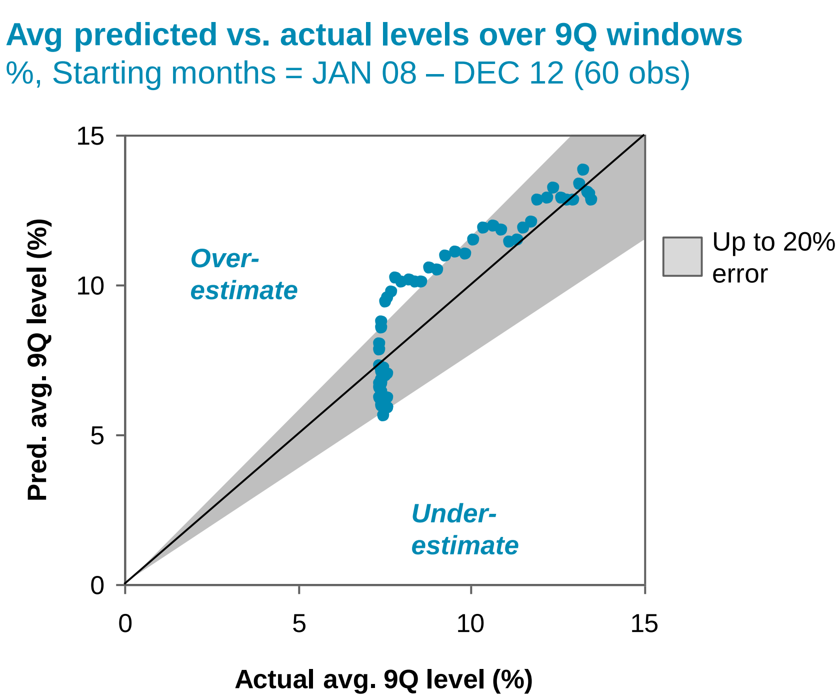
The in-sample back test of the model starting from January 2008 tracks fairly closely with the actual levels, capturing the correct directional behavior. The forecasted increases in Letter of Credit usage percentage are smaller in magnitude than the observed behavior.

Figure 252: Residual Plot for Commercial loans – Letter of Credit usage percentage



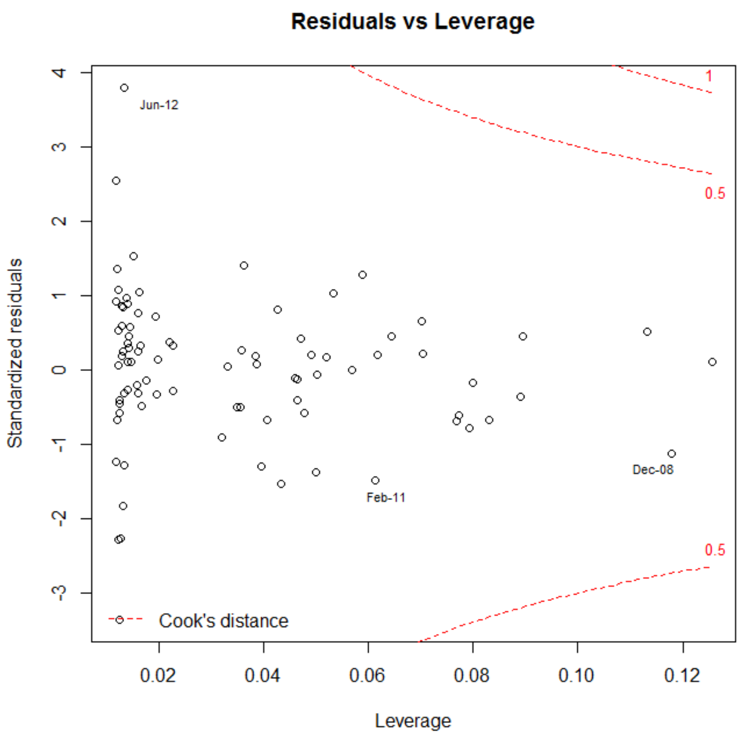
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 253: Estimation Scatterplot for Commercial loans – Letter of Credit usage percentage



Estimated average 9-quarter levels generally tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with most estimated average values within or close to 20% of actual average values.

Figure 254: Influential points for Commercial loans letter of credit usage



The segment has no highly influential points.

7.4.5.6. Model sensitivity

7.4.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the dependent variable due to a one standard deviation increase in an independent variable.

Due to the usage of the logit transformation, the relationship between the independent variables and the level of the draw percentage is non-linear. Therefore, a one standard deviation shift in an independent variable will have different impacts on the actual Letter of Credit usage percentage, depending on the level of the Letter of Credit usage percentage. Sensitivity of the level to movements in independent variables will decrease as the level approaches 0% or 100%, since applying the inverse logit transformation to the dependent variable must produce a level that is bounded between 0% and 100%.

Table 238: Sensitivity to changes to independent variables for Commercial loans – Letter of Credit usage percentage

Commercial loans – LC usage percentage (in USD MM) – model sensitivity				
Independent variable	**Transformation**	**Unit**	**Standardized coefficient**	**Std. dev of independent variable**
Baa to Treasury spread	First difference – YoY	%	0.17	1.31
5-Year Treasury rate	First difference – MoM, 1-month lag	%	0.15	0.16
Intercept	None (level)	None	N/A	N/A

In the selected model for Commercial loans – Letter of Credit usage percentage, the Baa to Treasury spread variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Baa to Treasury spread variable results in a 0.17 standard deviation increase in the predicted monthly change of the logit-transformed Letter of Credit usage percentage for the Commercial loan segment.

7.4.5.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. The coefficient of Baa to Treasury spread is significant individually.

Table 239: Statistical sensitivity tests for Commercial loans – Letter of Credit usage percentage

Commercial loans – Letter of Credit usage percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
Baa to Treasury spread	0.006746	0.007	0.10	Statistically significant
5-Year Treasury rate	0.051275	0.055	0.31	Statistically insignificant
Intercept	-0.008247		0.14	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.35	Statistically insignificant

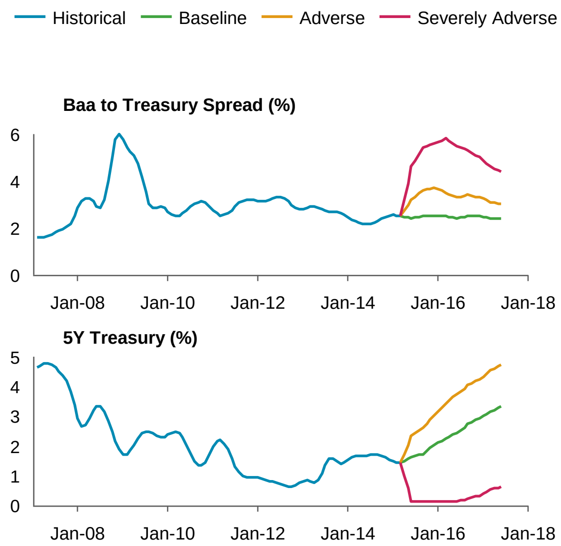
7.4.5.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 255: Final model forecast for Commercial loans – Letter of Credit usage percentage

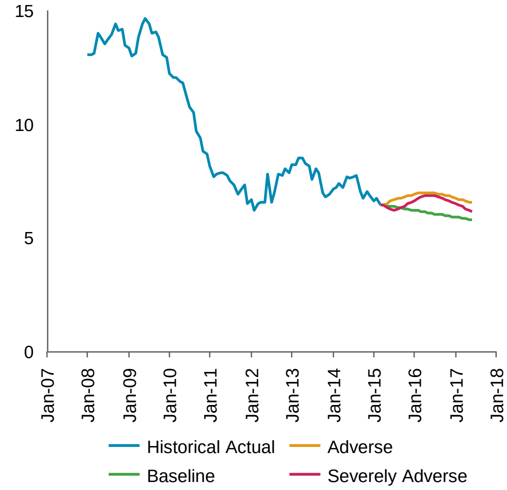
Historical and forecast independent variables



Historical and forecast levels for Commercial Letter of Credit usage percentage

%

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-0.70%	0.08%	-0.35%	-
Start to peak	N/A	0.54%	0.41%	1.63%
Start to trough	-0.70%	-0.03%	-0.35%	-0.08%



The Working Group considered the forecast behavior for the selected Commercial loans – Letter of Credit usage percentage model as reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts a very small rise in Letter of Credit usage, followed by a decline back to levels comparable to the start of the forecast horizon. This is consistent with business intuition that there could be a greater demand for Letters of Credit as credit conditions worsen with overall deterioration of the macroeconomic environment
- **Interest rate shock (Adverse) scenario**: The model predicts a very small rise in Letter of Credit usage, followed by a decline back to levels comparable to the start of the forecast horizon. This is consistent with business intuition that there could be a greater demand for Letters of Credit as credit conditions worsen with overall deterioration of the macroeconomic environment
- **Baseline scenario**: The model predicts a slight decline in Letter of Credit usage. The stable level of Letter of Credit usage is consistent with business intuition, as BNY Mellon is currently not actively encouraging borrowers to take out Letters of Credit, preferring to extend loans over Letters of Credit due to Supplementary Leverage Ratio constraints

7.4.6. Closed-end loans

7.4.6.1. Summary

A statistically sound model that is consistent with business intuition was found for Commercial loans – closed-end loans. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the closed-end loans time series for Commercial loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 240: Coefficient estimates for selected model for Commercial loans – closed-end loans

Commercial loans – closed-end loans (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Baa to Treasury spread	First difference – YoY	%	12.53	0.18
Total Bond Issuance (ex mortgage, Treasuries)	% change – MoM	%	-0.82	-0.36
TED spread	First difference – QoQ	%	74.03	0.37
Intercept	None (level)	$ MM	-9.55	N/A

The model contains the following drivers and variables:

- **Corporate credit** – Spread of Baa corporate bond yield to 10-year Treasury yield
- **Debt issuances –** Total US bond issuance volume, excluding mortgages and Treasuries
- **Perceived credit risk** – TED spread, i.e. difference between 3-month LIBOR and 3-month T-bill interest rate

The intuition of these variables is as follows:

- The Baa to Treasury spread variable has a positive coefficient. Widening spreads can indicate stress in credit markets, which can lead to increased demand for loans from BNY Mellon to replace alternative sources of funding
- The total bond issuance variable has a negative coefficient. Bond issuance is an alternative source of funding and serves as a substitute for bank loans
- The TED spread variable has a positive coefficient. As perceived systemic credit risk and spreads increase, borrowers may have greater demand for loans from BNY Mellon to replace alternative sources of funding

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 256: Candidate models for Commercial loans – closed-end loans

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Corporate credit		Baa Corporate Yield (Diff MoM)		Baa to Treasury Spread (Diff YoY)	Baa Corporate Yield (Diff MoM)
Debt issuances	Total Bond Issuance (ex Mortgage, Treasuries) (% MoM)	Corporate Debt Outstanding (% MoM, 1M Lag)		Total Bond Issuance (ex Mortgage, Treasuries) (% MoM)	Total Bond Issuance (ex Mortgage, Treasuries) (% MoM)
Equity markets			KBW Bank Index (% MoM)		
Imports	Real Imports (% MoM, 1M Lag)				Nominal Imports (% YoY)
Market volatility / uncertainty (equity)		Market Vol (% MoM)	Market Vol (% MoM)		
Perceived credit risk	TED Spread (Diff QoQ)			TED Spread (Diff QoQ)	
Yield spread			3M to 10Y T-Spread (Level, 1M Lag)		
Variation in balances explained through estimated first differences	**69%**	**90%**	**90%**	**66%**	**68%**
R-squared (differences)	**30%**	**29%**	**29%**	**28%**	**27%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.4.6.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.4.6.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The closed-end loan time series for the Commercial loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 241: Unit root tests and stationarity tests including a trend variable on levels

Commercial loans – closed-end loans – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-0.9	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.1	0.92	Fail to reject unit root
KPSS	5	0.34	<0.01	Reject stationarity

Table 242: Unit root tests and stationarity tests including a constant on first differences

Commercial loans – closed-end loans – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-8.5	<0.01	Reject unit root
Phillips-Perron	1	-8.5	<0.01	Reject unit root
KPSS	0	0.35	0.1	Fail to reject stationarity

Stationarity tests for Commercial loans – closed-end loans levels consistent results: The ADF and PP tests reject a unit root and the KPSS test rejects stationarity. These results suggest the levels are likely non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Commercial loans – closed-end loans segment is modeled on first differences.

7.4.6.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Commercial loans – closed-end loans. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.4.6.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 257: Summary of drivers for Commercial loans – closed-end loans

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When the general economy is under stress, borrowers may take out bank loans to replace alternative sources of funding that are drying up	US GDP growth, US unemployment rate
Financial economy	**Equity markets**	• Weakening equity markets are correlated with stress in economic conditions, which leads to increased demand • Alternatively, strong equity markets could also lead to increased demand driven by general economic growth	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Debt issuances	• Bank lending may increase as a component of total corporate debt • Bond issuance acts as a substitute for bank loans	Corporate debt outstanding, total bond issuance
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in market conditions may be a sign of stress in overall economic conditions, leading to increased bank lending as access to alternative funding dries up	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• As systemic credit risk rises, lending may either increase driven by demand as alternative funding options become less attractive, or decrease driven by supply as overall lending slows down	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.4.6.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Commercial loans – closed-end loans are statistically significant. The intercept is found to be statistically insignificant.

Table 243: Statistical significance tests of model and variables for Commercial loans – closed-end loans

Commercial loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Baa to Treasury spread	12.53	5%	10%	Statistically significant
Total Bond Issuance (ex mortgage, Treasuries)	-0.82	<1%	10%	Statistically significant
TED spread	74.03	<1%	10%	Statistically significant
Intercept	-9.55	27%	10%	Statistically not significant

7.4.6.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

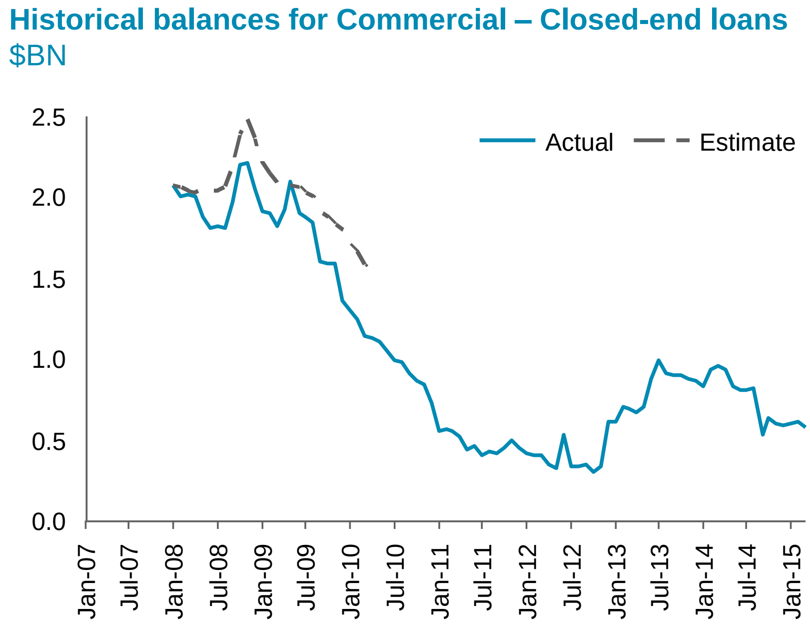
The diagnostic tests reviewed are exhibited below.

Table 244: Model Diagnostics for Commercial loans – closed-end loans

Commercial loans – closed-end loans (in USD MM) – Model diagnostics				
Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	28%	-	-
	Adjusted R-squared	25%	-	-
Heteroskedasticity	Breusch-Pagan test (P-value)	0.78	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum P-value up to 4 lags)	10%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.01	5	No multicollinearity

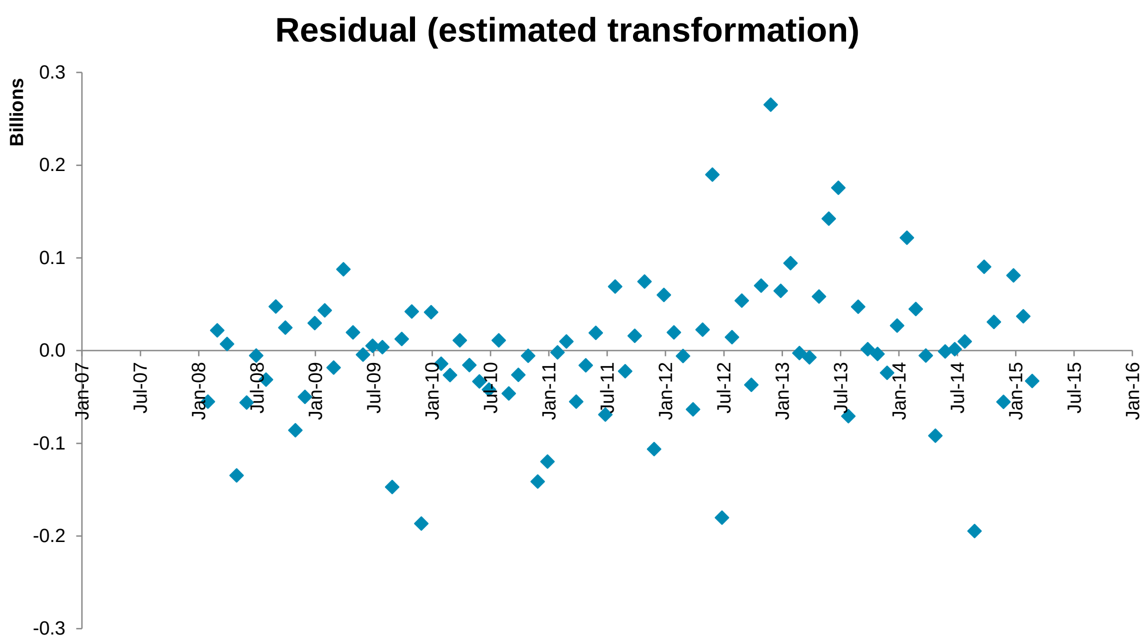
Linearity	RESET test	92%	10%	Linear specification appropriate

Figure 258: 9-quarter In-sample Prediction for Commercial loans – closed-end loans



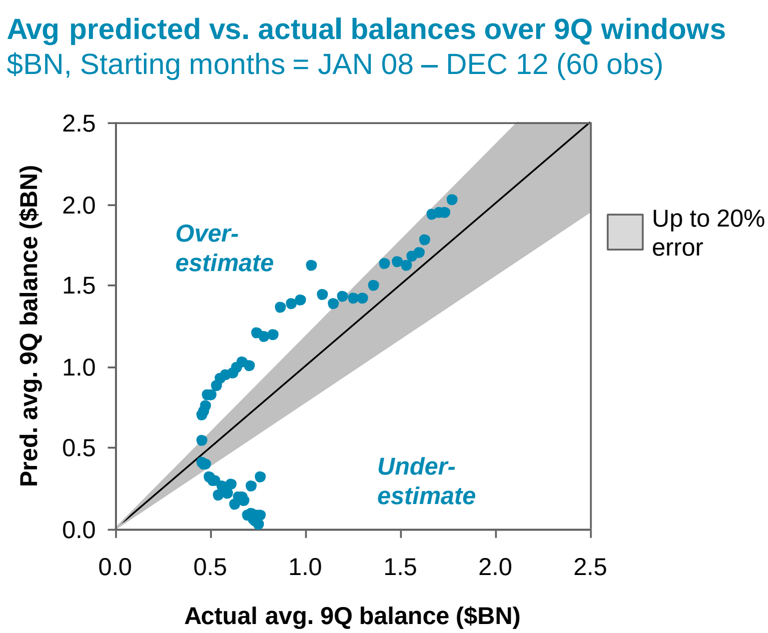
The in-sample back test of the model starting from January 2008 tracks fairly closely with the actual levels, generally capturing the correct directional behavior. The model misses a dip in closed-end loans in mid-2008, which leads to a slight overestimation of balances for the remaining months of the forecast.

Figure 259: Residual Plot for Commercial loans – closed-end loans ($ BN)



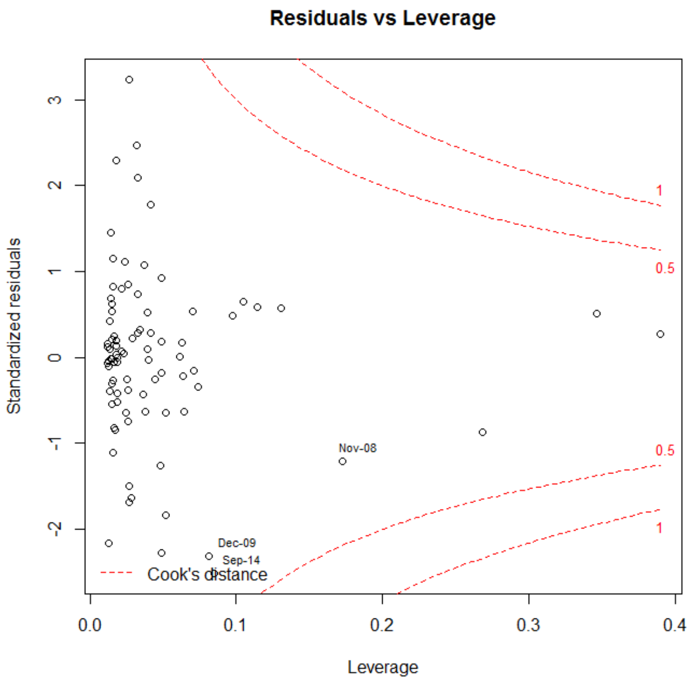
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 260: Estimation Scatterplot for Commercial loans – closed-end loans



For a significant number of different 9-quarter forecast windows, the model either overestimates or underestimates the average estimated balances over the forecast window. The model does not capture the full magnitude of the decline in balances from 2009 to 2011, in part because this time period is characterized by active management strategy to de-risk the balance sheet and reduce redundant exposures across legacy Bank of New York and legacy Mellon portfolios.

Figure 261: Influential points for commercial closed end loans



The segment has no highly influential points.

7.4.6.6. Model sensitivity

7.4.6.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 245: Sensitivity to changes to independent variables for Commercial loans – closed-end loans

Commercial loans – closed-end loans – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Baa to Treasury spread	First difference – YoY	%	0.18	1.31	0.02
Total Bond Issuance (ex mortgage, Treasuries)	% change – MoM	%	-0.36	40.83	-0.03
TED spread	First difference – QoQ	%	0.37	0.45	0.03
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model for Commercial loans – closed-end loans, the TED spread variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the TED spread variable results in a 0.37 standard deviation ($0.03 BN) increase in the predicted monthly change of the closed-end loans for the Commercial loan segment.

7.4.6.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 246: Statistical sensitivity tests for Commercial loans – closed-end loans

Commercial loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

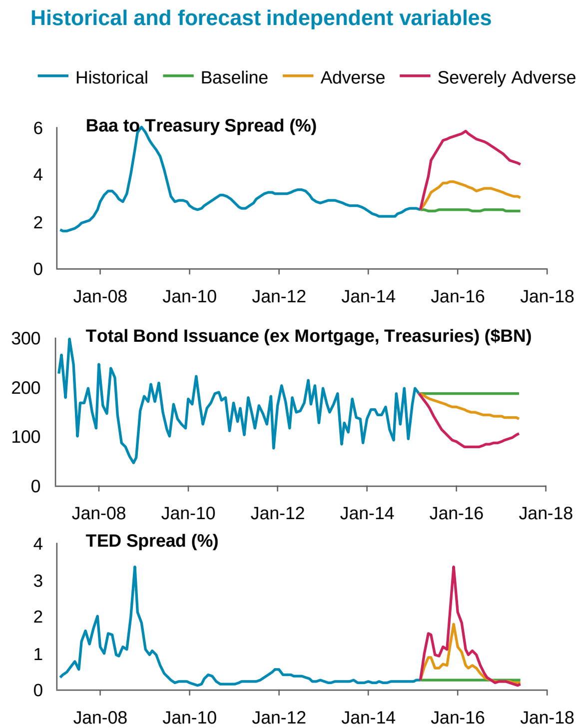
Tested independent variable	Original coefficient estimate	Sum of coefficients	P-value of shortened period coefficient	Conclusion
Baa to Treasury spread	12.53	14.141	0.76	Statistically insignificant
Total Bond Issuance (ex mortgage, Treasuries)	-0.82	-0.792	0.58	Statistically significant
TED spread	74.03	72.074	0.27	Statistically insignificant
Intercept	-9.55		0.62	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.60	Statistically insignificant

7.4.6.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

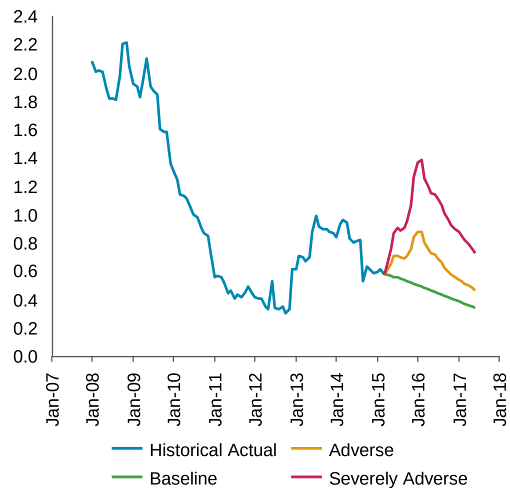
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 262: Final model forecast for Commercial loans – closed-end loans



Historical and forecast balances for Commercial – Closed-end loans
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-0.24 (-42%)	-0.11 (-19%)	0.15 (26%)	-
Start to peak	N/A	0.3 (52%)	0.81 (140%)	0.14 (7%)
Start to trough	-0.24 (-42%)	-0.11 (-19%)	N/A	-0.72 (-35%)



The Working Group considered the forecast behavior for the selected Commercial loans – closed-end loans model as reasonable.

- **Severe recession (Severely Adverse) scenario:** Closed-end loan balances grow rapidly before declining almost to original levels by the end of the 9-quarter forecast horizon. This behavior is directionally consistent with the expectation that clients will require more funding through loans at the start of a severe macroeconomic downturn, which then moderates as alternative, more attractive sources of funding become more accessible. The line of business indicated that the magnitude of the increase is reasonable
- **Interest rate shock (Adverse) scenario**: Similar to the severe recessions scenario, closed-end loan balances rise and then fall, although the spike is much milder in this case. The line of business indicated that this behavior is reasonable
- **Baseline scenario**: Closed-end loan balances remain relatively stable, with a slight decline. The line of business indicated that this behavior is reasonable

7.4.7. Model limitations

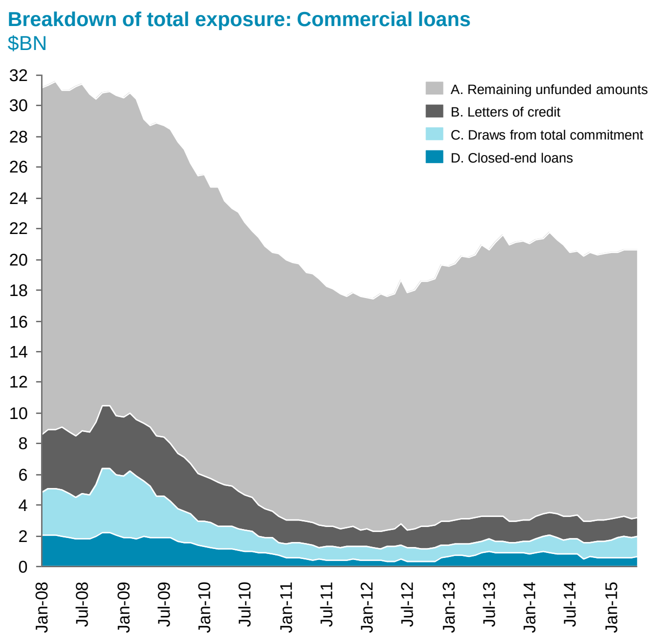
As discussed in Section 7.2, BNY Mellon underwent a period of balance sheet de-risking following the 2008–2009 financial crisis, concurrent with contraction in the overall lending market during this period. However, this period also coincides with the integration of the legacy Bank of New York and Mellon portfolios, which was characterized by active management decision to reduce redundant exposures shared across both legacy banks. As a result, the observed changes in forecast quantities reflect movements due to both the macroeconomic environment as well as factors idiosyncratic to BNY Mellon. The historical time series from the development data commingles both of these effects. Therefore, the developed models are potentially over-sensitive to changes in macroeconomic variables, and could produce more extreme forecasts than would be intuitively expected.

7.4.8. Synthesis of forecast results

After forecasts have been generated from the models, a few additional calculations are required to obtain the desired balance forecasts shown in the figure below:

- Balances for funded draws from commitments (Quantity C in figure) can calculated as the product of total commitment and draw percentage
- Unfunded Letter of Credit amounts (Quantity B in figure) can be calculated as the product of total commitment and Letter of Credit usage percentage
- Unused unfunded commitments (Quantity A in figure) can be calculated as total commitments minus balances for funded draws minus unfunded Letter of Credit amounts
- Total funded loan balances can be calculated as the sum of balances for funded draws plus balances for closed-end loans (Quantity C + Quantity D in figure)

Figure 263: Breakdown of total exposure for Commercial loans

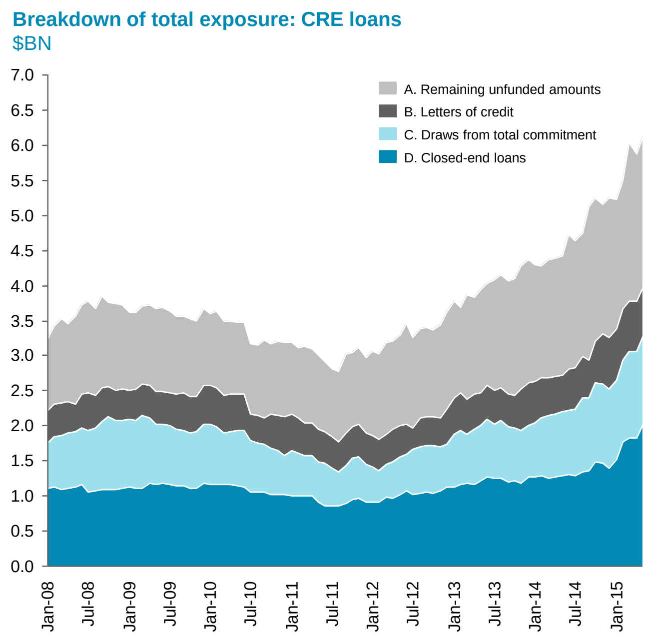


7.5. Commercial Real Estate loans

7.5.1. Business overview

BNY Mellon originates and purchases loans as part of its ongoing business. The Commercial Real Estate (CRE) loan segment comprises a relatively small loan type for BNY Mellon as measured by total commitment, compared to other segments like FI loans and Commercial loans: as of April 30, 2015, BNY Mellon has $3.7 BN in funded CRE loans plus $2.8 BN in unfunded commitments, including Letters of Credit. The figure below shows the breakdown over time for total exposure in this segment into the different unfunded and funded components described in Section 3.4.

Figure 264: Breakdown of total exposure for CRE loans



BNY Mellon's CRE facilities are focused on experienced owners and are structured with moderate leverage based on existing cash flows. CRE lending activities also include construction and renovation facilities. BNY Mellon's client base for this segment consists of experienced developers and long-term holders of real estate assets. Loans are approved on the basis of existing or projected cash flows, and supported by appraisals and knowledge of local market conditions. Development loans are structured with moderate leverage, and in many instances, involve some level of recourse to the developer.

As of March 31, 2015, 59% of the CRE portfolio was secured. The secured portfolio is diverse by project type, with 55% secured by residential buildings, 27% secured by office buildings, 10% secured by retail properties, and 8% secured by other categories. Approximately 98% of the unsecured portfolio consists of real estate investment trusts ("REITs"), which are predominantly investment grade, and real estate operating companies.

Total exposures decreased in the several years following the 2008–2009 financial crisis, driven in part by management decisions to de-risk the bank's balance sheet and reduce redundant exposures across the legacy Bank of New York and legacy Mellon loan portfolios. In the more recent years, balances have returned to growth as both of these strategic initiatives have expired. See Section 7.2 for further discussion on these initiatives.

7.5.2. Forecast quantities

In line with the methodology described in Section 3.4, the following quantities were forecasted for this segment:

1. Total commitment amount
2. Draw percentage, i.e. total drawn amount divided by total commitment amount (modeled as a percentage)
3. Letter of Credit usage percentage, i.e. total amount in unused Letters of Credit divided by total commitment amount (modeled as a percentage)
4. Closed-end loan balance

A statistical modeling approach was used for each of these quantities, with the exception of Letter of Credit usage percentage, which uses an empirically-based qualitative framework. The forecasting approaches for these four quantities are documented separately in Sections 7.3.3–7.3.6. Section 7.3.8 discusses how these quantities are used to develop forecasts for unfunded commitments, Letters of Credit, and total funded loans.

7.5.3. Total commitment

7.5.3.1. Summary

A statistically sound model that is consistent with business intuition was found for CRE loans – total commitment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for CRE loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 247: Coefficient estimates for selected model for CRE loans – total commitment

CRE loans – total commitment (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Nominal GDP growth	None (level)	%	7.24	0.25
Real estate loans	% change – MoM	%	54.94	0.25
Intercept	None (level)	$ MM	3.69	N/A

The model contains the following drivers and variables:

- **General economic health** – Monthly growth rate of Nominal US GDP
- **Real estate loans –** Total volume of US real estate loans

The intuition of these variables is as follows:

- The nominal GDP growth variable has a positive coefficient, with the rationale that commercial real estate activity will increase when the general economy is performing better
- The real estate loan variable has a positive coefficient, with the rationale that real estate loan volumes are a proxy indicator for the level of commercial real estate activity

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 265: Candidate models for CRE loans – total commitment

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Debt issuances	Corporate Debt Outstanding (% QoQ)	Corporate Debt Outstanding (% QoQ)	Corporate Debt Outstanding (% QoQ)		
Equity markets		MSCI World Index (Diff MoM)			
Financial stability of the US government	1M-3M Treasury Spread (Level, 1M Lag)	1M-3M Treasury Spread (Level, 1M Lag)			
General economic health					Nominal GDP growth (Level)
Market volatility/ uncertainty (equity)				S&P Vol (30D MAVG) (%QoQ)	
Perceived credit risk			TED Spread (Diff MoM, 1M Lag)		
Real estate loans	Real estate loans (% QoQ)			Real estate loans (% MoM)	Real estate loans (% MoM)
Variation in balances explained through estimated first differences	**87%**	**78%**	**80%**	**63%**	**63%**
R-squared (differences)	**17%**	**16%**	**9%**	**7%**	**6%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.5.3.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.5.3.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The total commitment time series for the CRE loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the tables below.

Table 248: Unit root tests and stationarity tests including a trend variable on balances

CRE loans – total commitments – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	6	-0.8	>0.10	Fail to reject unit root
Phillips-Perron	1	0.71	1	Fail to reject unit root
KPSS	5	0.37	<0.01	Reject stationarity

Table 249: Unit root tests and stationarity tests including a constant on first differences

CRE loans – total commitments – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-9.9	<0.01	Reject unit root
Phillips-Perron	1	-9.9	<0.01	Reject unit root
KPSS	5	0.66	0.02	Reject stationarity

Stationarity tests for CRE loans – total commitments balances yield mixed results: The ADF and PP tests fail to reject a unit root while the KPSS test fails to reject stationarity. These results suggest the balances may be non-stationary. The monthly first difference series passes the ADF and PP tests at a high significance and only fails the KPSS test. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that a potential reason for the failure was the “Tall Trees” exposure reduction program which was executed over a limited period of the modeling period and hence should not impact the stationarity of the series going forward.

Based on these results, the CRE loans – total commitments are modeled on their first differences

7.5.3.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for CRE loans – total commitments. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.5.3.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 266: Summary of drivers for CRE loans – total commitment

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Total commitment increases when general economic health improves as a result of increased CRE activity	US GDP growth, US unemployment rate
	Housing prices	• As CRE prices increase, demand for loans may increase as CRE activity becomes more attractive	CRE Price Index
Financial economy	**Debt issuances**	• Bank lending may increase as a component of total corporate debt • Bond issuance acts as a substitute for bank loans	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets lead to greater CRE lending	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates may lead to decreased appetite to offer commitments • Volatility and uncertainty may drive up demand if alternate sources of funding dry up	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to offer commitments	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
	Real estate loans	• Greater real estate lending indicates stronger real estate markets, which is associated with greater CRE activity	Real estate loan volume
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.5.3.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for CRE loans – total commitment are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 250: Statistical significance tests of model and variables for CRE loans – total commitment

CRE loans – total commitment (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Nom_GDP	7.241	<1%	10%	Statistically significant
RE_Loans_PMoM	54.940	4%	10%	Statistically significant
Intercept	3.692	81%	10%	Statistically not significant

7.5.3.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

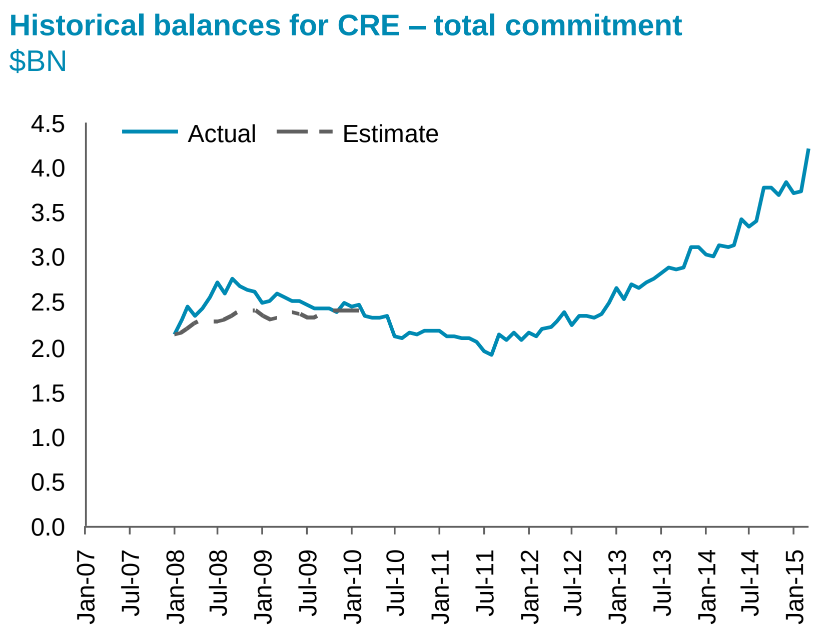
The diagnostic tests reviewed are exhibited below.

Table 251: Model Diagnostics for CRE loans – total commitment

CRE loans – total commitment (in USD MM) – Model diagnostics

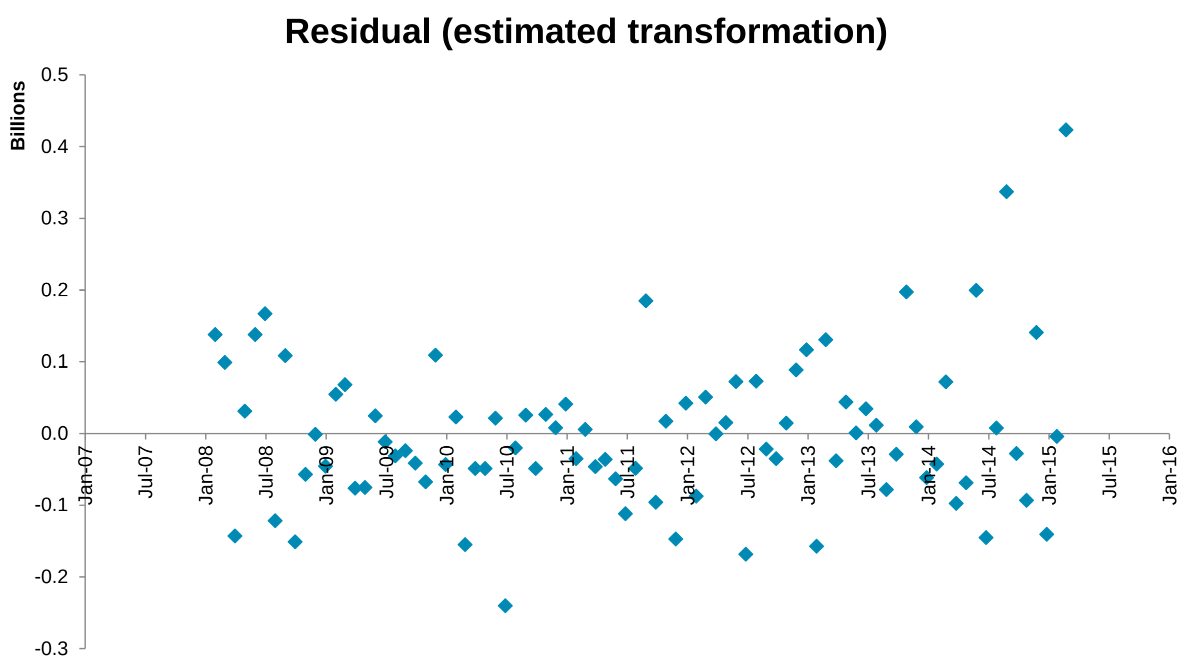
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	6%	-	-
	Adjusted R-squared	4%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.09	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.31	5	No multicollinearity
Linearity	RESET test	95%	10%	Linear specification appropriate

Figure 267: 9-quarter In-sample Prediction for CRE loans – total commitment



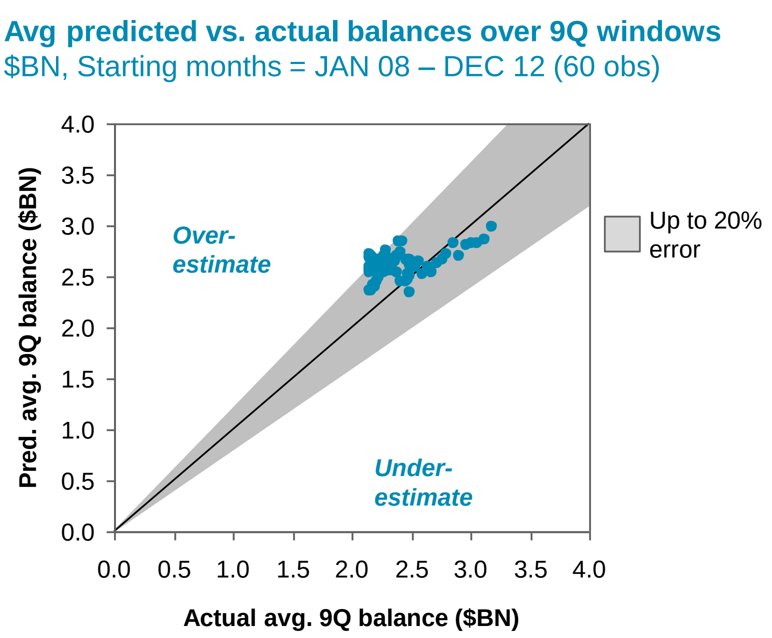
The in-sample back test of the model starting from January 2008 tracks fairly closely with the actual levels, capturing the correct directional behavior. The model does not pick up the full increase in the earlier months of the forecast period, but the estimated ending level is very close to the actual ending level.

Figure 268: Residual Plot for CRE loans – total commitment ($ BN)



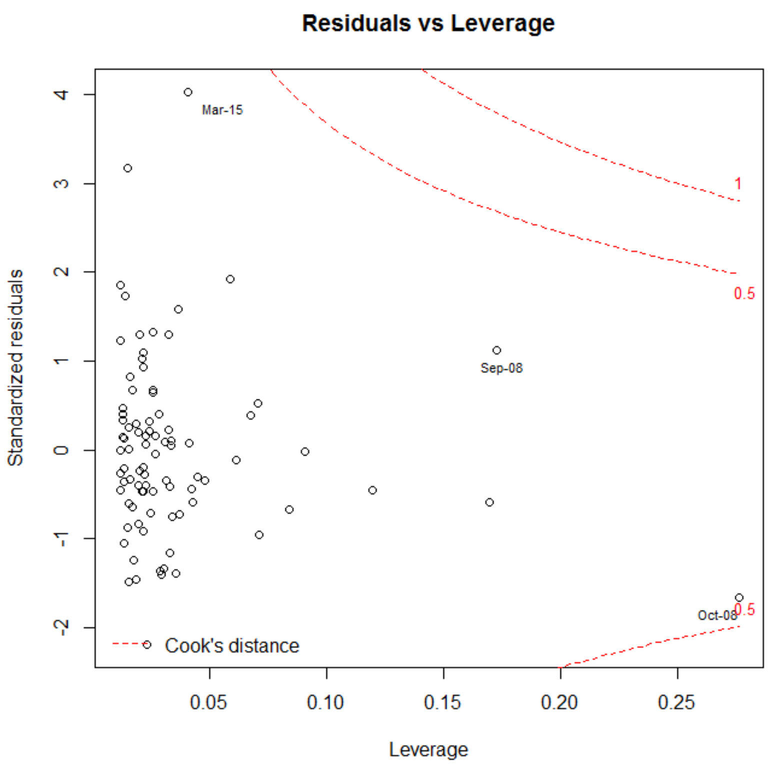
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 269: Estimation Scatterplot for CRE loans – total commitment



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within or close to 20% of actual average values.

Figure 270: Influential points for CRE Total commitments



The segment has no highly influential points.

7.5.3.6. Model sensitivity

7.5.3.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 252: Sensitivity to changes to independent variables for CRE loans – total commitment

CRE loans – total commitment – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Nominal GDP growth	None (level)	%	0.25	3.67	0.03
Real estate loans	Percent change – MoM	$ BN	0.25	0.52	0.03

Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the real estate loan variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the real estate loan variable results in a 0.25 standard deviation ($0.03 BN) increase in the predicted monthly change of the total commitment for the CRE loan segment.

7.5.3.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 253: Statistical sensitivity tests for CRE loans – total commitment

CRE loans – total commitment (in USD MM) – Statistical significance tests of model and variables

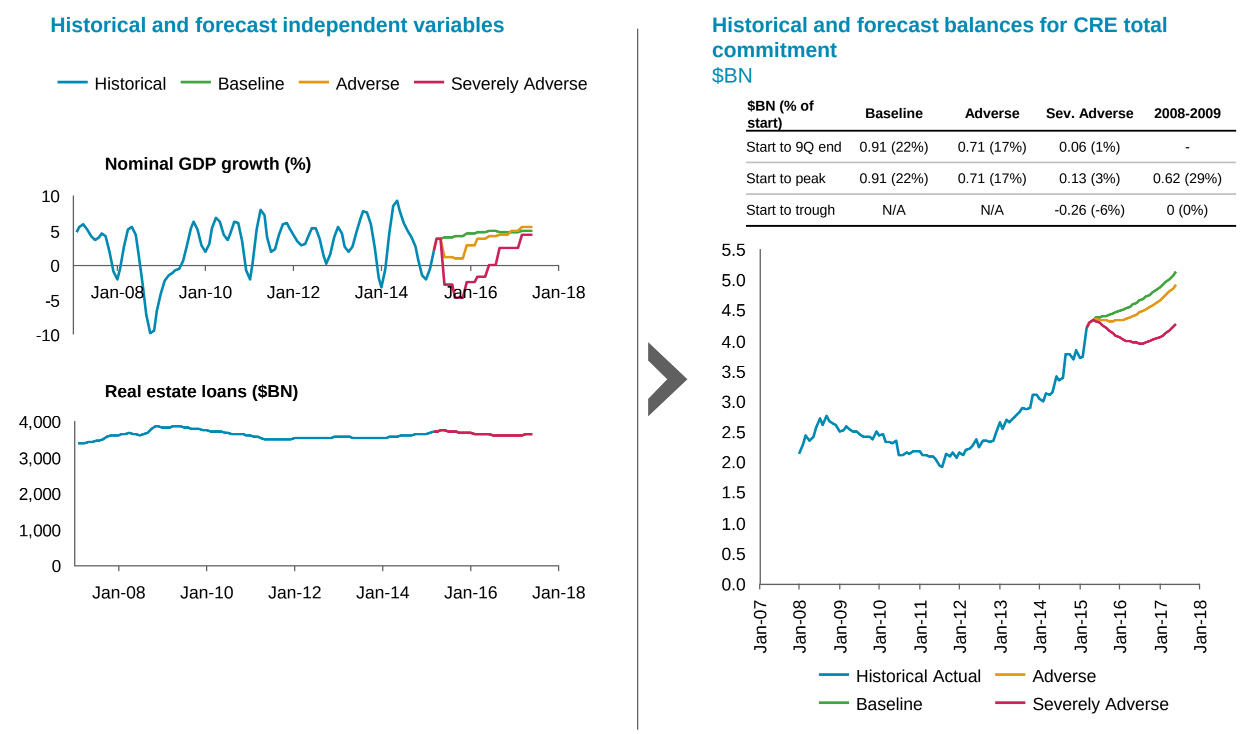
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
Nominal GDP growth	7.241	4.279	0.51	Statistically insignificant
Real estate loans	54.940	27.415	0.21	Statistically insignificant
Intercept	3.692		0.88	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.24	Statistically insignificant

7.5.3.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 271: Final model forecast for CRE loans – total commitment



The Working Group considered the forecast behavior for the selected CRE loans – total commitment model as reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts a decline in total commitments, followed by a recovery. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations that CRE activity and therefore demand for committed lines would decline under macroeconomic stress
- **Interest rate shock (Adverse) scenario**: The model growth in total commitments, at a slightly slower rate than in the baseline scenario. This was judged to be consistent with business intuition
- **Baseline scenario**: The model predicts that total commitments will grow at a more conservative rate than the observed historical growth rate over the most recent several years. This was judged to be consistent with business intuition

7.5.4. Draw percentage

7.5.4.1. Summary

A statistically sound model was found for CRE loans – draw percentage. Some management scrutiny may be needed for stress forecasts to ensure that the projected movements in draw percentage are not overly extreme given management expectations.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the draw percentage time series for CRE loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 254: Coefficient estimates for selected model for CRE loans – draw percentage

CRE loans – draw percentage (logit-transformed) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Dow Jones Industrial Average	% change – QoQ	%	-0.23	-0.22
1-week LIBOR 1-week OIS spread	First difference – MoM	%	4.97	0.18
Total bond issuance (ex MBS, government)	% change – MoM	%	-0.03	-0.18
Intercept	None (level)	None	0.74	N/A

The model contains the following drivers and variables:

- **Equity markets** – Dow Jones Industrial Average
- **Perceived credit risk –** Spread between 1-week LIBOR and 1-week OIS (overnight indexed swap) rate, which is an indicator of banks' perception of credit risk in the financial system
- **Debt issuances –** Total US debt issuance volume, excluding MBS and government

The intuition of these variables is as follows:

- The Dow Jones Industrial Average variable has a negative coefficient. This variable is interpreted as an indicator of macroeconomic strength or weakness; when overall macroeconomic conditions are weak or stressed, clients may increase their draws as access to regular alternate sources of funding is lost.
- The 1-week LIBOR 1-week OIS spread variable has a positive coefficient. Increases in this spread are associated with tightening in credit markets, and again clients may increase their draws as access to regular alternate sources of funding is lost
- The total bond issuance variable has a negative coefficient. Bond issuance serves as a substitute for bank loans, so greater bond issuance reduces the need to draw from bank commitments

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 272: Candidate models for CRE loans – draw percentage

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
Debt issuances	Total Bond Issuance (ex. MBS, gov) (% MoM)		Total Bond Issuance (ex. MBS, gov) (% MoM)	
Equity markets	DJI (% QoQ)	DJI (% QoQ)	DJI (% QoQ)	DJI (% MoM, 1M Lag)
Housing prices		HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	
Market volatility/ uncertainty (equity)				S&P Vol (30D MAVG) (% MoM)
Perceived credit risk	1 Week LIBOR 1 Week OIS Spread (Diff MoM)	1 Week LIBOR 1 Week OIS Spread (Diff MoM)		
Variation in levels explained through estimated logit first differences	**34%**	**65%**	**66%**	**30%**
R-squared (differences)	**11%**	**11%**	**11%**	**6%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.5.4.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.5.4.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The logit-transformed draw percentage time series for the CRE loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the logit-transformed levels are tested using unit root and stationarity tests including a time trend.

The first differences of the logit-transformed levels, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the tables below.

Table 255: Unit root tests and stationarity tests including a trend variable on levels

CRE loans – draw percentage – Unit root test with trend on logit-transformed level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-2.1	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.9	0.18	Fail to reject unit root
KPSS	5	0.22	<0.01	Reject stationarity

Table 256: Unit root tests and stationarity tests including a constant on first differences

CRE loans – draw percentage – Single mean unit root test on logit-transformed first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-11	<0.01	Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	9	0.1	0.57	Fail to reject stationarity

Stationarity tests for CRE loans – draw percentage logit uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the CRE loans – draw percentage logit balances are modeled on their first differences.

7.5.4.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for CRE loans – draw percentage. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.5.4.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 273: Summary of drivers for CRE loans – draw percentage

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When the general economy is under stress, borrowers draw on committed lines more often to replace alternative sources of funding that are drying up	US GDP growth, US unemployment rate
	Housing prices	• As CRE prices increase, draws may increase as CRE activity becomes more attractive	CRE Price Index
Financial economy	**Equity markets**	• Weakening equity markets are correlated with stress in economic conditions, which leads to increased draws	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in market conditions may be a sign of stress in overall economic conditions, leading to increased draws	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• As systemic credit risk rises, draws may either increase as alternative funding options become less attractive, or decrease as overall lending slows down	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
	Real estate loans	• Greater real estate lending indicates stronger real estate markets, which is associated with greater CRE activity and therefore possibly more draws	Real estate loan volume
Rates	**Short-term rates**	• Borrowers may be more willing to draw from commitments at lower rates	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit	• Increasing corporate yields and spreads makes borrowing more expensive, leading to lower draws	Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.5.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for CRE loans – draw percentage are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 257: Statistical significance tests of model and variables for CRE loans – draw percentage

CRE loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Dow Jones Industrial Average	-0.002	<1%	10%	Statistically significant
1-week LIBOR 1-week OIS spread	0.050	<1%	10%	Statistically significant
Total bond issuance (ex MBS, government)	0.000	5%	10%	Statistically significant
Intercept	0.007	49%	10%	Statistically not significant

7.5.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics

- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences of logit transform), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

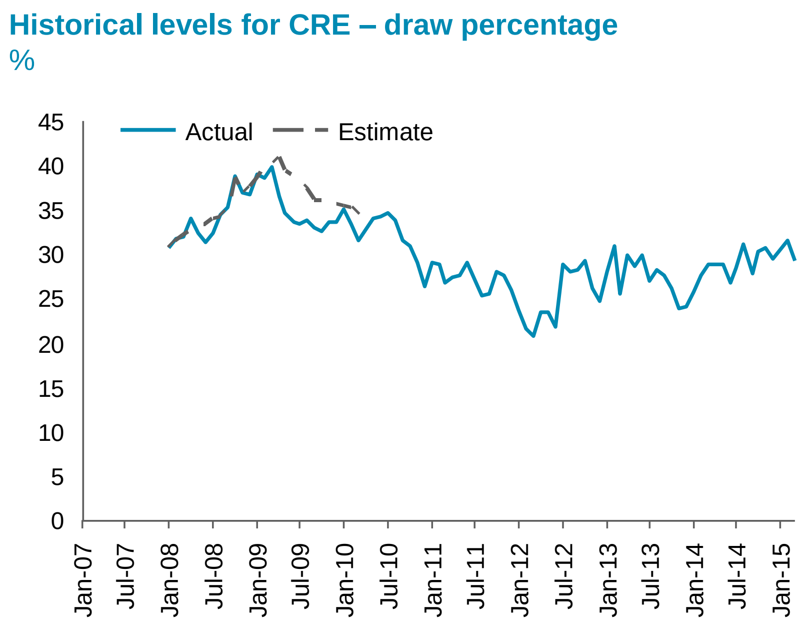
The diagnostic tests reviewed are exhibited below.

Table 258: Model Diagnostics for CRE loans – draw percentage

CRE loans – draw percentage (logit-transformed) – Model diagnostics

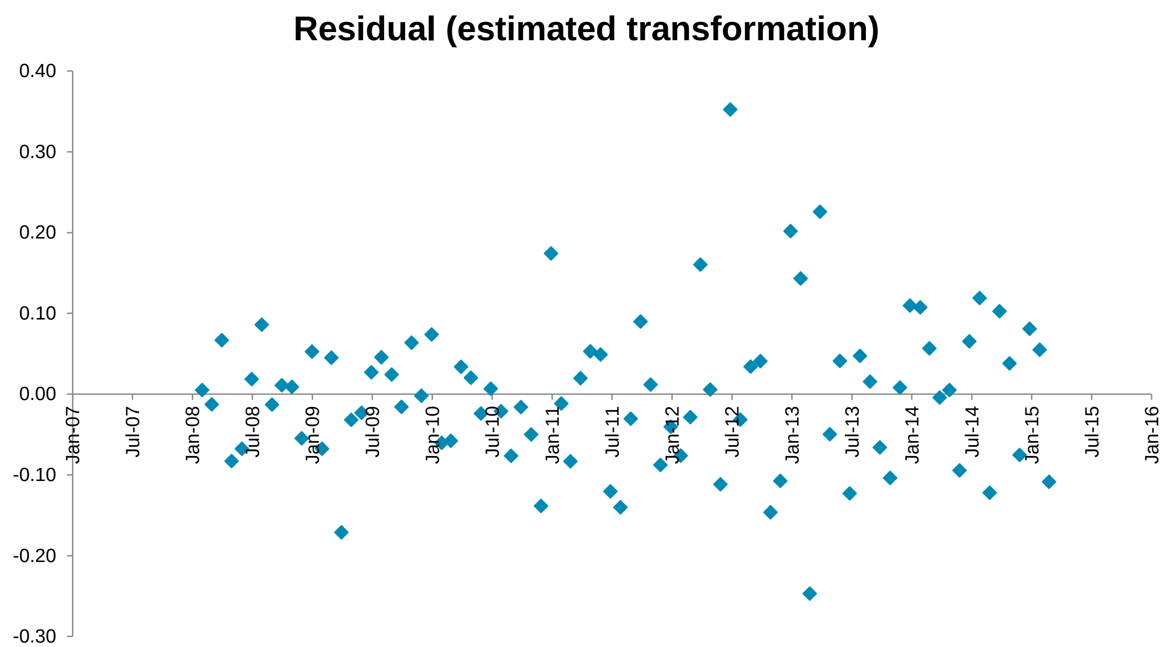
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	11%	-	-
	Adjusted R-squared	8%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.93	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	78%	10%	Linear specification appropriate

Figure 274: 9-quarter In-sample Prediction for CRE loans – draw percentage



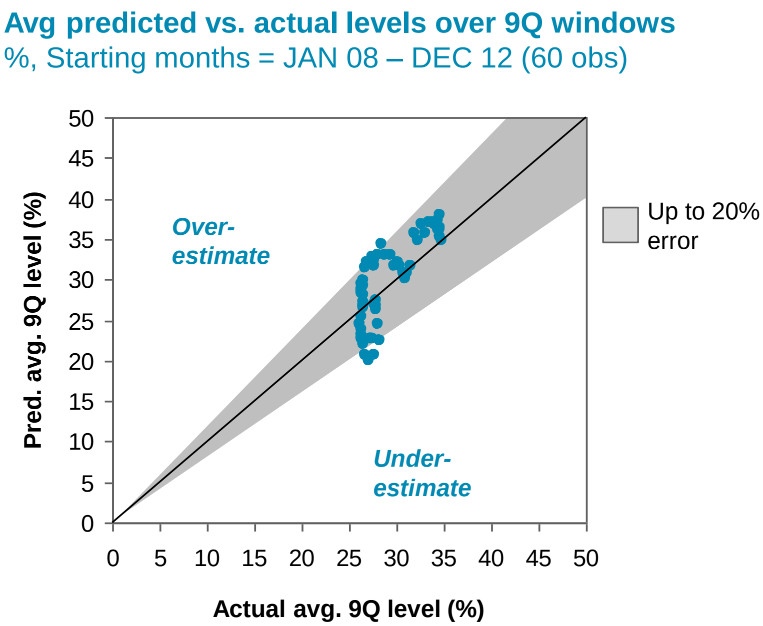
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, generally capturing the correct directional behavior as well as the magnitude of changes.

Figure 275: Residual Plot for CRE loans – draw percentage



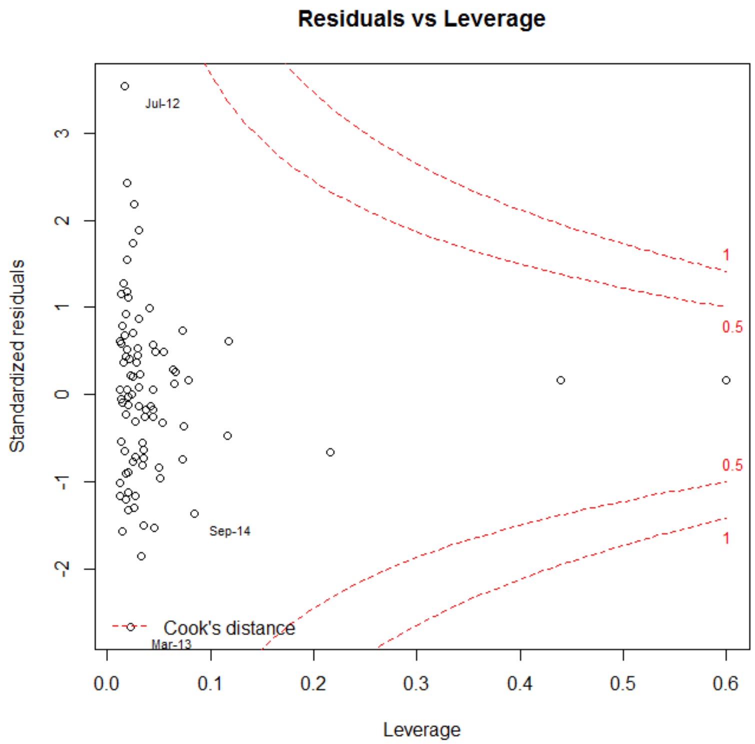
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 276: Estimation Scatterplot for CRE loans – draw percentage



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within or close to 20% of actual average values.

Figure 277: Influential points CRE Draw %



The segment has no highly influential points.

7.5.4.6. Model sensitivity

7.5.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the dependent variable due to a one standard deviation increase in an independent variable.

Due to the usage of the logit transformation, the relationship between the independent variables and the level of the draw percentage is non-linear. Therefore, a one standard deviation shift in an independent variable will have different impacts on the actual draw percentage, depending on the level of the draw percentage. Sensitivity of the level to movements in independent variables will decrease as the level approaches 0% or 100%, since applying the inverse logit transformation to the dependent variable must produce a level that is bounded between 0% and 100%.

Table 259: Sensitivity to changes to independent variables for CRE loans – draw percentage

CRE loans – draw percentage – model sensitivity				
Independent variable	**Transformation**	**Unit**	**Standardized coefficient**	**Std. dev of independent variable**
Dow Jones Industrial Average	% change – QoQ	%	-0.22	8.90
1-week LIBOR 1-week OIS spread	First difference – MoM	%	0.18	0.35
Total bond issuance (ex MBS, government)	% change – MoM	%	-0.18	51.73
Intercept	None (level)	None	N/A	N/A

In the selected model for CRE loans – draw percentage, the Dow Jones Industrial Average variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Dow Jones Industrial Average variable results in a 0.22 standard deviation decrease in the predicted monthly change of the logit-transformed draw percentage for the CRE loan segment.

7.5.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 260: Statistical sensitivity tests for CRE loans – draw percentage

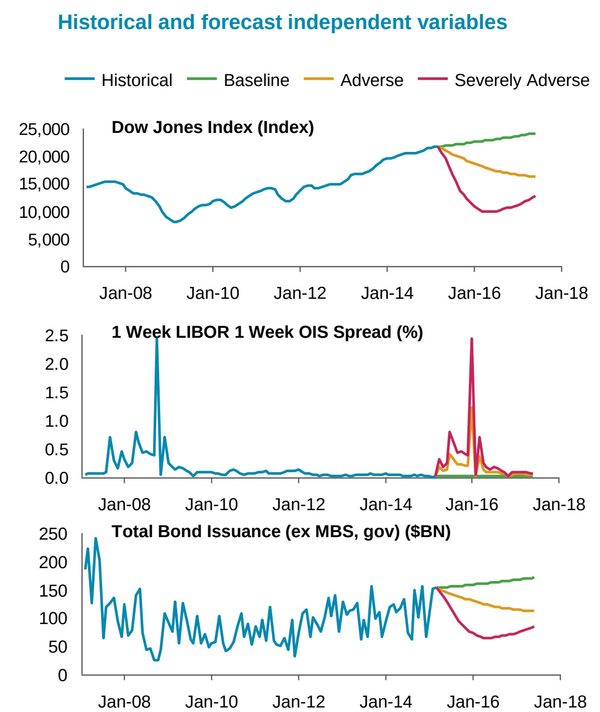
CRE loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**HAC P-value of shortened period coefficient**	**Conclusion**
DJI_PQoQ	-0.002	-0.003	0.88	Statistically insignificant
LIBOR_OIS_1wk_DMoM	0.050	0.050	0.26	Statistically insignificant
Tot_bond_exMBSgov_PMoM	0.000	0.000	0.29	Statistically insignificant
Intercept	0.007		0.53	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.55	Statistically insignificant

7.5.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

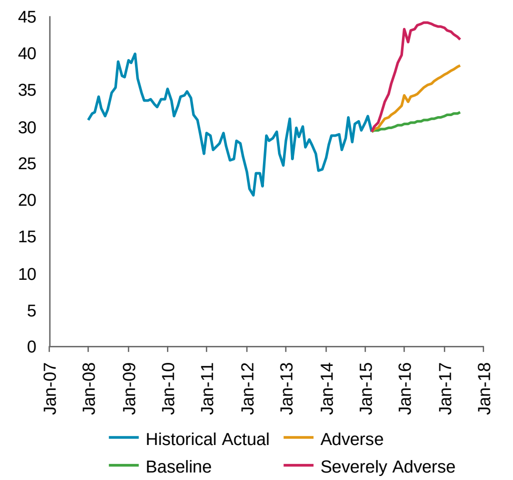
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 278: Final model forecast for CRE loans – draw percentage



Historical and forecast levels for CRE draw percentage
%

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	2.58%	9.00%	12.53%	-
Start to peak	2.58%	9.00%	14.85%	9.12%
Start to trough	N/A	N/A	N/A	0.00%



The Working Group determined that the forecast behavior for the selected CRE loans – draw percentage model is directionally intuitive, but may require scrutiny during management review to decrease the magnitude of observed spikes under stress scenarios.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant spike in draw percentage, followed by a decline. In a review of the forecasts with the line of business, this was noted to be directionally consistent with their expectations that under severe stress, borrowers will increase draws on their committed facilities for contingency funding, particularly in REITs. This is also consistent with observed behavior during the 2008–2009 financial crisis. However, the Working Group and line of business deemed the magnitude of the spike to be overly large, and thus this model's outputs should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario**: The model predicts a rise in draw percentage, directionally similar to the severe recession scenario but lower in magnitude. Similar to severe recession scenario, the line of business suggested that the magnitude of the rise may be overstated
- **Baseline scenario**: The model predicts that draw percentage will rise slowly, ending in nine quarters at a level near the starting level. This was judged to be consistent with business intuition

7.5.5. Letter of Credit usage percentage

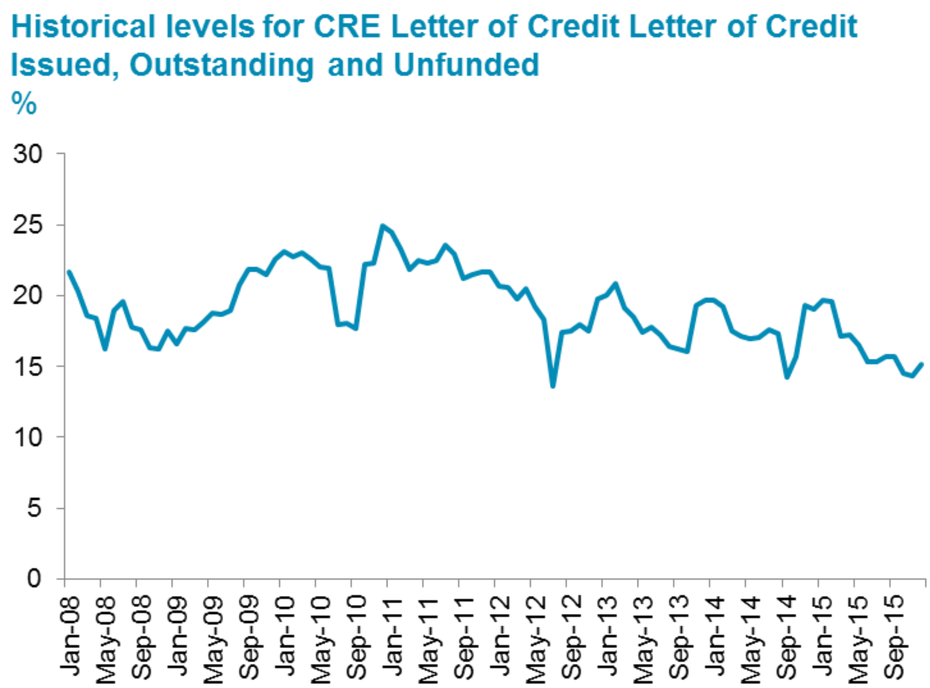
7.5.5.1. Summary

The qualitative framework for the CRE Letter of Credit percentage is to use 19.07% for all scenarios. This equals the observed average in the historical time series between January 2008 and December 2015.

A modeling approach was initially pursued for CRE Letter of Credit percentage (it is included above). However, the line of business indicated that Letter of Credit percentage for this segment is not expected to be sensitive to macroeconomic factors. The line of business indicated that Letters of Credit are a standard component of credit facilities used to finance commercial real estate projects. As many CRE projects take years to complete and funding is tied to progress of the projects, involved parties frequently request guarantees in forms of Letters of Credit. As a result, Letters of Credit for this segment are closely tied to total commitment amounts. Forecasting Letters of Credit as a percent usage of Total Commitments captures the changes to the size of the CRE business, which will cause Letters of Credit to rise or fall respectively. Forecasting Letters of Credit as a fixed balance would not capture these changes.

The modeling team corroborated this intuition by assessing the historical time series for this quantity, shown in the figure below. Throughout the historical period, the Letter of Credit percentage remains stable.

Figure 279: Historical levels for CRE loans – Letter of Credit usage percentage



Given this alignment of business intuition and empirical evidence, the Working Group decided that a qualitative framework was most appropriate for this quantity and decided to hold the value constant across all scenarios at the average value of 19.07% observed in the historical time series between January 2008 and December 2015. The table below shows additional summary statistics for this time series.

Table 261: Summary statistics for historical time series for CRE loans – Letter of Credit usage percentage

Statistic	Value
Mean	19.07%
Sample standard deviation	2.58%
Average absolute deviation from mean	2.15%
Maximum	24.91%
Minimum	13.57%

7.5.6. Closed-end loans

7.5.6.1. Summary

A statistically sound model that is consistent with business intuition was found for CRE loans – closed-end loans. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the closed-end loan time series for CRE loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 262: Coefficient estimates for selected model for CRE loans – closed-end loans

CRE loans – closed-end loans (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Real estate loans	% change – QoQ	%	11.43	0.32
Unemployment rate	First difference – MoM	%	-43.20	-0.19
Intercept	None (level)	$ MM	7.88	N/A

The model contains the following drivers and variables:

- **Real estate loans** – Total volume of US real estate loans
- **General economic health** – US unemployment rate

The intuition of these variables is as follows:

- The real estate loan variable has a positive coefficient, with the rationale that real estate loan volumes are a proxy indicator for the level of commercial real estate activity
- The unemployment rate variable has a negative coefficient, with the rationale that when unemployment rises, general economic conditions are worsening and therefore dampening commercial real estate activity

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 280: Candidate models for CRE loans – closed-end loans

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
General economic health					Unemployment rate (Diff MoM)
Corporate credit				Baa Corporate Yield (Diff MoM, 1M Lag)	
Debt issuances	ABS Issuance (% MoM, 1M Lag)				
Exports			Nominal Exports (Diff QoQ)		
Housing prices	HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	
Long-term rates		3Y Treasury (Diff MoM)			
Market volatility / uncertainty (rates)			10 Year US T-Note Volatility Index (% MoM)		
Real estate loans	Real estate loans (% QoQ)	Real estate loans (% QoQ)		Real estate loans (Diff QoQ)	Real estate loans (% QoQ)
Variation in balances explained through estimated first differences	**86%**	**88%**	**73%**	**88%**	**69%**
R-squared (differences)	**18%**	**16%**	**16%**	**16%**	**11%**

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.5.6.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.5.6.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The closed-end loan time series for the CRE loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the tables below.

Table 263: Unit root tests and stationarity tests including a trend variable on levels

CRE loans – closed-end loans – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-0.2	>0.10	Fail to reject unit root
Phillips-Perron	1	1.05	1	Fail to reject unit root
KPSS	5	0.34	<0.01	Reject stationarity

Table 264: Unit root tests and stationarity tests including a constant on first differences

CRE loans – closed-end loans – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-7.7	<0.01	Reject unit root
Phillips-Perron	1	-7.7	<0.01	Reject unit root
KPSS	0	0.78	<0.01	Reject stationarity

Stationarity tests for CRE loans – draw percentage logit uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. The monthly first difference series passes the ADF and PP tests at a high significance and only the KPSS test fails. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that a potential reason for the failure was the “Tall Trees” exposure reduction program which was executed over a limited period of the modeling period and hence should not impact the stationarity of the series going forward.

Based on these results, the CRE loans – closed-end loans are modeled on their first differences.

7.5.6.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for CRE loans – closed-end loans. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.5.6.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 281: Summary of drivers for CRE loans – closed-end loans

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Loan volumes increase when general economic health improves as a result of increased CRE activity	US GDP growth, US unemployment rate
	Housing prices	• As CRE prices increase, demand for loans may increase as CRE activity becomes more attractive	CRE Price Index
Financial economy	**Debt issuances**	• Bank lending may increase as a component of total corporate debt • Bond issuance acts as a substitute for bank loans	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets lead to greater CRE lending	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates may lead to decreased appetite to extend loans • Volatility and uncertainty may drive up demand if alternate sources of funding dry up	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to extend loans	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
	Real estate loans	• Greater real estate lending indicates stronger real estate markets, which is associated with greater CRE activity	Real estate loan volume
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.5.6.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold

- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for CRE loans – closed-end loans are statistically significant. The intercept is found to be statistically insignificant.

Table 265: Statistical significance tests of model and variables for CRE loans – closed-end loans

CRE loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	1%	10%	Statistically significant
Real estate loans	11.430	<1%	10%	Statistically significant
Unemployment rate	-43.199	8%	10%	Statistically significant
Intercept	7.875	11%	10%	Statistically not significant

7.5.6.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

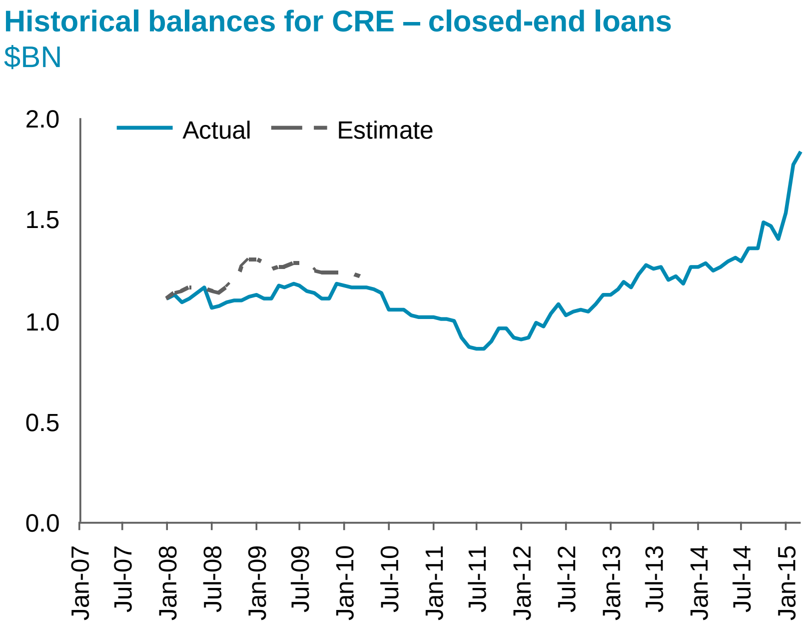
The diagnostic tests reviewed are exhibited below.

Table 266: Model Diagnostics for CRE loans – closed-end loans

CRE loans – closed-end loans (in USD MM) – Model diagnostics

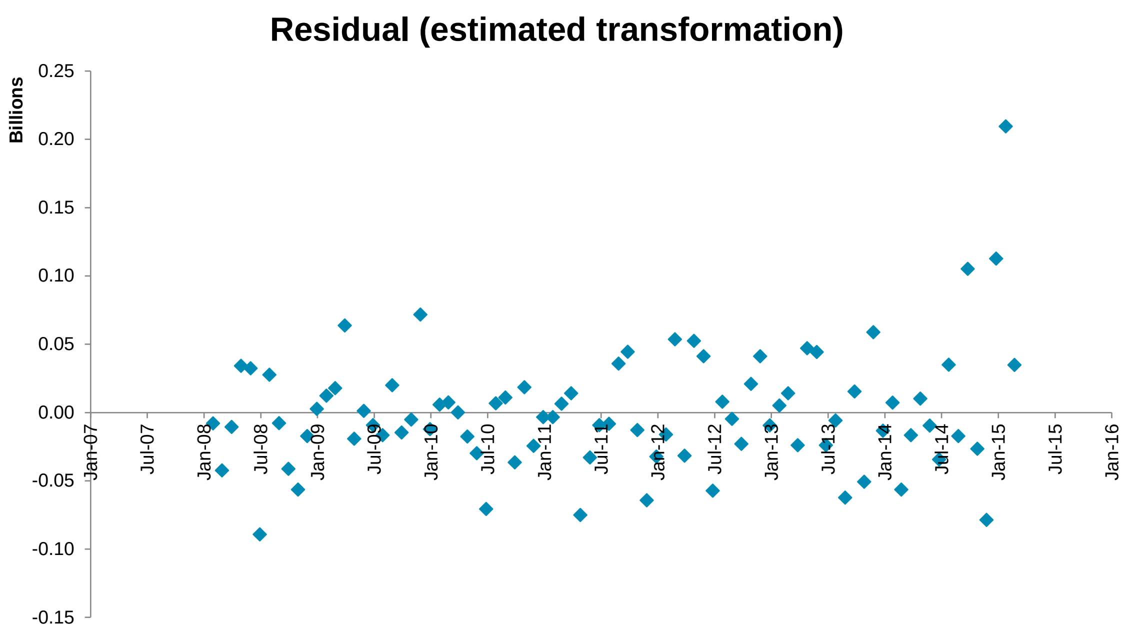
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	11%	-	-
	Adjusted R-squared	9%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	26%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	23%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.05	5	No multicollinearity
Linearity	RESET test	25%	10%	Linear specification appropriate

Figure 282: 9-quarter In-sample Prediction for CRE loans – closed-end loans



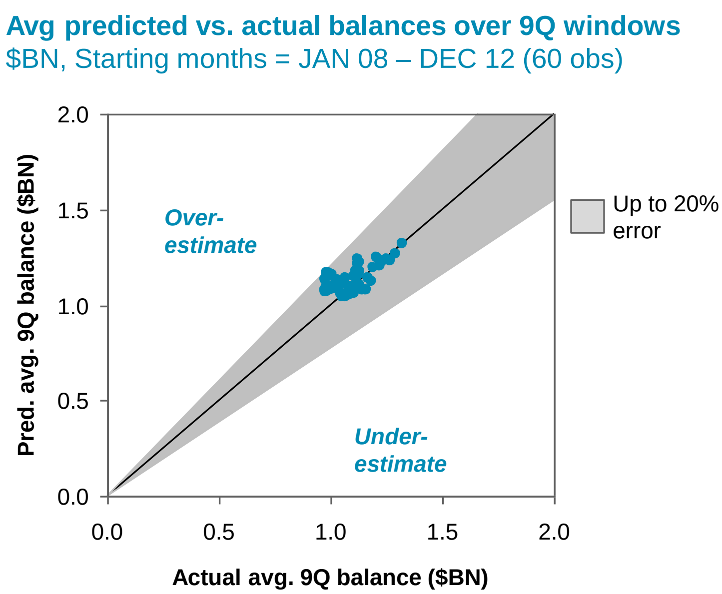
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, generally capturing the correct directional behavior as well as the magnitude of changes. The model overestimates balances slightly, especially in the middle of the forecast window.

Figure 283: Residual Plot for CRE loans – closed-end loans ($ BN)



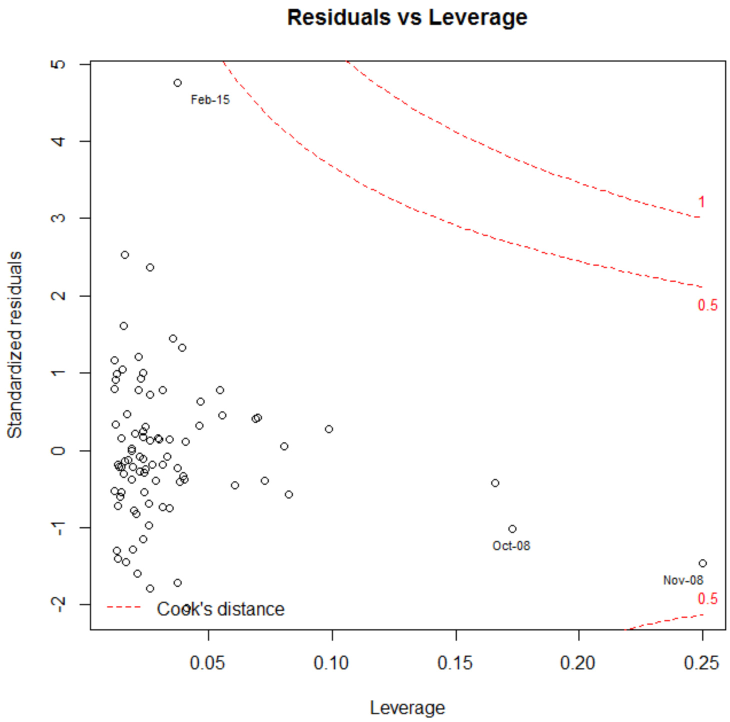
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 284: Estimation Scatterplot for CRE loans – closed-end loans



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 285: Influential points for CRE Closed end loans



The segment has no highly influential points.

7.5.6.6. Model sensitivity

7.5.6.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 267: Sensitivity to changes to independent variables for CRE loans – closed-end loans

CRE loans – closed-end loans – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Real estate loans	% change – QoQ	%	0.32	1.40	0.01
Unemployment rate	First difference – MoM	%	-0.19	0.20	-0.01
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model for CRE loans – closed-end loans, the real estate loan volume variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the real estate loan volume variable results in a 0.32 standard deviation ($0.01 BN) increase in the predicted monthly change of the closed-end loans for the CRE loan segment.

7.5.6.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically significant collectively. This suggests the model may not maintain stability when removing observations from the development data. In addition, the coefficient of the real estate loans variable is significant individually.

Table 268: Statistical sensitivity tests for CRE loans – closed-end loans

CRE loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

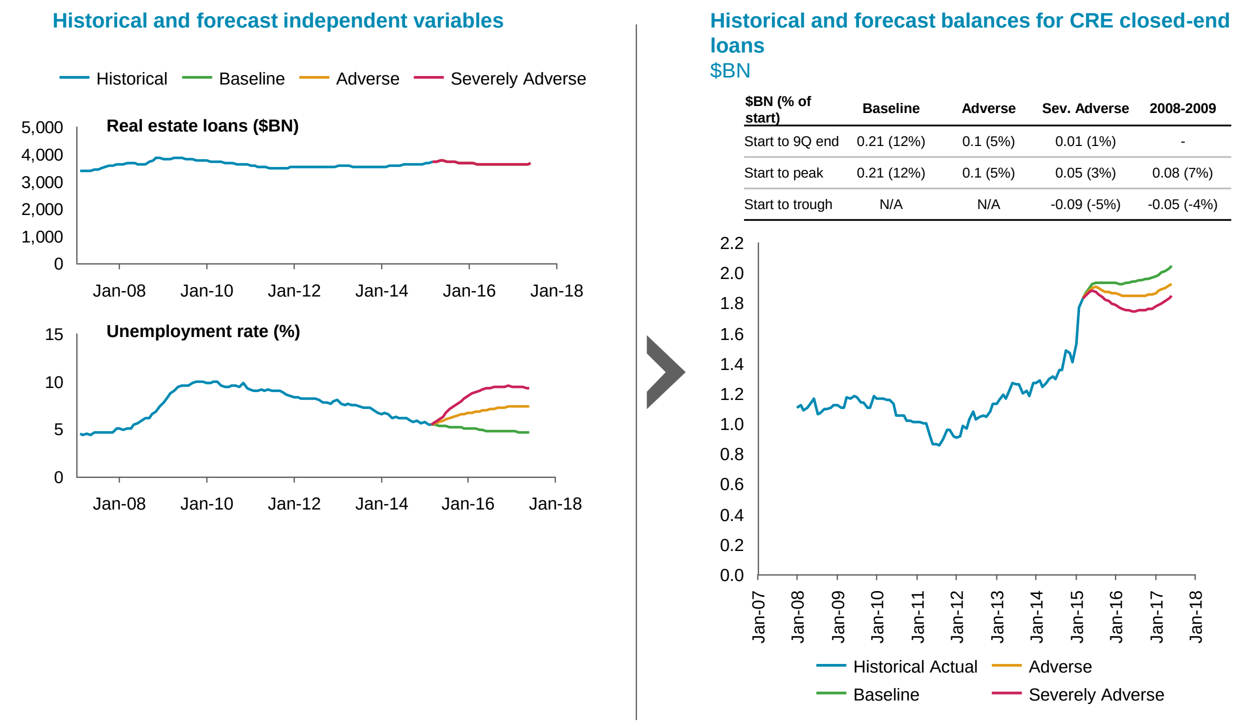
Tested independent variable	Original coefficient estimate	Sum of coefficients	P-value of shortened period coefficient	Conclusion
Real estate loans	11.430	7.745	0.05	Statistically significant
Unemployment rate	-43.199	-20.109	0.48	Statistically insignificant
Intercept	7.875		0.83	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.10	Statistically significant

7.5.6.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 286: Final model forecast for CRE loans – closed-end loans



The Working Group considered the forecast behavior for the selected CRE loans – closed-end loans model as reasonable.

- **Severe recession (Severely Adverse) scenario:** Closed-end loan balances decline and then recover back to near starting levels by the end of nine quarters. The line of business confirmed that this behavior is directionally consistent with the expectation CRE activity will decline in a severe macroeconomic downturn
- **Interest rate shock (Adverse) scenario**: Closed-end loan balances remain relatively flat
- **Baseline scenario**: Closed-end loan balances grow slowly, at a rate closer to observed rates earlier in the forecast period than to rates in recent years, which have been higher. Given the relatively lumpy nature of the CRE business, the line of business did not feel that this growth was unintuitive

7.5.7. Model limitations

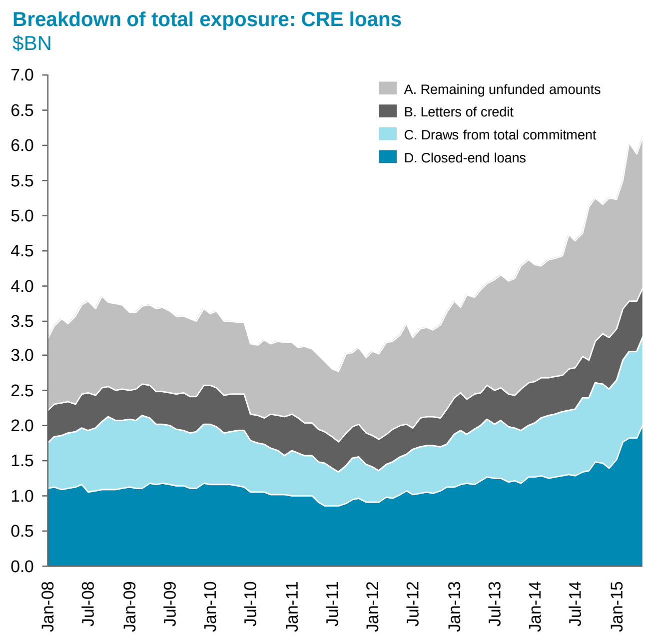
As discussed in Section 7.2, BNY Mellon underwent a period of balance sheet de-risking following the 2008–2009 financial crisis, concurrent with contraction in the overall lending market during this period. However, this period also coincides with the integration of the legacy Bank of New York and Mellon portfolios, which was characterized by active management decision to reduce redundant exposures shared across both legacy banks. As a result, the observed changes in forecast quantities reflect movements due to both the macroeconomic environment as well as factors idiosyncratic to BNY Mellon. The historical time series from the development data commingles both of these effects. Therefore, the developed models are potentially over-sensitive to changes in macroeconomic variables, and could produce more extreme forecasts than would be intuitively expected.

7.5.8. Synthesis of forecast results

After forecasts have been generated from the models, a small set of additional calculations is required to obtain the desired balance forecasts shown in the figure below:

- Balances for funded draws from commitments (Quantity C in figure) can calculated as the product of total commitment and draw percentage
- Unfunded Letter of Credit amounts (Quantity B in figure) can be calculated as the product of total commitment and Letter of Credit usage percentage
- Unused unfunded commitments (Quantity A in figure) can be calculated as total commitments minus balances for funded draws minus unfunded Letter of Credit amounts
- Total funded loan balances can be calculated as the sum of balances for funded draws plus balances for closed-end loans (Quantity C + Quantity D in figure)

Figure 287: Breakdown of total exposure for CRE loans

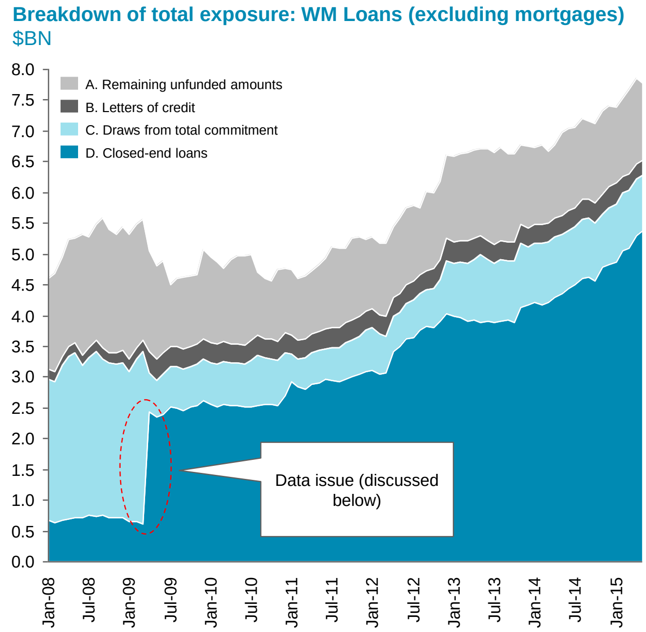


7.6. Wealth Management loans (excluding mortgages)

7.6.1. Business overview

BNY Mellon originates and purchases loans as part of its ongoing business. The Wealth Management (WM) loan segment includes all BNY Mellon Wealth Management loans except mortgages, which are treated in a separate segment. As of April 30, 2015, the WM loan segment has $15 BN in funded loans plus $43 BN in unfunded commitments, including Letters of Credit. The figure below shows the breakdown over time for total exposure in this segment into the different unfunded and funded components described in Section 3.4.

Figure 288: Breakdown of total exposure for WM loans (excluding mortgages)



Borrowers in this segment are primarily high-net-worth individuals, and most of the loans are non-purpose loans. The exposures in this segment are primarily loans and facilities secured by marketable securities. Smaller components of this segment include other secured exposures (secured by aircraft, art, etc.), commercial real estate lending to Wealth Management clients, and unsecured exposures. The table below shows the breakdown of funded and unfunded balances in this segment by these categories, as of March 31, 2015 (does not include unused advised exposures).

Table 269: Funded and unfunded exposures for WM loans (excluding mortgages) by category

WM loan exposures (excluding mortgages) as of March 31, 2015 (in USD MM)

Category	Funded loans	Unfunded exposure (including Letters of Credit)	Total exposure
Secured by marketable securities	5,541	374	5,915
Other secured	38	68	106
Commercial real estate	194	3	197
Unsecured	356	797	1,153
Total	6,129	1,242	7,371

7.6.2. Forecast quantities

In line with the methodology described in Section 3.4, the following quantities were forecasted for this segment:

1. Total commitment amount
2. Draw percentage, i.e. total drawn amount divided by total commitment amount (modeled as a percentage)
3. Letter of Credit usage percentage, i.e. total amount in unused Letters of Credit divided by total commitment amount (modeled as a percentage)
4. Closed-end loan balance

A statistical modeling approach was used for each of these quantities, with the exception of Letter of Credit usage percentage, which uses an empirically-based qualitative framework. The forecasting approaches for these four quantities are documented separately in Sections 7.3.3–7.3.6. Section 7.3.8 discusses how these quantities are used to develop forecasts for unfunded commitments, Letters of Credit, and total funded loans.

7.6.3. General data issues

As discussed in Section 4.2 on development data, the historical data for the Wealth Management segment showed a data issue between March and April 2009, where a large volume of draws from facilities were reclassified as closed-end loans. The issue arises from the integration of legacy Mellon balances into BNY Mellon's Wealth Management loan portfolio. Up to March 2009, a significant volume legacy Mellon balances are classified as draws from committed facilities. Starting in April 2009, the identifiers for these exposures are changed, which causes them to be classified as closed-end loans instead, as they then become draws from advised facilities.

This data issue produces an invalid data point in the first difference dependent variables at April 2009. The impact of the data issue on the behavior of each forecast quantity is as follows:

- Total commitment – drop in draw volumes implies equal drop in total commitment volumes
- Draw percentage – drop in draw volumes impacts both numerator and denominator of draw percentage, but with greater relative impact on the numerator, leading to a drop in draw percentage
- Letter of Credit usage percentage – drop in total commitment implies sharp increase in calculated Letter of Credit usage percentage
- Closed-end loans – reclassification of draws to closed-end loans implies sharp increase in closed-end loan volumes

The line of business indicated that the legacy data and systems are no longer available to assist in resolving the data issue. Therefore, for the purposes of modeling, the legacy Mellon balances that cause the data issue are considered to be draws from committed facilities up to March 2009, and then draws from advised facilities (which are included in closed-end loans, as per Section 3.4 on methodology) starting from April 2009. Since the dependent variables are first differences, the discontinuity only impacts the April 2009 value for the dependent variables. Therefore, a dummy variable has been added into the independent variables, with value 0 for all months except April 2009, in order to remove the effect of this data point on the calculated regressions.

7.6.4. Total commitment

7.6.4.1. Summary

A statistically sound model that uses macroeconomic factors consistent with business intuition was found for WM loans – total commitment. However, the forecasts produced by this model were deemed to be potentially unreasonable, requiring greater management scrutiny.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for Wealth Management loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 270: Coefficient estimates for selected model for WM loans – total commitment

WM loans – total commitment (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
S&P volatility (30-day moving average)	First difference – YoY	Index	-32.00	-0.12
1-year Treasury	First difference – QoQ	%	-108.23	-0.13
Intercept	None (level)	$ MM	-0.64	N/A
Dummy for April 2009		$ MM	-2,315.77	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – 30-day moving average of close-of-day values of VIX, measuring S&P volatility
- **Long-term rates –** 1-year US Treasury rate

The intuition of these variables is as follows:

- The S&P volatility variable has a negative coefficient, with the rationale that when equity markets are volatile or uncertain, demand for commitments decreases. Additionally, volatility may have a negative impact on the value of securities that borrowers use to secure WM commitments
- The 1-year Treasury rate has a negative coefficient, with the rationale that higher interest rates will make loans more expensive and therefore reduce demand. Additionally, higher interest rates may have a negative impact on the value of securities that borrowers use to secure WM commitments

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs. In addition to these variables, a dummy variable was used to address a specific issue identified in the historical data, which is discussed further in Section 7.6.4.2.2.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 289: Candidate models for WM loans – total commitment

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Long-term rates	1Y Treasury (Diff QoQ)		1Y Treasury (Diff QoQ)		
Market volatility/ uncertainty (equity)	S&P Vol (30D MAVG) (Diff YoY)	S&P Vol (30D MAVG) (Diff YoY)	S&P Vol (30D MAVG) (Diff YoY)		
Market volatility/ uncertainty (rates)				10 Year US T-Note Volatility Index (Diff YoY)	
Short-term rates		Prime rate (Diff MoM)		Prime rate (Diff MoM)	Prime rate (Diff MoM)
Yield spread	3M to 10Y T Spread (Level)				3M to 10Y T Spread (Level)
Variation in balances explained through estimated first differences	**94%**	**88%**	**87%**	**92%**	**97%**
R-squared (differences)	**82%**	**82%**	**81%**	**81%**	**81%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.6.4.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.6.4.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The total commitment time series for the WM loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 271: Unit root tests and stationarity tests including a trend variable on balances

WM loans – total commitments – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-2.1	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.7	0.76	Fail to reject unit root
KPSS	5	0.28	<0.01	Reject stationarity

Table 272: Unit root tests and stationarity tests including a constant on first differences

WM loans – total commitments – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	11	-3.1	0.03	Reject unit root
Phillips-Perron	1	-9	<0.01	Reject unit root
KPSS	2	0.13	0.45	Fail to reject stationarity

Stationarity tests for WM loans – total commitments balances uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the WM loans – total commitments deposit balances are modeled on their first differences.

7.6.4.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

One data adjustment was made to the historical time series for WM loans – total commitments. As discussed in Section 7.6.3, a data issue was detected between March and April 2009, where a large volume of draws from facilities were reclassified as closed-end loans, which reduced the volume of total commitments. The line of business verified the cause of this data issue, and also its roots in the integration of legacy Mellon balances into BNY Mellon systems. The line of business also indicated that the legacy data and systems are no longer available to assist in resolving the data issue.

Since the dependent variable is a first difference, the discontinuity only impacts the April 2009 value for the dependent variable. Therefore, a dummy variable has been added into the independent variables, with value 0 for all months except April 2009, in order to remove the effect of this data point on the calculated regressions.

As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.6.4.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 290: Summary of drivers for WM loans – total commitment

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Total commitment increases when general economic health improves	US GDP growth, US unemployment rate
Financial economy	**Assets under custody**	• With more AUC, BNY Mellon can offer more secured lending to high-net-worth individuals	BNY Mellon AUC
	Equity markets	• Stronger equity markets lead to greater lending to high-net-worth individuals, including greater value of marketable securities	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates may lead to decreased appetite to offer commitments	VIX, market volatility index
	Market volatility/ uncertainty (rates)	• Volatility and uncertainty may drive down demand as this may discourage borrowers from making high-value purchases	10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to offer commitments	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates	• On the other hand, borrowing becomes more expensive, which may reduce demand	1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.6.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for WM loans – total commitment are statistically significant. The intercept is found to be statistically insignificant.

Table 273: Statistical significance tests of model and variables for WM loans – total commitment

WM loans – total commitment (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
S&P volatility (30-day moving average)	-31.996	3%	10%	Statistically significant

1-year Treasury	-108.226	3%	10%	Statistically significant
Intercept	-0.637	96%	10%	Statistically not significant
Dummy for April 2009	-2,315.77	N/A	N/A	N/A

7.6.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

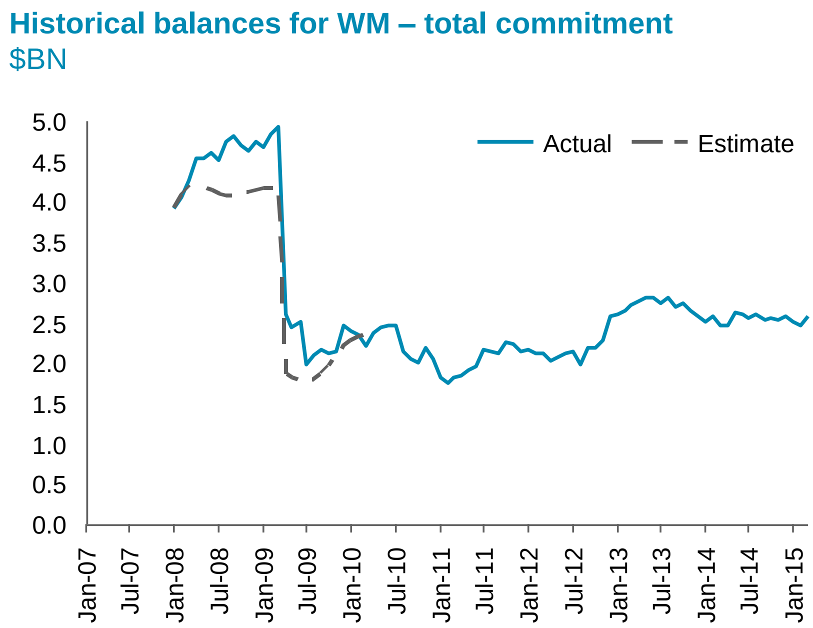
- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

Table 274: Model Diagnostics for WM loans – total commitment

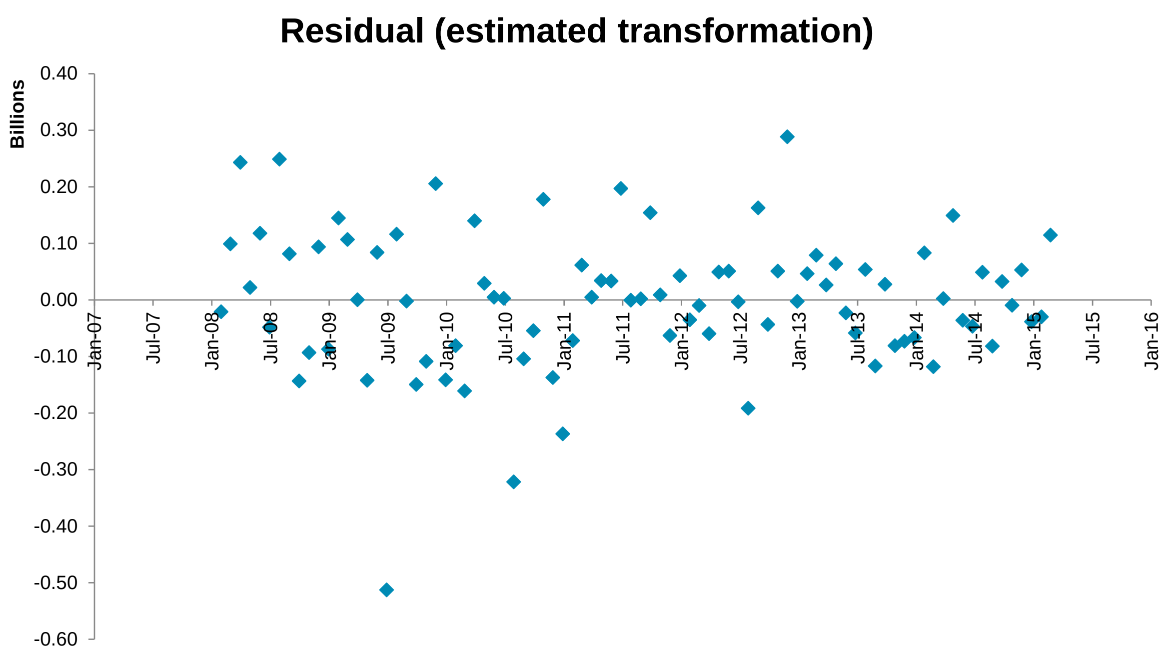
Wealth Management loans – total commitment (in USD MM) – Model diagnostics				
Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	81%	-	-
	Adjusted R-squared	81%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	97%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	36%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.36	5	No multicollinearity
Linearity	RESET test	89%	10%	Linear specification appropriate

Figure 291: 9-quarter In-sample Prediction for WM loans – total commitment



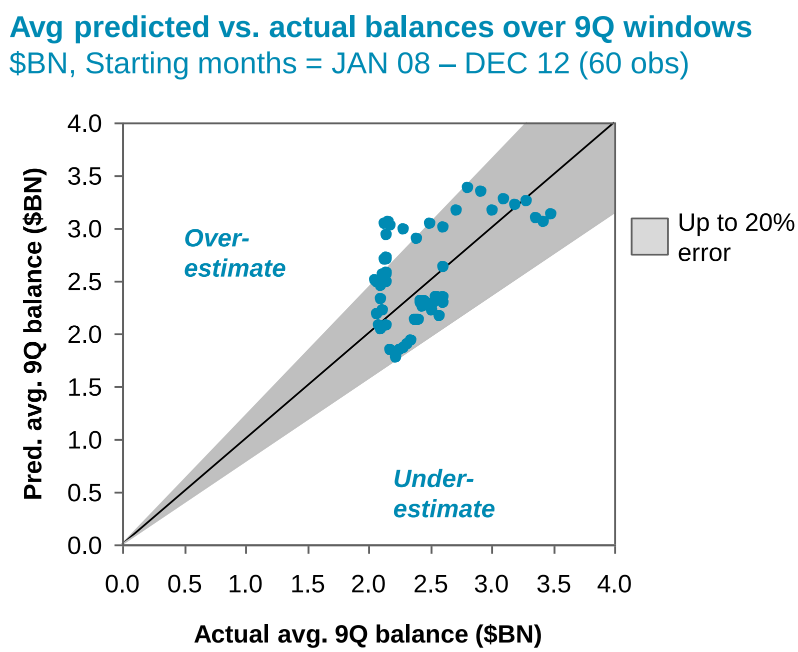
The in-sample back test of the model starting from January 2008 tracks fairly closely with the actual levels, capturing the correct directional behavior. The model fails to pick up most of the increase in balances over 2008, which leads to underestimation across most of the forecast window.

Figure 292: Residual Plot for WM loans – total commitment ($ BN)



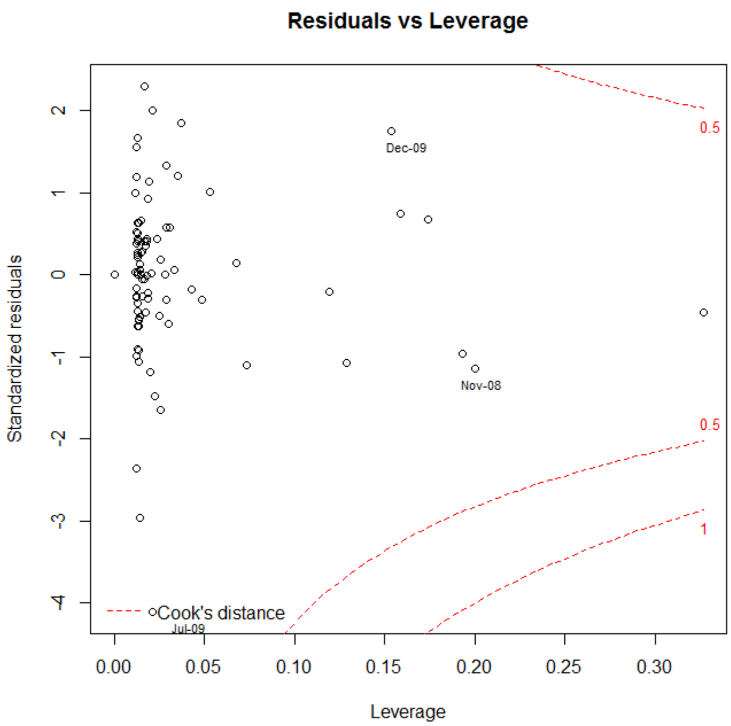
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 293: Estimation Scatterplot for WM loans – total commitment



Estimated average 9-quarter levels tracked fairly closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within or close to 20% of actual average values.

Figure 294: Influential points for Wealth Managment Total commitment



The segment has no highly influential points.

7.6.4.6. Model sensitivity

7.6.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 275: Sensitivity to changes to independent variables for WM loans – total commitment

WM loans – total commitment – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
S&P volatility (30-day moving average)	First difference – YoY	Index	-0.12	1.09	-0.03
1-year Treasury	First difference – QoQ	%	-0.13	0.38	-0.04

Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the 1-year Treasury rate variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the 1-year Treasury rate variable results in a 0.13 standard deviation ($0.04 BN) decrease in the predicted monthly change of the total commitment for the WM loan segment.

7.6.4.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 276: Statistical sensitivity tests for WM loans – total commitment

WM loans – total commitment (in USD MM) – Statistical significance tests of model and variables

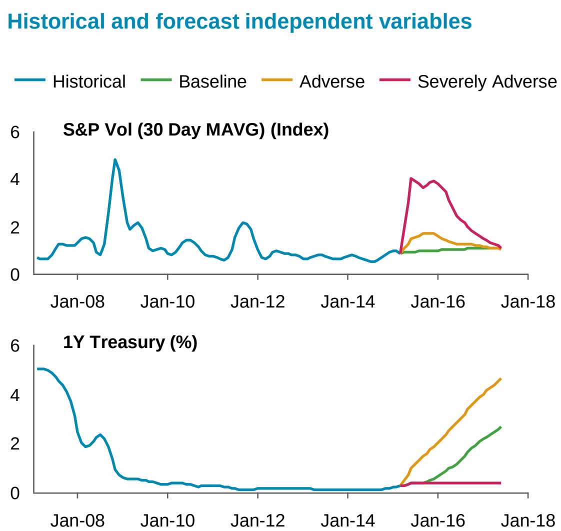
Tested independent variable	Original coefficient estimate	Sum of coefficients	P-value of shortened period coefficient	Conclusion
SP_Vol_DYoY	-31.996	-31.851	0.98	Statistically insignificant
Treasury1y_DQoQ	-108.226	-106.291	0.82	Statistically insignificant
Intercept	-0.637		0.76	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.98	Statistically insignificant

7.6.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

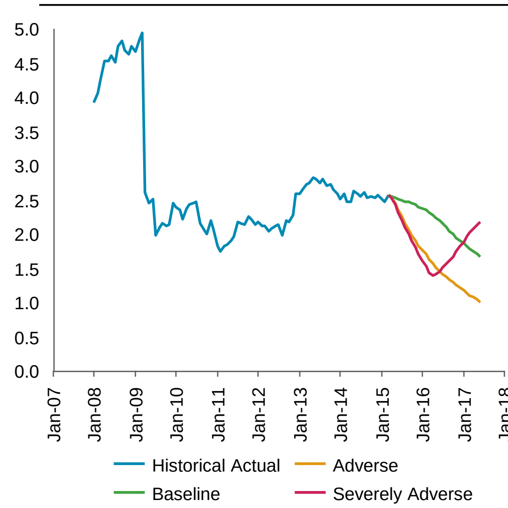
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 295: Final model forecast for WM loans – total commitment



Historical and forecast balances for WM total commitment
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-0.9 (-35%)	-1.58 (-61%)	-0.39 (-15%)	-
Start to peak	N/A	N/A	N/A	1.03 (26%)
Start to trough	-0.9 (-35%)	-1.58 (-61%)	-1.17 (-46%)	-1.94 (-50%)



The Working Group considered the forecast behavior for the selected WM loans – total commitment model as directionally reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant decline in total commitments, followed by a rebound. In a review of the forecasts with the line of business, this was noted to be directionally consistent with the possibility that both supply and demand for committed lines would decline under macroeconomic stress. However, the magnitude of the decline was deemed to be overly severe, especially considering the relative insensitivity of high-net-worth clients to macroeconomic conditions. Therefore, the results of this model should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario**: The model predicts a steep decline in total commitments. Similar to the severe recession scenario, the magnitude of this change was deemed to be overly severe, and may require particular attention during management review and challenge
- **Baseline scenario**: The model predicts that a decline in total commitments. Similar to the stress scenarios, the magnitude of this change was deemed to be overly severe, and may require particular attention during management review and challenge

7.6.5. Draw percentage

7.6.5.1. Summary

A statistically sound model that is consistent with business intuition was found for WM loans – draw percentage. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the draw percentage time series for Wealth Management loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 277: Coefficient estimates for selected model for WM loans – draw percentage

WM loans – draw percentage (logit-transformed) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Dow Jones Industrial Average	% change – MoM	%	0.0075	0.14
Market volatility index	First difference – YoY	Index	0.0013	0.13
Intercept	None (level)	None	0.0037	N/A
Dummy for April 2009		None	-1.476	N/A

The model contains the following drivers and variables:

- **Equity markets** – Dow Jones Industrial Average
- **Market volatility/uncertainty (equity)** – Market volatility index, constructed using maximum close-of-day values of the VIX in each period

The intuition of these variables is as follows:

- The Dow Jones Industrial Average variable has a positive coefficient. Overall equity market performance is linked to the value of marketable securities held by BNY Mellon for its Wealth Management clients, so better market performance increases the volume of loans that can be drawn against marketable securities
- The market volatility index variable has a positive coefficient and is interpreted as an indicator of market stress. When there is market stress, demand for loans may rise as access to alternate sources of funding may decline

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs. In addition to these variables, a dummy variable was used to address a specific issue identified in the historical data, which is discussed further in Section 7.6.5.2.2.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 296: Candidate models for WM loans – draw percentage

	Candidate models		
Drivers Considered	**1**	**2**	**3**
Equity markets		DJI (% MoM)	DJI (% MoM)
Long-term rates	3Y Treasury (Diff MoM)	20Y Treasury (Diff MoM, 1M Lag)	
Market volatility/ uncertainty (equity)	S&P Vol (30D MAVG) (% MoM)		Market Vol (Diff YoY)
Variation in levels explained through estimated logit first differences	**86%**	**86%**	**89%**
R-squared (differences)	**70%**	**70%**	**69%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.6.5.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.6.5.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The logit-transformed draw percentage time series for the WM loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the logit-transformed levels are tested using unit root and stationarity tests including a time trend.

The first differences of the logit-transformed levels, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 278: Unit root tests and stationarity tests including a trend variable on levels

WM loans – draw percentage – Unit root test with trend on logit-transformed level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	3	-1.2	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.5	0.35	Fail to reject unit root
KPSS	5	0.31	<0.01	Reject stationarity

Table 279: Unit root tests and stationarity tests including a constant on first differences

WM loans – draw percentage – Single mean unit root test on logit-transformed first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-7	<0.01	Reject unit root
Phillips-Perron	1	-9.8	<0.01	Reject unit root
KPSS	5	0.24	0.21	Fail to reject stationarity

Stationarity tests for WM loans – draw percentage logit transform uniformly reject stationarity across all three tests. These results suggest the logit is non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the WM loans – draw percentage deposit balances are modeled on their first differences.

7.6.5.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

One data adjustment was made to the historical time series for WM loans – draw percentage. As discussed in Section 7.6.3, a data issue was detected between March and April 2009, where a large volume of draws from facilities were reclassified as closed-end loans, which reduced the volume of total commitments. The line of business verified the cause of this data issue, and also its roots in the integration of legacy Mellon balances into BNY Mellon systems. The line of business also indicated that the legacy data and systems are no longer available to assist in resolving the data issue.

Since the dependent variable is a first difference, the discontinuity only impacts the April 2009 value for the dependent variable. Therefore, a dummy variable has been added into the independent variables, with value 0 for all months except April 2009, in order to remove the effect of this data point on the calculated regressions.

As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.6.5.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 297: Summary of drivers for WM loans – draw percentage

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• When the general economy is under stress, high-net-worth borrowers draw on committed lines more often to replace alternative sources of funding that are drying up	US GDP growth, US unemployment rate
Financial economy	**Assets under custody**	• With more AUC, borrowers can draw more against marketable securities	BNY Mellon AUC
	Equity markets	• Weakening equity markets are correlated with stress in economic conditions, which leads to increased draws • Alternatively, stronger equity markets lead to higher valuation of marketable securities, and therefore greater potential volume of draws from secured facilities	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in market conditions may be a sign of stress in overall economic conditions, leading to increased draws to cover funding needs • Alternatively, volatility may drive down draws by discouraging borrowers from making high-value purchases	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• As systemic credit risk rises, draws may either increase as alternative funding options become less attractive, or decrease as overall lending slows down	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Borrowers may be more willing to draw from commitments at lower rates	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.6.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for WM loans – draw percentage are statistically significant. The intercept is found to be statistically insignificant.

Table 280: Statistical significance tests of model and variables for WM loans – draw percentage

WM loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
DJI_PMoM	0.007	5%	10%	Statistically significant
Market_Vol_DYoY	0.001	7%	10%	Statistically significant
Intercept	0.004	75%	10%	Statistically not significant
Dummy for April 2009	-1.476	N/A	N/A	N/A

7.6.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences of logit transform), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

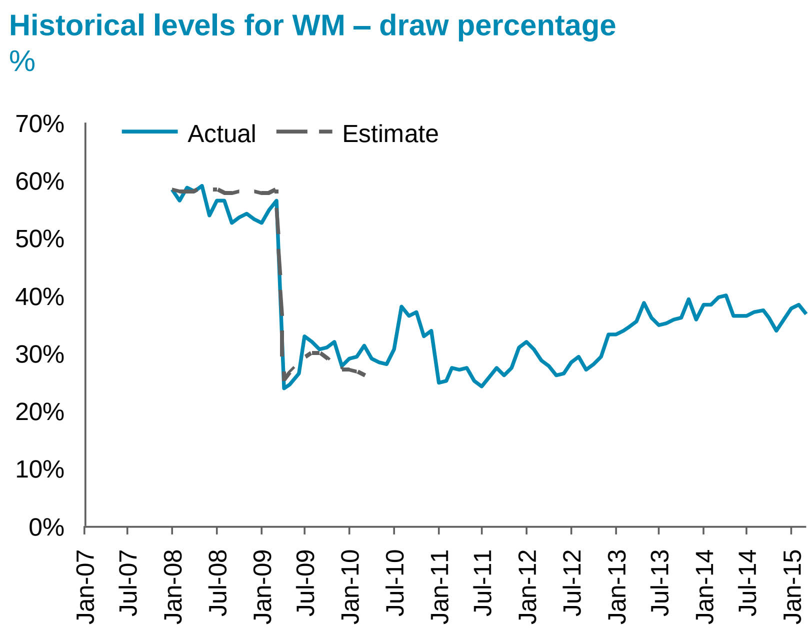
The diagnostic tests reviewed are exhibited below.

Table 281: Model Diagnostics for WM loans – draw percentage

WM loans – draw percentage (logit-transformed) – Model diagnostics

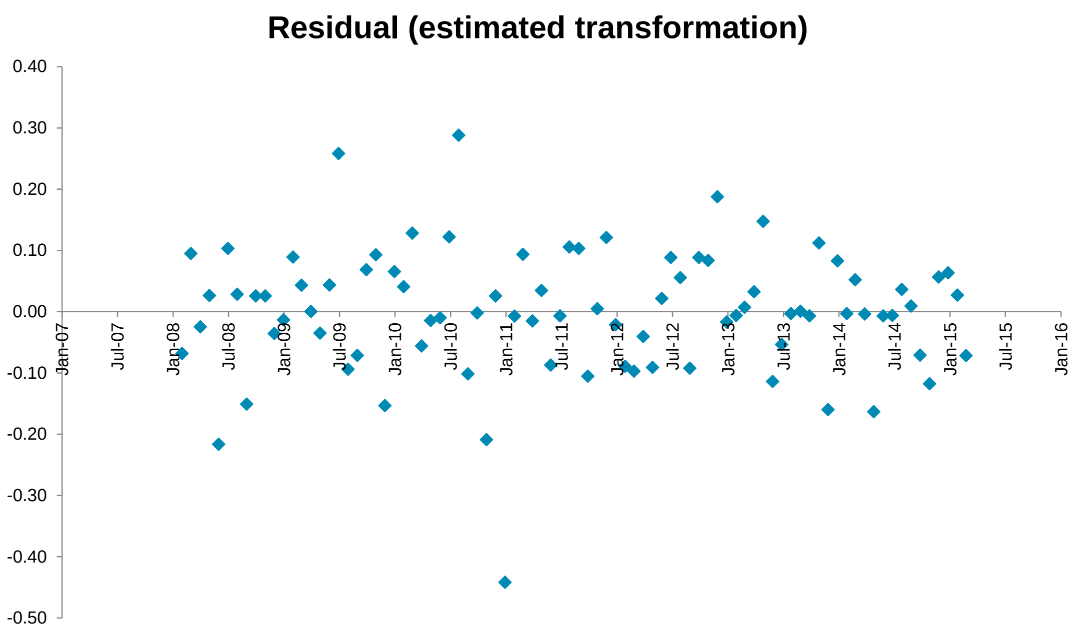
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	69%	-	-
	Adjusted R-squared	68%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.47	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	37%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.28	5	No multicollinearity
Linearity	RESET test	14%	10%	Linear specification appropriate

Figure 298: 9-quarter In-sample Prediction for WM loans – draw percentage



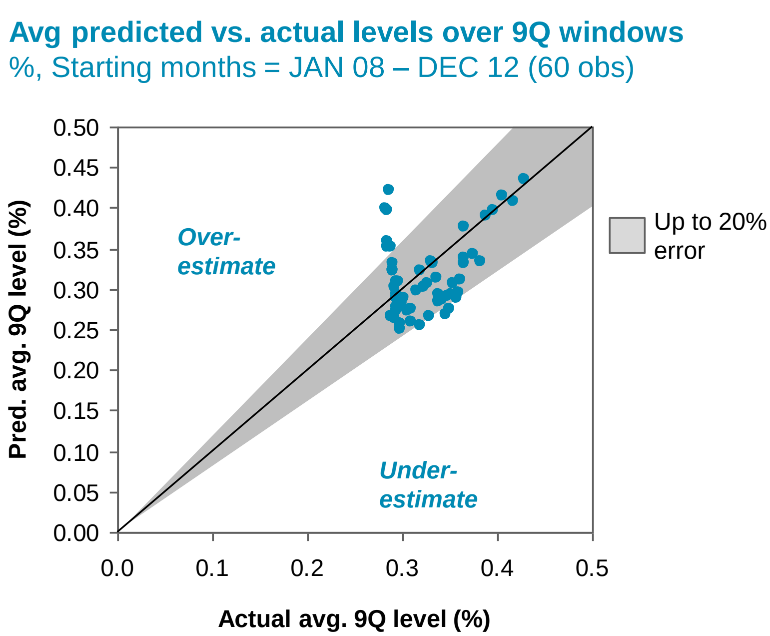
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

Figure 299: Residual Plot for WM loans – draw percentage



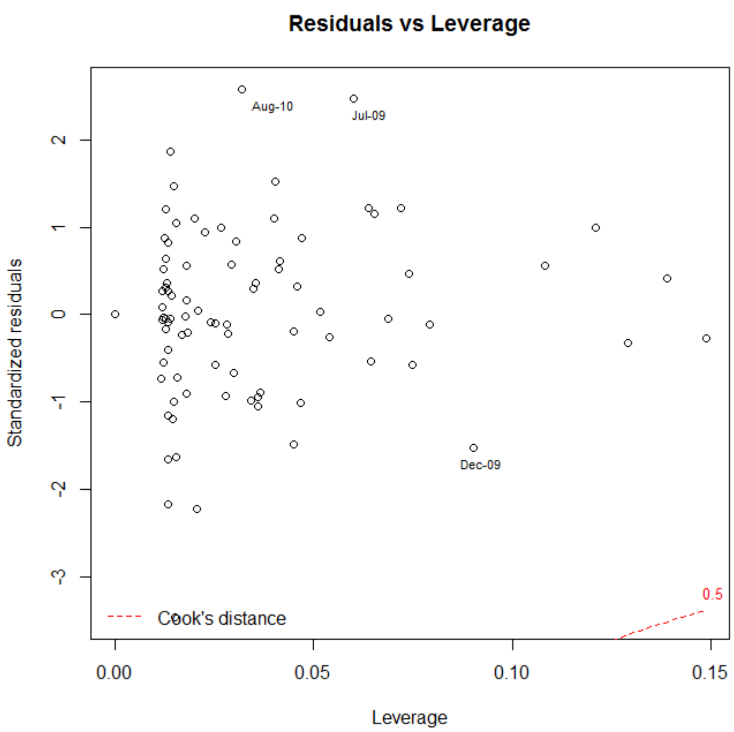
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 300: Estimation Scatterplot for WM loans – draw percentage



Estimated average 9-quarter levels tracked fairly closely with actual average 9-quarter levels for different 9-quarter forecast windows, with almost all estimated average values within or close to 20% of actual average values.

Figure 301: Influential points for Wealth Management Draw %



The segment has no highly influential points.

7.6.5.6. Model sensitivity

7.6.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the dependent variable due to a one standard deviation increase in an independent variable.

Due to the usage of the logit transformation, the relationship between the independent variables and the level of the draw percentage is non-linear. Therefore, a one standard deviation shift in an independent variable will have different impacts on the actual draw percentage, depending on the level of the draw percentage. Sensitivity of the level to movements in independent variables will decrease as the level approaches 0% or 100%, since applying the inverse logit transformation to the dependent variable must produce a level that is bounded between 0% and 100%.

Table 282: Sensitivity to changes to independent variables for WM loans – draw percentage

WM loans – draw percentage – model sensitivity				
Independent variable	**Transformation**	**Unit**	**Standardized coefficient**	**Std. dev of independent variable**
Dow Jones Industrial Average	Percent change – MoM	Index	0.14	3.24
Market volatility index	First difference – YoY	Index	0.13	17.85
Intercept	None (level)	None	N/A	N/A

In the selected model for WM loans – draw percentage, the Dow Jones Industrial Average variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Dow Jones Industrial Average variable results in a 0.14 standard deviation increase in the predicted monthly change of the logit-transformed draw percentage for the WM loan segment.

7.6.5.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 283: Statistical sensitivity tests for WM loans – draw percentage

WM loans – draw percentage (logit-transformed) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
Dow Jones Industrial Average	0.007	0.008	0.65	Statistically insignificant
Market volatility index	0.001	0.001	0.72	Statistically insignificant
Intercept	0.004		0.93	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.91	Statistically insignificant

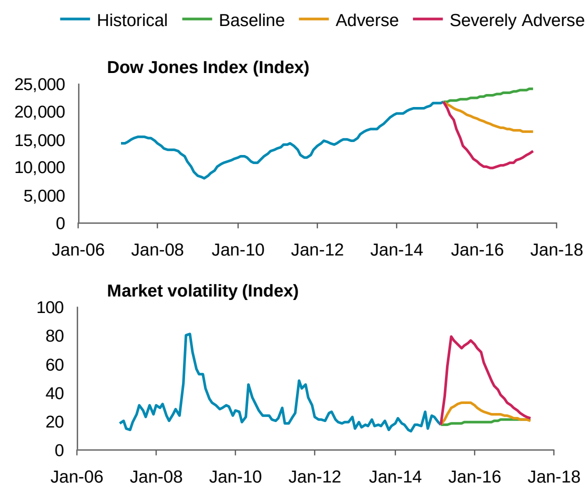
7.6.5.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

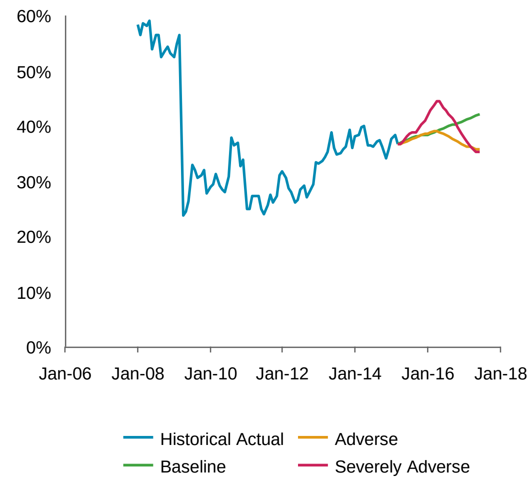
Figure 302: Final model forecast for WM loans – draw percentage

Historical and forecast independent variables



Historical and forecast levels for WM draw %
%

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	5.31%	-1.04%	-1.61%	-
Start to peak	5.31%	2.27%	7.75%	0.67%
Start to trough	N/A	-1.04%	-1.61%	N/A



The Working Group determined that the forecast behavior for the selected WM loans – draw percentage model produces intuitive forecast results, and this was corroborated by the line of business.

- **Severe recession (Severely Adverse) scenario:** The model predicts an increase in draw percentage, followed by a decline. This line of business indicated that this is consistent with business intuition, as clients may have greater need for funds during severe stress. The magnitude of the increase was also deemed appropriate, as historically the draw percentage has not deviated significantly even during periods of macroeconomic stress
- **Interest rate shock (Adverse) scenario**: The model predicts a slight increase in draw percentage, followed by a decline. The line of business indicated that this is consistent with business intuition
- **Baseline scenario**: The model predicts a gradual increase in draw percentage, in line with the slow growth trend in draw percentage in recent years

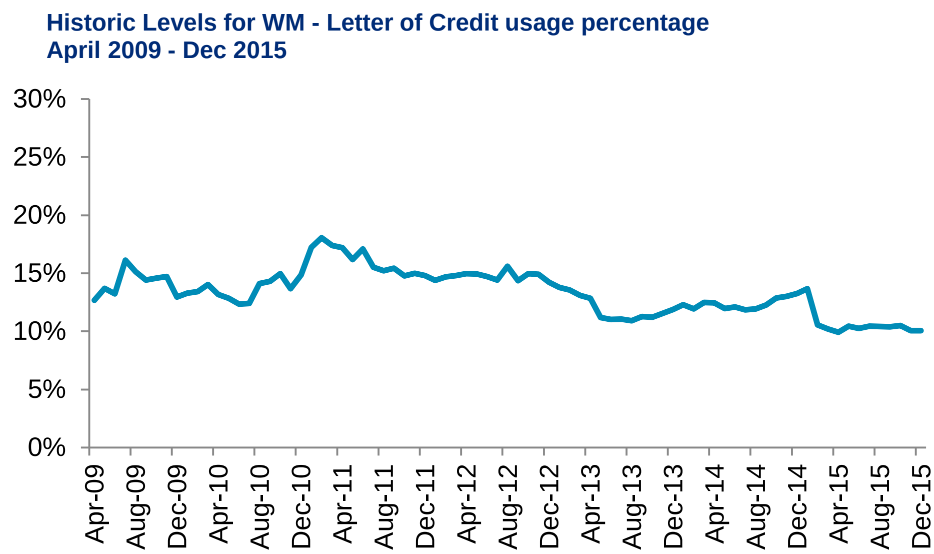
7.6.6. Letter of Credit usage percentage

7.6.6.1. Summary

A modeling approach was initially pursued for Wealth Management loans –Letters of Credit percentage. However, the line of business input indicated that Letters of Credit for this segment is not expected to be sensitive to macroeconomic factors. For the Wealth Management line of business, Letters of Credit tend to be issued on a one-off basis when high-net-worth clients request support for transactions. The need for support for these transactions is not linked to macroeconomic factors (to which high net worth individuals remain relatively insensitive), but rather the idiosyncratic needs of a particular client. As a result, the line of business expects the Total Letters of Credit to be tied to the total number of clients, which can be approximated based on Total commitments in this segment. As a result, Total commitments are a better indication of the Total Letter of Credit volume in a given period than any macroeconomic factor.

The modeling team corroborated this intuition by assessing the historical time series for this quantity. Throughout the historical period, the Letters of Credit usage percentage remains relatively stable, as shown in the Figure below (which excludes a few months due to a data issue affecting Total commitments). Given this stability, a qualitative framework was pursued.

Figure 303: Historical levels for WM loans – Letter of Credit usage percentage



The qualitative framework for forecasting WM loan –Letters of Credit percentage is using historical average, 13.35%, which was observed in the historical time series between April 2009 and December 2015, excluding a few months due to a certain data issue which affected Total commitments balances. Distribution of historical Wealth Management Loans –Letters of Credit percentage is summarized in table 1.

Table 284: Summary statistics for historical time series for Wealth Management loans – Letter of Credit usage percentage

Statistic	Value
Mean	13.35%
Maximum	18.06%
Minimum	9.93%

7.6.7. Closed-end loans

7.6.7.1. Summary

A statistically sound model that is consistent with business intuition was found for WM loans – closed-end loans. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the closed-end loan time series for Wealth Management loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 285: Coefficient estimates for selected model for WM loans – closed-end loans

WM loans – closed-end loans (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Market volatility index	% change – MoM	Index	-0.60	-0.08
Unemployment rate	First difference – MoM	%	-95.93	-0.10
Intercept	None (level)	$ MM	32.23	N/A
Dummy for April 2009		$ MM	1,810.1	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – Market volatility index, constructed using maximum close-of-day values of the VIX in each period
- **General economic health** – US unemployment rate

The intuition of these variables is as follows:

- The market volatility index variable has a negative coefficient. As market uncertainty rises, high-net-worth individuals may have lower demand for loans as they may be less likely to make high-value purchases, although this effect is not expected to be large
- The unemployment rate variable has a negative coefficient. Unemployment rates are interpreted as an indicator of general economic health; as general economic conditions deteriorate, high-net-worth individuals may have lower demand for loans as they may be less likely to make high-value purchases, although this effect is not expected to be large

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs. In addition to these variables, a dummy variable was used to address a specific issue identified in the historical data, which is discussed further in Section 7.6.7.2.2.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 304: Candidate models for WM loans – closed-end loans

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
General economic health	Nom Disposable Income (Level, 1M Lag)	Nom Disposable Income (Level, 1M Lag)	Nom Disposable Income (Level, 1M Lag)		Unemp rate (Diff MoM)
Housing prices	HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	HPI (% MoM, 1M Lag)	
Long-term rates	30Y Treasury (Diff YoY)			20Y Treasury (Diff YoY)	
Market volatility / uncertainty (equity)					Market Vol (% MoM)
Perceived credit risk		Ovrnt LIBOR-1wk OIS spread (Diff MoM)		1 week LIBOR 1 week OIS spread (Diff MoM, 1M Lag)	
Variation in balances explained through estimated first differences	**99%**	**99%**	**99%**	**98%**	**99%**
R-squared (differences)	**89%**	**89%**	**89%**	**89%**	**89%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.6.7.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.6.7.2.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The closed-end loan time series for the WM loan balance segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 286: Unit root tests and stationarity tests including a trend variable on levels

WM loans – closed-end loans – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-2.8	>0.10	Fail to reject unit root
Phillips-Perron	1	-2.7	0.24	Fail to reject unit root
KPSS	5	0.15	0.05	Reject stationarity

Table 287: Unit root tests and stationarity tests including a constant on first differences

WM loans – closed-end loans – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-5.4	<0.01	Reject unit root
Phillips-Perron	1	-10	<0.01	Reject unit root
KPSS	2	0.05	0.9	Fail to reject stationarity

Stationarity tests for WM loans – closed-end loans balances uniformly reject stationarity across all three tests. These results suggest the balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the WM loans – closed-end loans deposit balances are modeled on their first differences.

7.6.7.2.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

One data adjustment was made to the historical time series for WM loans – draw percentage. As discussed in Section 7.6.3, a data issue was detected between March and April 2009, where a large volume of draws from facilities were reclassified as closed-end loans, which reduced the volume of total commitments. The line of business verified the cause of this data issue, and also its roots in the integration of legacy Mellon balances into BNY Mellon systems. The line of business also indicated that the legacy data and systems are no longer available to assist in resolving the data issue.

Since the dependent variable is a first difference, the discontinuity only impacts the April 2009 value for the dependent variable. Therefore, a dummy variable has been added into the independent variables, with value 0 for all months except April 2009, in order to remove the effect of this data point on the calculated regressions.

As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.6.7.3. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 305: Summary of drivers for WM loans – closed-end loans

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Loan volume increases when general economic health improves	US GDP growth, US unemployment rate
Financial economy	**Assets under custody**	• With more AUC, BNY Mellon can offer more secured lending to high-net-worth individuals	BNY Mellon AUC
	Equity markets	• Stronger equity markets lead to greater lending to high-net-worth individuals, including greater value of marketable securities	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates may lead to decreased appetite to extend loans • Volatility and uncertainty may drive down demand as this may discourage borrowers from making high-value purchases	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to extend loans	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.6.7.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results

are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for WM loans – closed-end loans are statistically significant. The intercept is found to be statistically significant.

Table 288: Statistical significance tests of model and variables for WM loans – closed-end loans

WM loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market volatility index	-0.599	4%	10%	Statistically significant
Unemployment rate	-95.933	1%	10%	Statistically significant
Intercept	32.226	0%	10%	Statistically significant
Dummy for April 2009	1,810.1	N/A	N/A	N/A

7.6.7.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

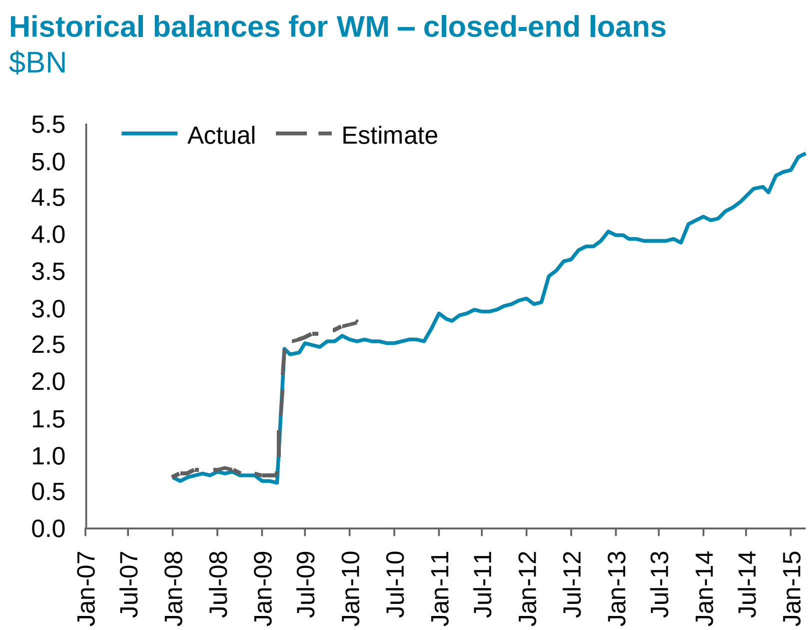
Table 289: Model Diagnostics for WM loans – closed-end loans

WM loans – closed-end loans (in USD MM) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	89%	-	-
	Adjusted R-squared	88%	-	-

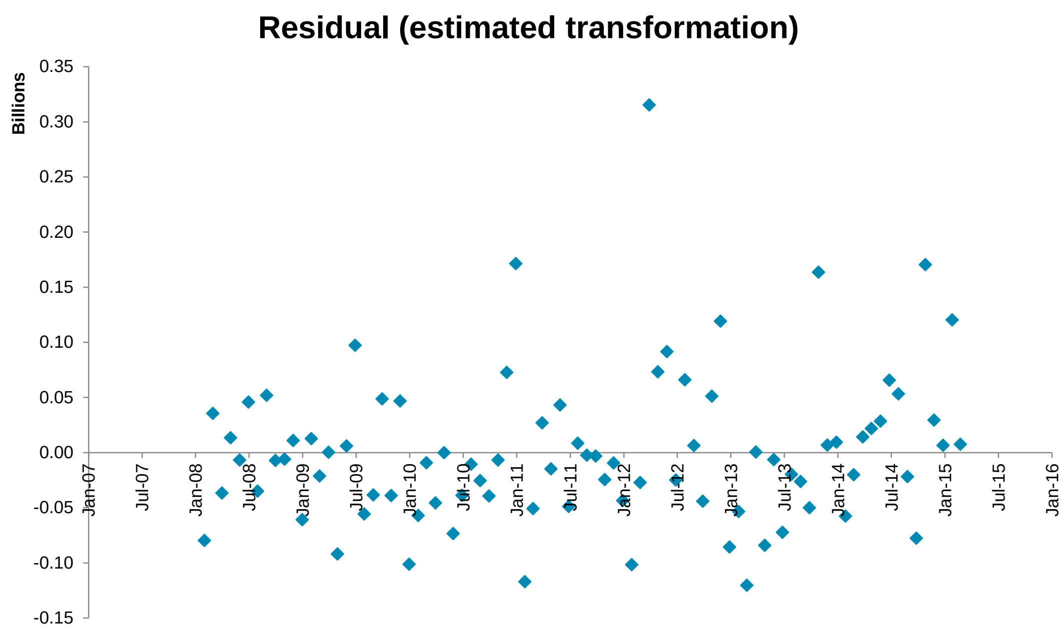
Heteroskedasticity	Breusch-Pagan test (p-value)	0.59	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	85%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.03	5	No multicollinearity
Linearity	RESET test	43%	10%	Linear specification appropriate

Figure 306: 9-quarter In-sample Prediction for WM loans – closed-end loans



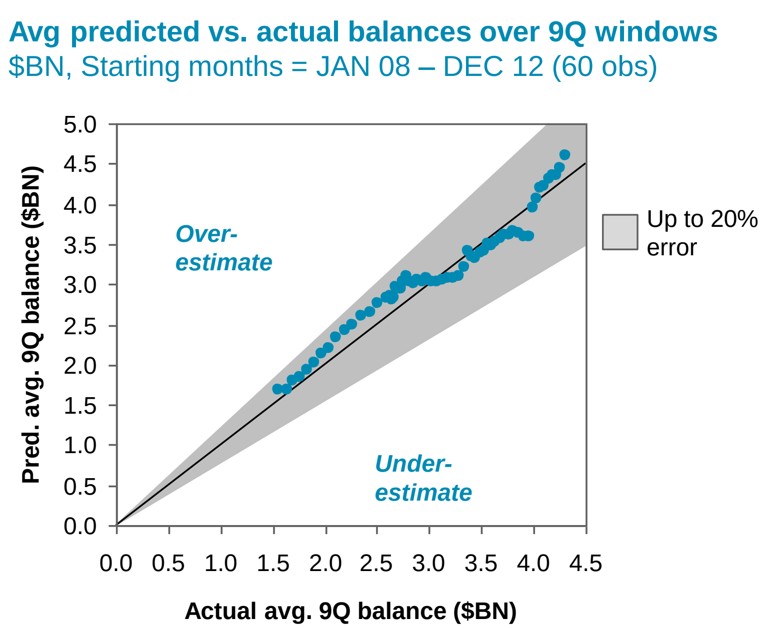
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

Figure 307: Residual Plot for WM loans – closed-end loans ($ BN)



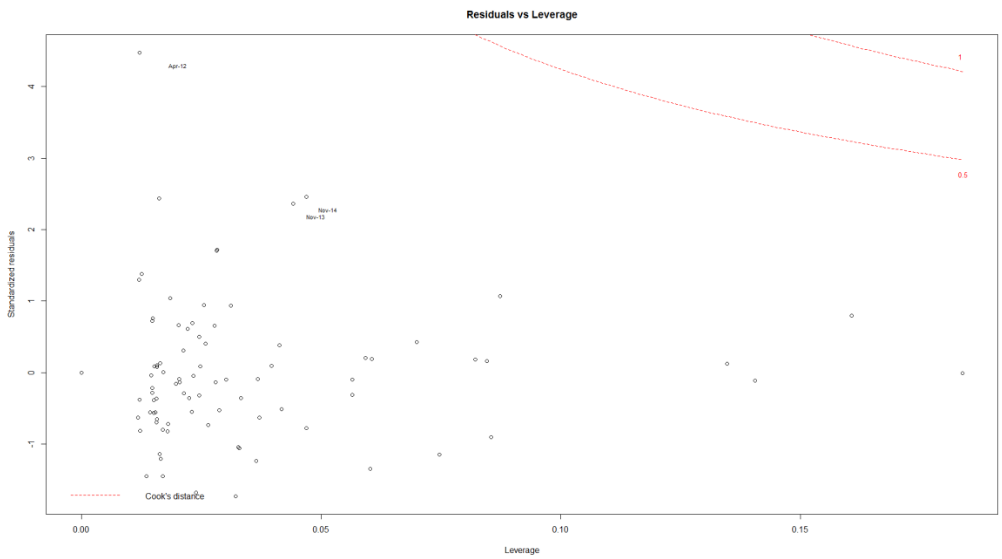
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 308: Estimation Scatterplot for WM loans – closed-end loans



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 309: Influential points for Wealth Management Closed end loans



The segment has no highly influential points.

7.6.7.6. Model sensitivity

7.6.7.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 290: Sensitivity to changes to independent variables for WM loans – closed-end loans

WM loans – closed-end loans – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Market volatility index	% change – MoM	Index	-0.08	26.66	-0.02
Unemployment rate	First difference – MoM	%	-0.10	0.20	-0.02
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model for WM loans – closed-end loans, the unemployment rate variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the unemployment rate variable results in a 0.10 standard deviation ($0.02 BN) decrease in the predicted monthly change of the closed-end loans for the WM loan segment.

7.6.7.6.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. However, because the individual market volatility coefficient is significant the model may not remain stable over time.

Table 291: Statistical sensitivity tests for WM loans – closed-end loans

WM loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

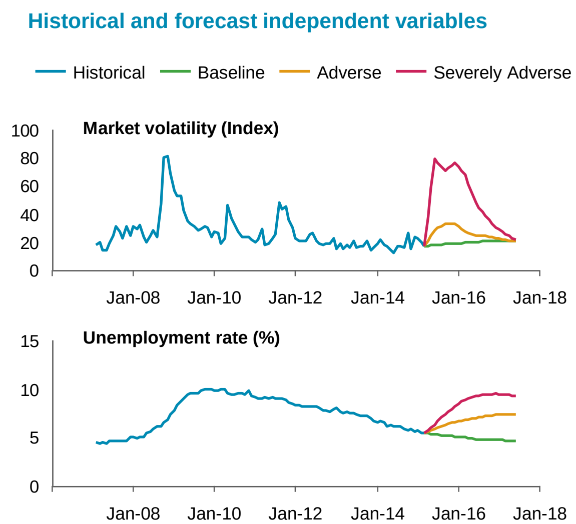
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
Market Vol	-0.599	-0.262	0.03	Statistically significant
Unemployment rate	-95.933	-84.524	0.94	Statistically insignificant
Intercept	32.226		0.29	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.14	Statistically insignificant

7.6.7.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

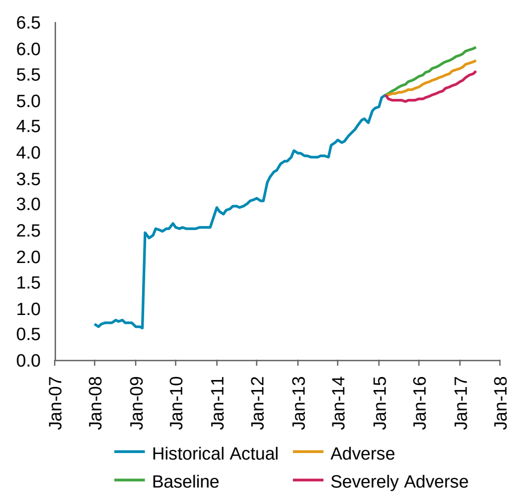
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 310: Final model forecast for WM loans – closed-end loans



Historical and forecast balances for WM closed-end loans
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	0.93 (18%)	0.67 (13%)	0.45 (9%)	-
Start to peak	0.93 (18%)	0.67 (13%)	0.45 (9%)	1.94 (286%)
Start to trough	N/A	N/A	-0.11 (-2%)	-0.06 (-9%)



The Working Group determined that the forecast behavior for the selected WM loans – closed-end loans model produces intuitive forecast results, and this was corroborated by the line of business.

- **Severe recession (Severely Adverse) scenario:** Closed-end loan balances decline slightly in the beginning of the forecast window, but then grow slowly over the remaining quarters. The line of business indicated that the direction of this forecast this aligns with business intuition that this segment is relatively insensitive to macroeconomic conditions
- **Interest rate shock (Adverse) scenario**: Closed-end loan balances grow slowly, at a rate lower than in the Baseline scenario
- **Baseline scenario**: Closed-end loan balances grow roughly in line with the historical growth rate

7.6.8. Model limitations

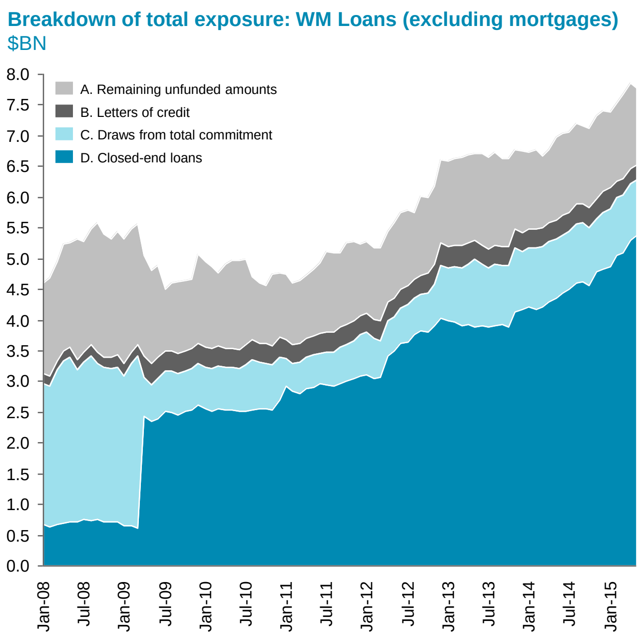
Beyond that data issue discussed in Section 7.6.3, no specific limitations were noted for the models in this segment. As additional historical data becomes available, the models should be updated and recalibrated to improve their predictive power.

7.6.9. Synthesis of forecast results

After forecasts have been generated from the models, a small set of additional calculations is required to obtain the desired balance forecasts shown in the figure below:

- Balances for funded draws from commitments (Quantity C in figure) can calculated as the product of total commitment and draw percentage
- Unfunded Letter of Credit amounts (Quantity B in figure) can be calculated as the product of total commitment and Letter of Credit usage percentage
- Unused unfunded commitments (Quantity A in figure) can be calculated as total commitments minus balances for funded draws minus unfunded Letter of Credit amounts
- Total funded loan balances can be calculated as the sum of balances for funded draws plus balances for closed-end loans (Quantity C + Quantity D in figure)

Figure 311: Breakdown of total exposure for WM loans (excluding mortgages)



7.7. Margin loans

7.7.1. Business overview

BNY Mellon originates and purchases loans as part of its ongoing business. The margin loans segment is comprised of closed-end loans from Pershing; in addition, there are margin loan unfunded commitments that began in August 2011. As of April 30, 2015, BNY Mellon had $11.8 BN in funded margin loans.

Margin loans are loans primarily to broker dealer clients. They are collateralized with marketable securities and borrowers are required to maintain a daily collateral margin in excess of 100% of the value of the loan. Margin loans included $8.4 BN of loans at March 31, 2015 and $8.7 BN at December 31, 2014 related to a term loan program that offers fully collateralized loans to broker dealers.

The collateral for margin loans includes fixed income securities and equities. Specifically, potential collateral sources include Treasuries, Agencies, MBS, Russell 3000 equities and investment grade corporates, among others. The collateral is assigned haircuts according to the risk posed by the collateral. The maturities of these loans vary, but generally range from three months to one year.

All margin loans are originated through Pershing LLC. Along with non-purpose loans to various parties, margin loans to clients and introducing broker-dealers account for Pershing's primary funding needs in the ordinary course of business. Margin loans to clearing clients are primarily financed with free credits in client accounts and loans to introducing brokers are funded mainly by broker-dealer credits, as well as repos and stock loans using broker-dealer securities.

7.7.2. Closed-end loans

7.7.2.1. Summary

A statistically sound model that is consistent with business intuition was found for margin loans – closed-end loans. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity**: the model is estimated on month-over-month differences in margin loans, which are found to be stationary
- **Statistical significance**: the coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests**: the model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 292: Coefficient estimates for selected model for margin loans – closed-end loans

Margin loans – closed-end loans (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized Coefficient**
Market Volatility	Difference MoM	$ MM	-7.78	-0.22
MSCI World Index	Difference QoQ	$ MM	0.48	0.22
Nominal Disposable Income	None (level)	%	14.92	0.26
Intercept	None (level)	$ MM	24.13	N/A

The model contains the following drivers and variables:

- **Equity markets** – MSCI World Index, a benchmark for global stock funds based on securities from 23 countries
- **Market volatility/uncertainty (equity)** – Market volatility index, constructed using maximum close-of-day values of VIX in each period
- **General economic health** – US nominal disposable income, the amount of money available to households for spending and saving after income taxes

The intuition of these variables is as follows:

- The market volatility index variable has a negative coefficient; as market volatility rises, demand for margin loans may decrease as investors sell off highly leveraged products to hedge against further losses
- The MSCI World Index has a positive coefficient, with the rationale that margin loans will increase as investment options grow more attractive, driving increased investment activity
- Nominal disposable income has a positive coefficient indicating that margin loans will increase as general economic health improves

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 312: Candidate models for margin loans – closed-end loans

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Corporate credit	Baa to Treasury Spread (Diff YoY)	Baa to Treasury Spread (Diff YoY)			Baa to Treasury Spread (Diff YoY)
Equity markets			MSCI World Index (Diff QoQ)	MSCI World Index (Diff QoQ)	MSCI World Index (% MoM)
General economic health	Nominal Disposable Income (Level)			Nominal Disposable Income (Level)	Nominal Disposable Income (Level, 1M lag)
Hedge fund index		HFRX NA Index (Diff QoQ)	HFRX NA Index (Diff QoQ)		
Market volatility/uncertainty	Market Vol (Diff MoM)	Market Vol (% QoQ)	S&P Vol (30D MAVG) (% QoQ)	Market Vol (Diff MoM)	
Variation in balances explained through estimated first differences	**97%**	**97%**	**95%**	**95%**	**97%**
R-squared (differences)	**29%**	**24%**	**24%**	**24%**	**23%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.7.2.2. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.7.2.3. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The time series for the margin loans segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 293: Unit root tests and stationarity tests including a trend variable on balances

Margin loans – closed-end loans – Unit root test with trend on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-1.4	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.9	0.64	Fail to reject unit root
KPSS	5	0.1	0.15	Fail to reject stationarity

Table 294: Unit root tests and stationarity tests including a constant on first differences

Margin loans – closed-end loans – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	0	-8.6	<0.01	Reject unit root
Phillips-Perron	1	-8.6	<0.01	Reject unit root
KPSS	2	0.21	0.25	Fail to reject stationarity

Stationarity tests for Margin loans balances yield mixed results: The ADF and PP tests fail to reject a unit root while the KPSS test fails to reject stationarity. These results suggest the balances may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Margin Loan balances are modeled on their first differences.

7.7.2.4. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

As discussed under Section 4.2 on development data, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes. This data required cleansing to distinguish between Pershing margin loans and margin loans from the securities financing portfolio, which are treated separately in the Securities Financing segment. After the two segments had been identified and separated, no adjustments were necessary for Pershing margin loans – closed-end loans.

7.7.2.5. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 313: Summary of drivers for margin loans – closed-end loans

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• A better performing economy will encourage clients to take on loans to make investments	• Real GDP growth
Financial economy	**Equity markets**	• Strong market performance entices more investments and trading activity from clients resulting in greater loan demand	• S&P500, Dow Jones
	Market volatility/ uncertainty	• Higher market volatility results in clients moving to safer assets, resulting in less loan demand at Pershing	• VIX, rates volatility, US LIBOR-OIS spread, equity indices, FDIC insurance on DDA dummy variable, Fed stress indices
	Hedge fund index	• Stronger hedge fund performance leads to greater lending to FIs and broker-dealers	• HFRX index, Eurekahedge HF index, Eurekahedge FoF index
Rates	**Corporate credit**	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	• Baa corporate yield, Baa to Treasury spread
	Short-term rates	• Increasing rates and spreads makes lending more attractive as a source of income, within the bank's risk appetite • On the other hand, borrowing becomes more expensive, which may reduce demand	• Overnight LIBOR, Fed Funds rate, Treasury yields, SONIA, EONIA, Money Market fund yield indices, repo rates

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.7.2.6. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for margin loans – closed-end loans are statistically significant. The intercept is found to be statistically insignificant.

Table 295: Statistical significance tests of model and variables for margin loans – closed-end loans

Margin loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market Volatility	-7.78	3%	10%	Statistically significant
MSCI World Index	0.48	4%	10%	Statistically significant
Nominal Disposable Income	14.92	1%	10%	Statistically significant
Intercept	24.13	43%	10%	Statistically not significant

7.7.2.7. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

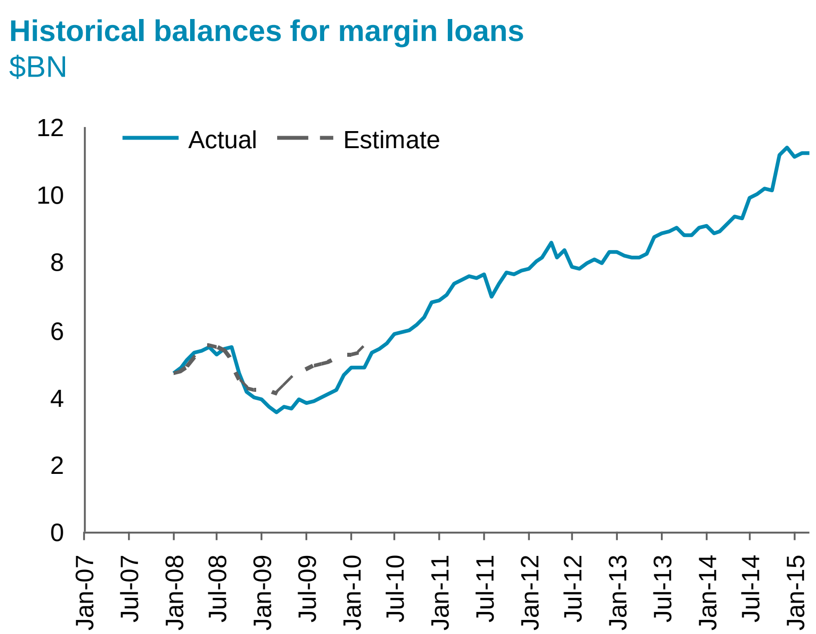
- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The diagnostic tests reviewed are exhibited below.

Table 296: Model Diagnostics for margin loans – closed-end loans

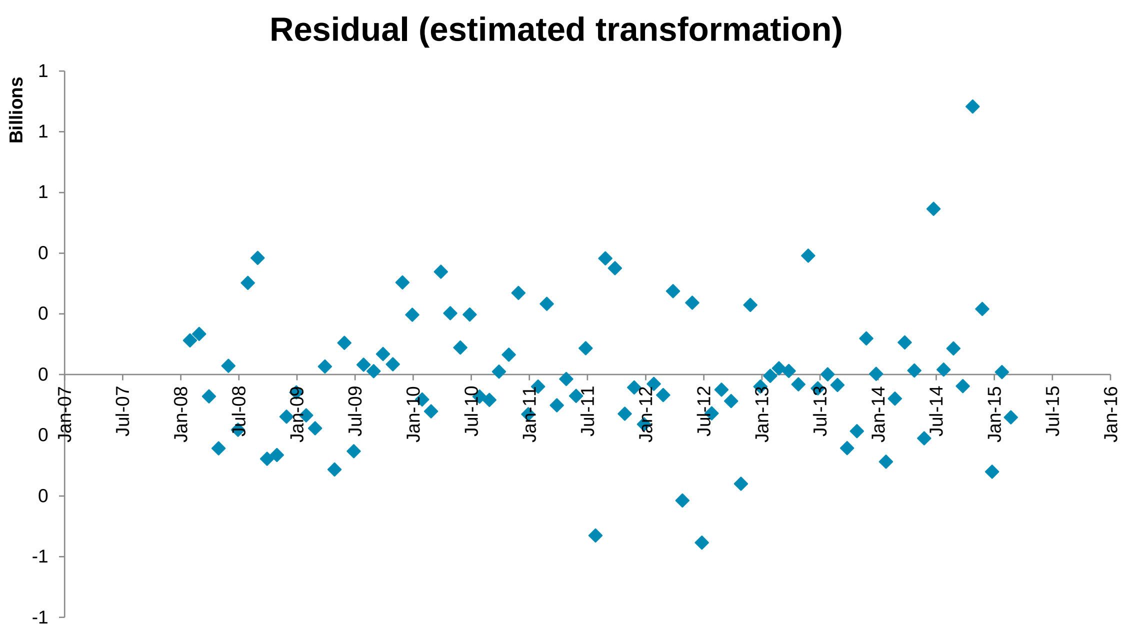
Margin loans – closed-end loans (in USD MM) – Model diagnostics				
Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	24%	-	-
	Adjusted R-squared	21%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.37	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	40%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.18	5	No multicollinearity
Linearity	RESET test	11%	10%	Linear specification appropriate

Figure 314: 9-quarter In-sample Prediction for margin loans – closed-end loans



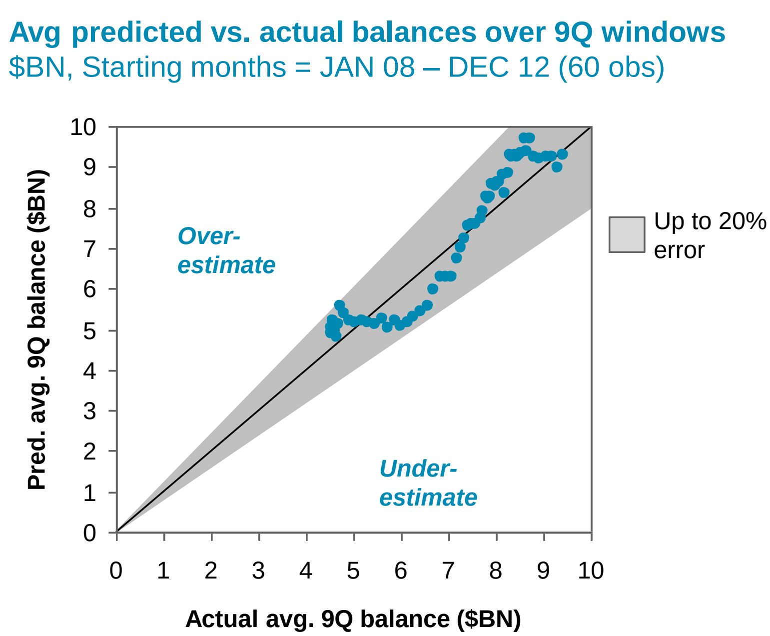
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, capturing the correct directional behavior. The model does not capture the full decline in balances from 2009 through 2010.

Figure 315: Residual Plot for margin loans – closed-end loans ($ BN)



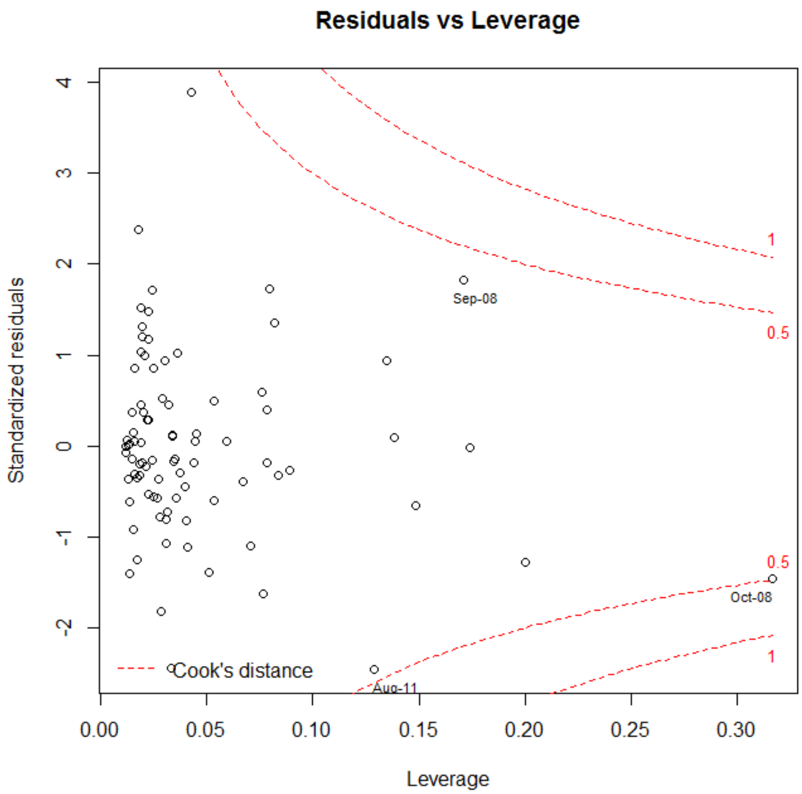
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 316: Estimation Scatterplot for margin loans – closed-end loans



Estimated average 9-quarter levels tracked with actual average 9-quarter levels for different 9-quarter forecast windows, with all estimated average values within 20% of actual average values.

Figure 317: Influential points for Margin Loans



The segment has no highly influential points.

7.7.2.8. Model sensitivity

7.7.2.9. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 297: Sensitivity to changes to independent variables for margin loans – closed-end loans

Margin loans – closed-end loans – model sensitivity

Independent variable	Transformation	Unit	Standardized Coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Market Volatility	Difference MoM	$ MM	-0.22	7.18	-0.06
MSCI World Index	Difference QoQ	$ MM	0.22	117.33	0.06

Nominal Disposable Income	None (level)	%	0.26	4.31	0.07
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the Nominal Disposable Income variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Nominal Disposable Income results in a 0.26 standard deviation ($0.07 BN) increase in the predicted monthly change of the margin loan segment.

7.7.2.10. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 298: Statistical sensitivity tests for margin loans – closed-end loans

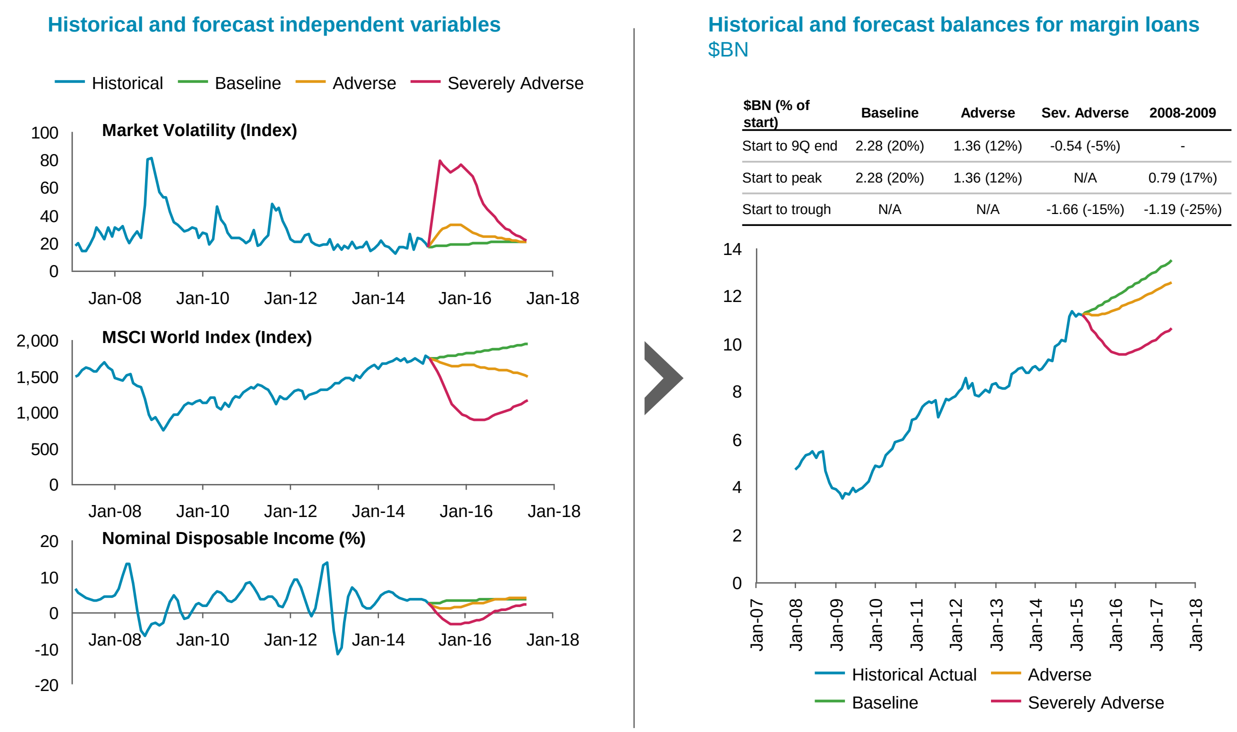
Margin loans – closed-end loans (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of Coefficients**	**P-value of shortened period Coefficient**	**Conclusion**
Market Volatility	-7.78	-6.626	0.37	Statistically insignificant
MSCI World Index	0.48	0.569	0.16	Statistically insignificant
Nominal Disposable Income	14.92	12.917	0.72	Statistically insignificant
Intercept	24.13		0.61	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.41	Statistically insignificant

7.7.2.11. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 318: Final model forecast for margin loans – closed-end loans



The Working Group considered the forecast behavior for the selected margin loans – closed end loans model as mostly reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts a decrease in margin loan balances followed by a moderate increase. This behavior is primarily driven by the MSCI market variable, where the index stabilizes and begins to recover through the stress period; this variable is interpreted as an indicator of investment activity. The forecast behavior was consistent with business expectations
- **Interest rate shock (Adverse) scenario**: Business intuition is that margin loans will decrease under macroeconomic stress. As interest rates are shocked, borrowing becomes relatively more expensive and a decrease in margin loans is expected. This is seen in the forecast behavior with more moderate balance growth relative to the baseline
- **Baseline scenario**: The model predicts that margin loans will grow at a moderate rate over the 9-quarter period. The business deemed this growth – which is near the average historical growth rate – in line with expectations

7.7.3. Total commitment

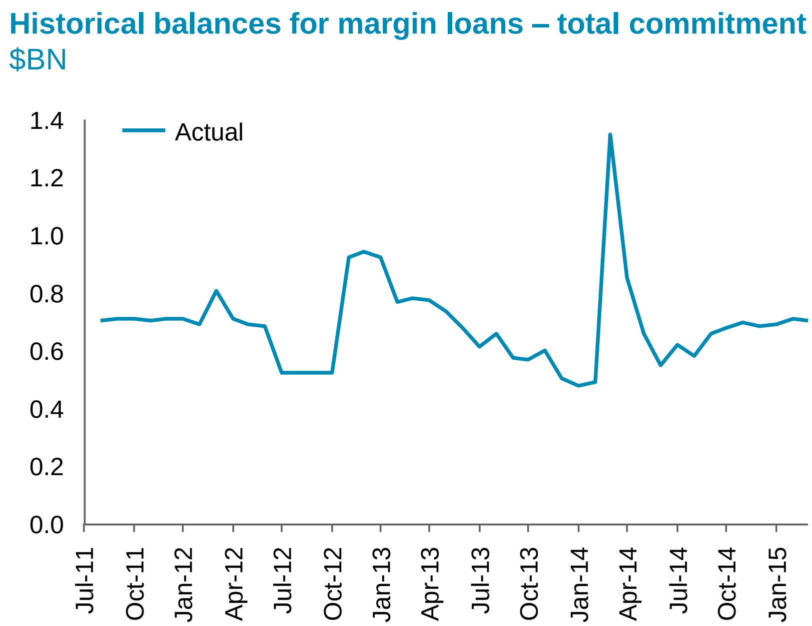
7.7.3.1. Summary

Margin loan unfunded commitment balances exist from August 2011 to March 2015 and the modeling team assessed whether this time series would be suitable for a statistical model. Reviewing the historical data, it was determined that a statistical model would not be viable because:

- The commitment balances do not have a strong relationship to any macroeconomic factors
- The historical time series is very short, and covers a period of relatively homogeneous interest rates and spreads

The balances are shown in the figure below.

Figure 319: Historical levels for margin loans – total commitment



The qualitative framework agreed for forecasting the total commitment in margin loans is to hold the value constant across all scenarios at the average value of $624.8 Million observed in the historical time series between August 2011 and December 2015. This approach is taken in order to utilize all of the limited data available on this segment, and to avoid over- or under-weighting any particular point. Further, line of business feedback indicated that using the average was a reasonable approach given that this segment consists of a small number of clients, and as such movements in balances were likely to be driven by idiosyncratic, client-specific factors that may not have direct linkage to the economic environment. The table below shows additional summary statistics for this time series.

Table 299: Summary statistics for historical time series for margin loans – total commitment

Statistic	Value ($ MM)
Mean	$624.8
Sample standard deviation	$127.4
Average absolute deviation from mean	$97.2
Maximum	$941.9
Minimum	$317.0

7.7.4. Model limitations

Upon review of the macroeconomic drivers, the Pershing business expressed that margin loans are largely driven by the economic health of the US market. As a result, it was suggested that an S&P 500 or Russell 2000 index could be used in future improvements of the model. The business also highlighted that in recent years, the prime portion of the business has increased as a percentage of the whole; as a result, there might be a higher correlation to market indices found if the data series extended farther back historically than 2008.

As discussed, the historical time series for margin loan unfunded commitments was both short and spanned a period of relatively homogenous interest rates and spreads. As more historical data becomes available for margin loan unfunded commitments, BNY Mellon should explore whether a viable model can be developed to replace the qualitative framework.

7.8. Overdrafts

7.8.1. Business overview

BNY Mellon originates and purchases loans as part of its ongoing business. Overdrafts are loans originated when more balances are drawn from an account than the account holds, resulting in a deficit and corresponding loan in the amount of the deficit. As of April 30, 2015, BNY Mellon had $6.2 BN in funded overdrafts, with no unfunded commitments in the segment.

Overdrafts primarily relate to custody and securities clearance clients. As the world's largest provider of securities servicing activities, BNY Mellon often books overdrafts daily due to settlement failures, failed wires, system problems, human error, and other operational difficulties. Overdrafts can be created through either clients' or BNY Mellon's actions. Repayment of these loans usually occurs within two business days.

7.8.2. Summary

A statistically sound model that is consistent with business intuition was found for overdrafts. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity**: the model is estimated on month-over-month differences in overdrafts, which are found to be stationary
- **Statistical significance**: the coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests**: the model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 300: Coefficient estimates for selected model for overdrafts

Overdrafts (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized Coefficient
MSCI World Index	Difference MoM, 1M lag	$ MM	8.69	0.32
S&P Volatility (30D MAVG)	% change – MoM	%	23.65	0.29
Intercept	None (level)	$ MM	-73.88	N/A

The model contains the following drivers and variables:

- **Equity markets –** MSCI World Index, a benchmark for global stock funds based on securities from 23 countries
- **Market volatility/uncertainty (equity) –** 30-day moving average of VIX, which measures implied volatility of S&P 500 index options

The intuition of these variables is as follows:

- The MSCI World Index has a positive coefficient, with the rationale that overdraft balances will increase as equity investments become more attractive, driving greater volume of investment activity
- The S&P volatility variable has a positive coefficient; when equity markets are more volatile, clients are more likely to overdraw from available balances

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 320: Candidate models for overdrafts

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
Equity markets		MSCI WORLD Index (Diff MoM, 1M Lag)	MSCI WORLD Index (Diff MoM, 1M Lag)	
Market volatility / uncertainty (equity)	S&P Vol (30D MAVG) (Diff MoM)	S&P Vol (30D MAVG) (% MoM)		S&P Vol (30D MAVG) (% MoM)
Perceived credit risk	TED Spread (Diff MoM, 1M Lag)			
Short-term rates	Ovrnt Repo Rate (Diff MoM, 1M Lag)			
Variation in balances explained through estimated first differences	**57%**	**42%**	**25%**	**8%**
R-squared (differences)	**27%**	**14%**	**6%**	**4%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.8.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.8.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The time series for the overdrafts segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 301: Unit root tests and stationarity tests including a trend variable on balances

Overdrafts – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-1.7	>0.10	Fail to reject unit root
Phillips-Perron	1	-4.7	<0.01	Reject unit root
KPSS	4	0.16	0.04	Reject stationarity

Table 302: Unit root tests and stationarity tests including a constant on first differences

Overdrafts – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-13	<0.01	Reject unit root
Phillips-Perron	1	-13	<0.01	Reject unit root
KPSS	0	0.03	0.97	Fail to reject stationarity

Stationarity tests for Overdraft loans yield mixed results: The ADF test fails to reject a unit root while the PP test rejects the unit root and the KPSS test rejects stationarity. These results suggest the balances may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Overdraft loan balances are modeled on their first differences.

7.8.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for overdrafts. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.8.4. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 321: Summary of drivers for overdrafts

Driver Bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Deposit and overdraft balances increase when general economic health improves	• Real GDP growth
Financial economy	**Relative credit worthiness of BNYM**	• Deposit balances increase if BNYM is perceived as a relative "safe haven"; this leads to lower overdrafts as clients are less likely to use all deposited balances	• Spread between BNYM CDS and industry average CDS (North American, EU, UK bank indices), spread of BNYM debt rate to industry peer rate
	Perceived credit risk	• When perceived credit risk increases and credit markets freeze up, demand for overdrafts may either increase as alternative funding options become unavailable, or decrease as overall lending slows down	• Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
	Equity markets	• Overdraft balances increase as equity investments become more attractive, driving greater volume of investment activity	• DJI, MSCI Global, KBW Bank Index
	Market volatility/ uncertainty	• Overdraft and deposit balances increase as market volatility and uncertainty increases	• VIX, rates volatility, US LIBOR-OIS spread
Rates	**Short-term rates**	• Increasing rates will drive deposit balances down; as a result, overdrafts will increase as clients are more likely to overdraw on available balances	• Overnight LIBOR, Fed Funds rate, Treasury yields, SONIA, EONIA, Money Market fund yield indices, repo rates

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.8.5. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for overdrafts are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 303: Statistical significance tests of model and variables for overdrafts

Overdrafts (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	1%	10%	Statistically significant
MSCI World Index	8.69	1%	10%	Statistically significant
S&P Volatility (30D MAVG)	23.65	<1%	10%	Statistically significant
Intercept	-73.88	68%	10%	Statistically not significant

7.8.6. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

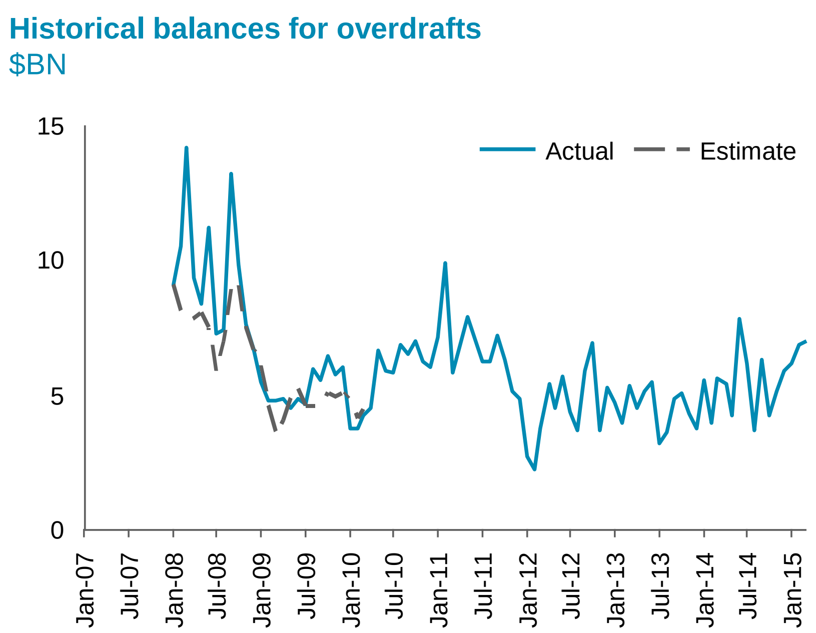
The diagnostic tests reviewed are exhibited below.

Table 304: Model Diagnostics for overdrafts

Overdrafts (in USD MM) – Model diagnostics

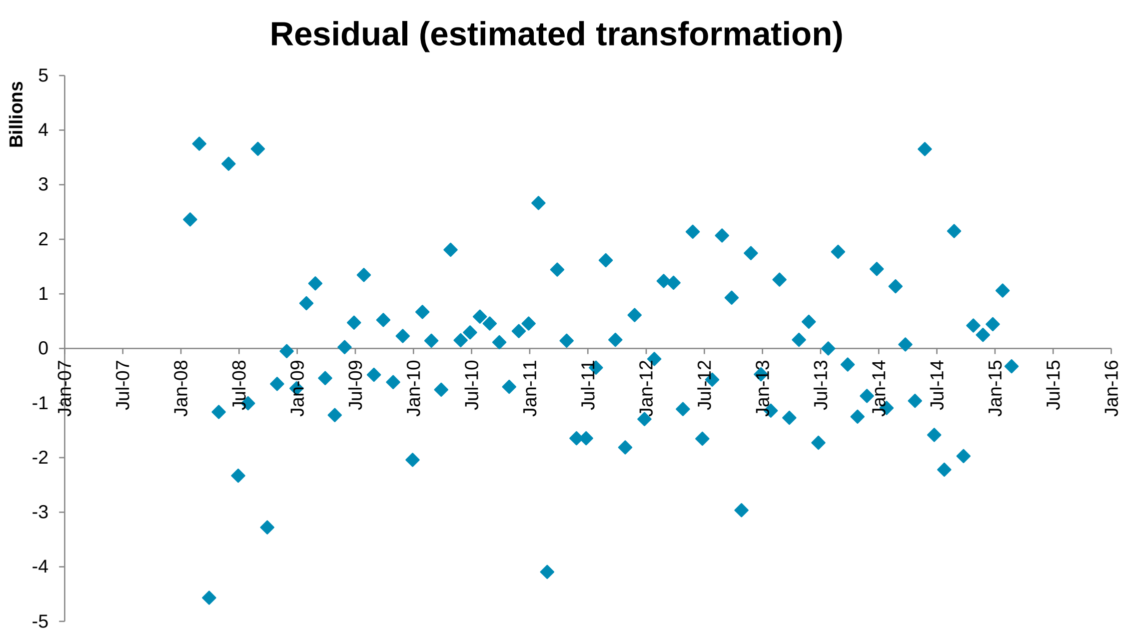
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	14%	-	-
	Adjusted R-squared	12%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.20	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.07	5	No multicollinearity
Linearity	RESET test	12%	10%	Linear specification appropriate

Figure 322: 9-quarter In-sample Prediction for overdrafts



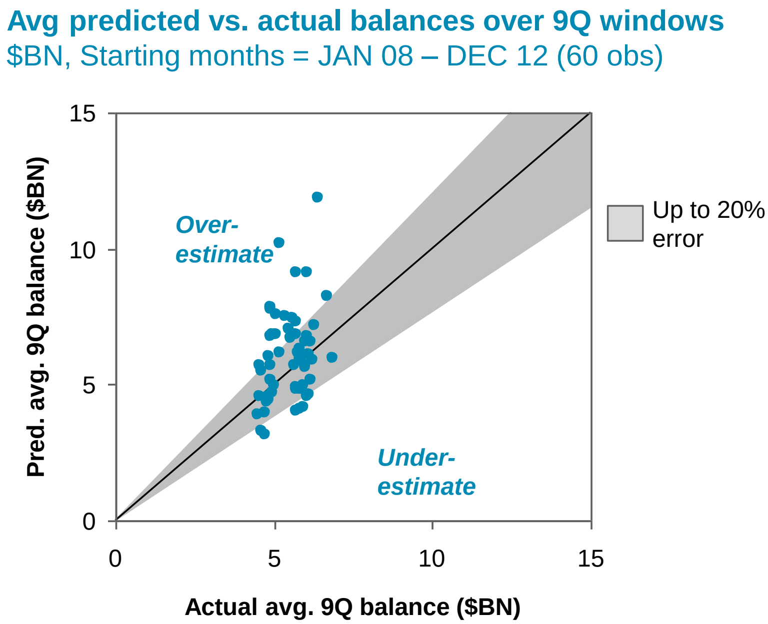
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes, outside of several large spikes arising from the high month-to-month volatility in the historical time series.

Figure 323: Residual Plot for overdrafts ($ BN)



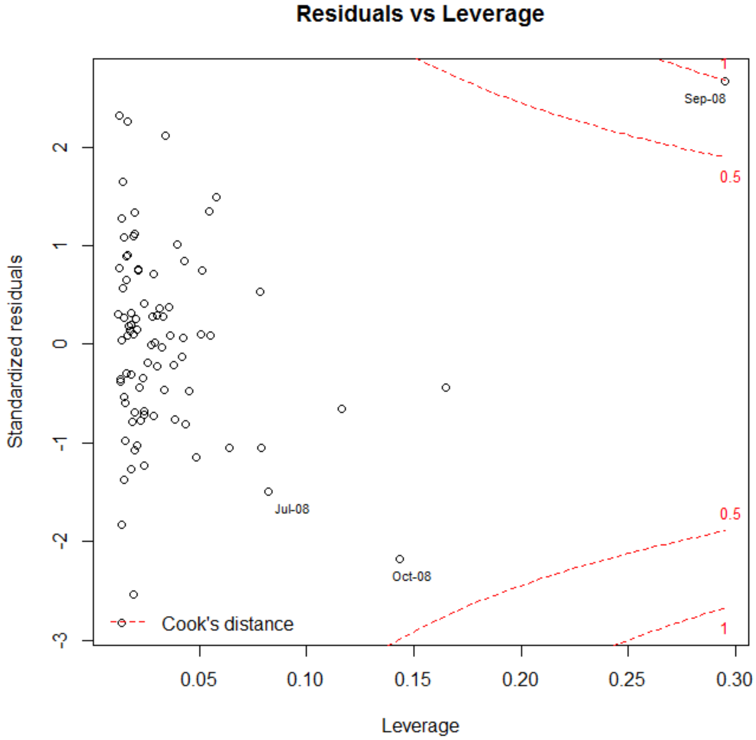
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 324: Estimation Scatterplot for overdrafts



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for some of the 9-quarter forecast windows. The model does not capture the high month-over-month volatility in the historical overdraft balances, which leads to some overestimation or underestimation over 9-quarter forecast windows, depending on which month is taken as the starting month of the forecast.

Figure 325: Influential points for Overdrafts



For this segment September 2008 is a highly influential point. However, this is not surprising because balances spike due to the crisis and does not invalidate the model

7.8.7. Model sensitivity

7.8.7.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 305: Sensitivity to changes to independent variables for overdrafts

Overdrafts – model sensitivity

Independent variable	Transformation	Unit	Standardized Coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
MSCI World Index	Difference MoM, 1M lag	$ MM	0.32	61.09	0.54
S&P Volatility (30D MAVG)	% change – MoM	%	0.29	20.12	0.49

Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the MSCI World Index has the standardized coefficient with the largest magnitude. A one standard deviation increase in the MSCI World Index variable results in a 0.32 standard deviation ($0.54 BN) increase in the predicted monthly change of the overdrafts segment.

7.8.7.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 306: Statistical sensitivity tests for overdrafts

Overdrafts (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of Coefficients	HAC P-value of shortened period Coefficient	Conclusion
MSCI World Index	8.69	7.777	0.43	Statistically insignificant
S&P Volatility (30D MAVG)	23.65	23.857	0.63	Statistically insignificant
Intercept	-73.88		0.66	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.70	Statistically insignificant

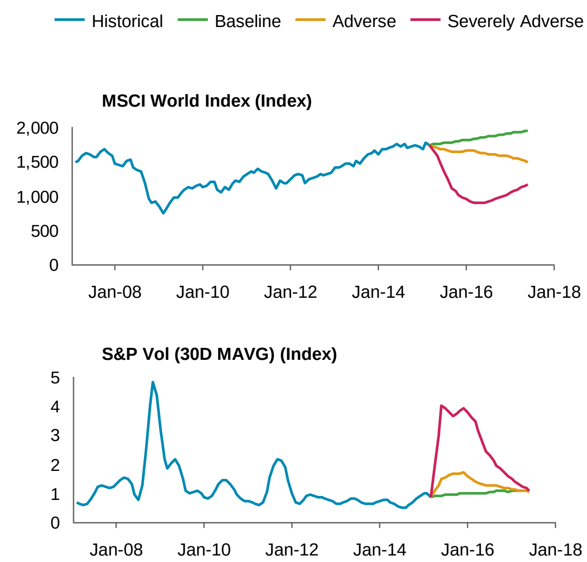
7.8.7.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

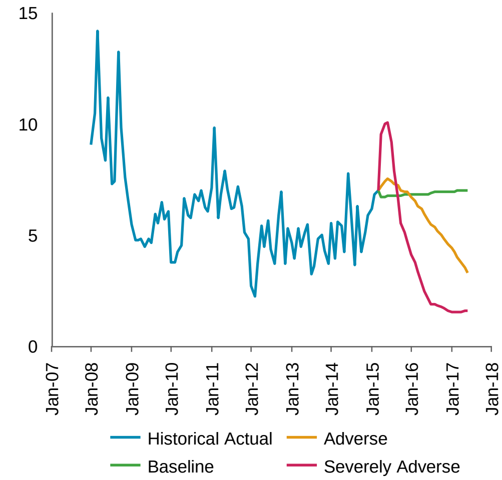
Figure 326: Final model forecast for overdrafts

Historical and forecast independent variables



Historical and forecast balances for overdrafts
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-0.01 (0%)	-3.71 (-53%)	-5.43 (-78%)	-
Start to peak	N/A	0.55 (8%)	3.04 (43%)	5.15 (57%)
Start to trough	-0.3 (-4%)	-3.71 (-53%)	-5.46 (-78%)	-4.57 (-51%)



The Working Group considered the forecast behavior for the selected overdrafts model as directionally reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts an increase followed by a significant decline in overdrafts. In a review of the forecasts with the line of business, this was noted to be directionally consistent with expectations. As liquidity pressure increases at the start of the 9-quarter period, a spike in balances is forecast. Friction in the market leads to a greater overall level of overdrafts, which is then followed by a steep decline as market conditions continue to deteriorate. Although the forecast behavior was consistent with business expectations, the magnitude of the decline in balances was deemed to be too great as there is a $4–5 BN floor based on business-as-usual operational activity. As a result, management scrutiny is highly recommended to ensure that the forecast remains within expectations
- **Interest rate shock (Adverse) scenario**: Business intuition is that overdrafts will rise as cash balances decrease due to rising interest rates. Management scrutiny is highly recommended to correct for forecasts that do not align to business intuition
- **Baseline scenario**: The model predicts that overdrafts will grow at a slow rate over the 9-quarter period. Given the volatility of the segment, it is difficult to predict the magnitude of change, but this slow growth was deemed reasonable by the line of business

7.8.8. Model limitations

Any model based on macroeconomic factors would not be able to capture the high month-over-month volatility in the historical overdraft balances. Therefore, the model results should be interpreted as the general expected trend for the balances, without the volatility that arises from more idiosyncratic, client-level behavior.

7.9. Wealth Management mortgages

7.9.1. Business overview

Wealth Management (WM) mortgages are mortgages extended to high-net-worth individuals through BNY Mellon's Wealth Management bank. This is currently a growth portfolio at BNY Mellon. Wealth Management mortgages are primarily interest-only adjustable rate mortgages with a weighted-average loan-to-value ratio of 60% at origination. As of March 31, 2015, the Wealth Management mortgage portfolio consisted of the following geographic concentrations: California – 21%; New York – 20%; Massachusetts – 15%; Florida – 8%; and other – 36%.

7.9.2. Summary

A statistically sound model that is consistent with business intuition was found for overdrafts. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity**: the model is estimated on month-over-month differences in overdrafts, which are found to be stationary
- **Statistical significance**: the coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests**: the model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 307: Coefficient estimates for selected model for WM Mortgages

Balance – WM Mortgages (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
S&P Volatility (30-day moving average)	First difference – MoM, 1-month lag	Index	-84.598	-0.34
1-year Treasury rate	First difference – MoM	%	-302.870	-0.31
Intercept	None (level)	$ MM	46.156	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – 30-day moving average of VIX, which measures implied volatility of S&P 500 index options
- **Short-term rates –** 1-year US Treasury rate

The intuition of these variables is as follows:

- The S&P volatility variable has a negative coefficient; when equity markets are more volatile, clients are less likely to take out mortgage loans due to decreased appetite for additional investment, e.g. in real estate
- The 10-year Treasury rate variable has a negative coefficient; when short term rates rise, clients are less likely to take out mortgage loans as they become more expensive

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3.

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

7.9.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

7.9.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The time series for the segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 308: Unit root tests and stationarity tests including a trend variable on balances

Wealth Management Mortgages – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-2.3	>0.10	Fail to reject unit root
Phillips-Perron	1	-3.9	0.01	Reject unit root
KPSS	5	0.21	0.01	Reject stationarity

Table 309: Unit root tests and stationarity tests including a constant on first differences

Wealth Management Mortgages – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	3	-4.4	<0.01	Reject unit root
Phillips-Perron	1	-15	<0.01	Reject unit root
KPSS	1	0.28	0.15	Fail to reject stationarity

Stationarity tests for Wealth Management mortgages yield mixed results: The ADF test fails to reject a unit root while the PP test rejects the unit root and the KPSS test rejects stationarity. These results suggest the balances may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Wealth Management mortgages balances are modeled on their first differences.

7.9.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

As a result of data that was not appropriately classed, the first six months of data points was removed from the original dataset. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

7.9.4. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 327: Summary of drivers for Wealth Management mortgages

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Total demand for mortgages increases as the general economy improves	US GDP growth, US unemployment rate
Financial economy	**Debt issuances**	• Greater issuances happen when rates are favorable, and also implies that overall cost of debt is low, resulting in more demand for mortgages	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets leads to a wealth effect that increases demand for mortgages	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Hedge fund index	• Stronger hedge fund performance leads to a wealth effect for those wealthy individuals with investments in hedge funds resulting in a greater demand from them for mortgages to purchase homes	HFRX index, Eurekahedge HF index, Eurekahedge FoF index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty in equity and rates leads to uncertainty in portfolios of wealthy individuals and thus less appetite to take on additional investments such as real estate	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to decreased appetite to offer mortgages, although perceived systemic credit risk should not affect the high-net-worth segment very strongly	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increasing rates and spreads makes it less likely that wealthy individuals will take on more debt in the form of mortgages	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

7.9.5. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

Statistical significance of the model – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold.

Individual statistical significance of coefficient estimates – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%.

The table below reports the results of the significance tests. All of the coefficient estimates in the model are statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 310: Statistical significance tests of model and variables for Wealth Management mortgages

Wealth Management mortgages – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P -value	Threshold	Conclusion
Joint test of all variables (F-test)	-	5%	10%	Statistically significant
S&P Volatility (30-day moving average)	-84.598	2%	10%	Statistically significant
1-year Treasury rate	-302.870	3%	10%	Statistically significant
Intercept	46.156	<1%	10%	Statistically significant

7.9.6. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

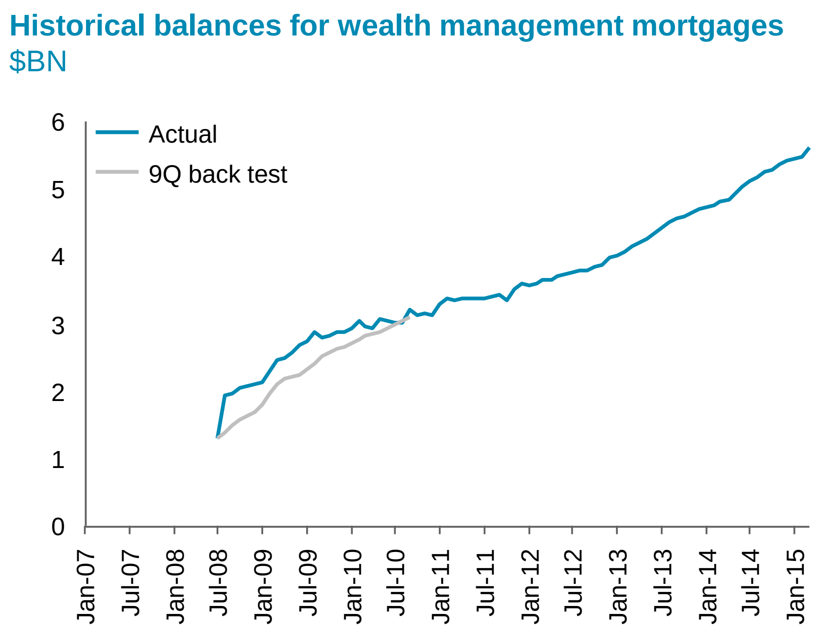
The diagnostic tests reviewed are exhibited below.

Table 311: Model Diagnostics for Wealth Management mortgages

Wealth Management mortgages – Model diagnostics

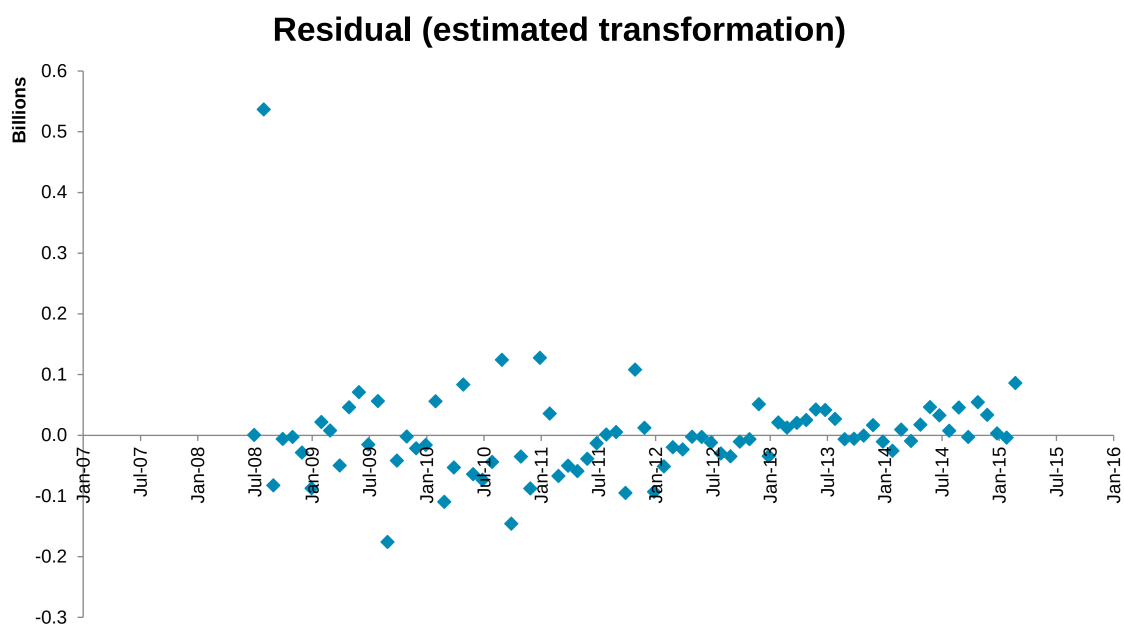
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	8%	-	-
	Adjusted R-squared	5%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.11	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	28%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.74	5	No multicollinearity
Linearity	RESET test	62%	10%	Linear specification appropriate

Figure 328: 9-quarter In-sample Prediction for Wealth Management mortgages



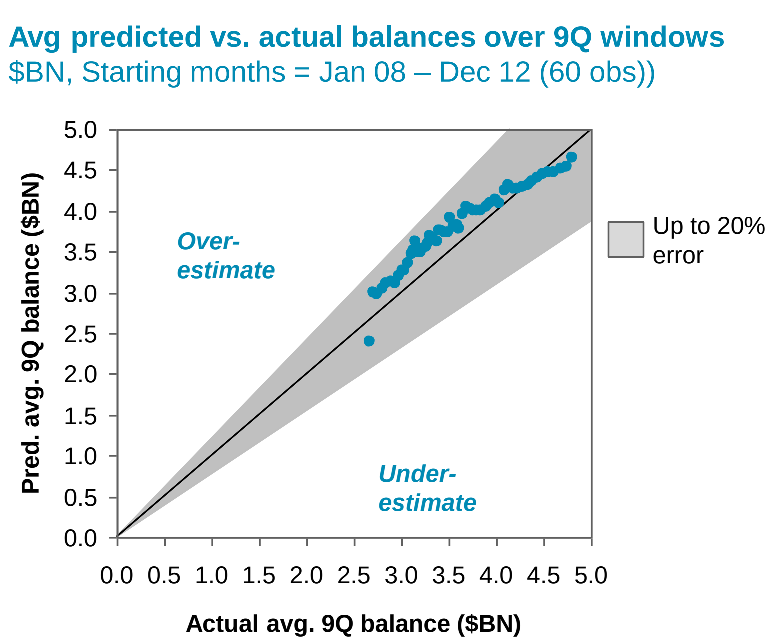
The in-sample back test of the model starting from January 2008 tracks closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes. The estimate does not capture the initial magnitude of the balance increase.

Figure 329: Residual plot for Wealth Management mortgages ($ BN)



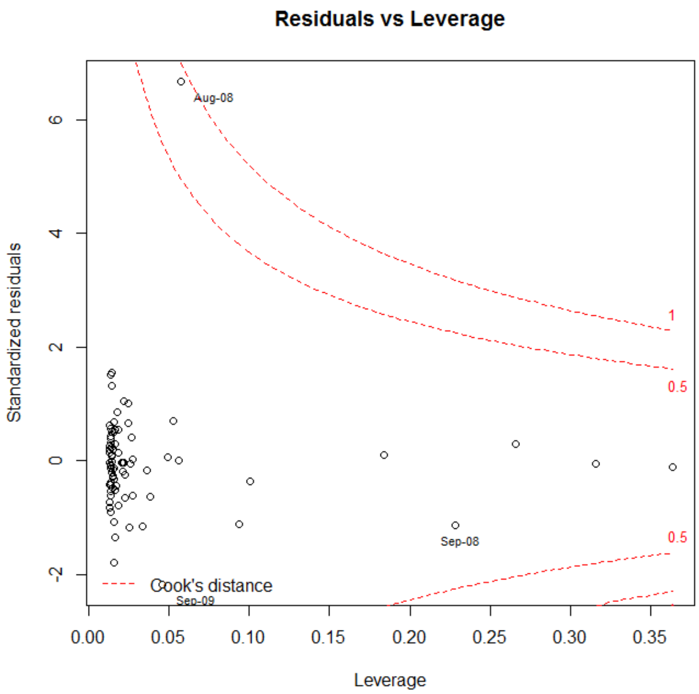
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 330: Estimation Scatterplot for Wealth Management mortgages



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for some of the 9-quarter forecast windows. The model captures the trend in the historical balances, which leads to very few points of significant overestimation or underestimation over 9-quarter forecast windows.

Figure 331: Influential points for Wealth Management mortages



The segment does not have any highly influential points.

7.9.7. Model sensitivity

7.9.7.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 312: Sensitivity to changes to independent variables for Wealth Management mortgages

Wealth Management mortgages – model sensitivity

Independent variable	Transformation	Unit	Standardized Coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
S&P Volatility (30-day moving average)	First difference – MoM	Index	-0.34	0.319	-0.06
1-year Treasury rate	First difference – MoM	%	-0.31	0.14	-0.05

Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the S&P volatility variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in S&P volatility variable results in a 0.32 standard deviation ($0.06 BN) decrease in the predicted monthly change of the total commitment for the segment.

7.9.7.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 313: Statistical sensitivity tests for Wealth Management mortgages

Wealth Management mortgages (in USD MM) – Statistical significance tests of model and variables

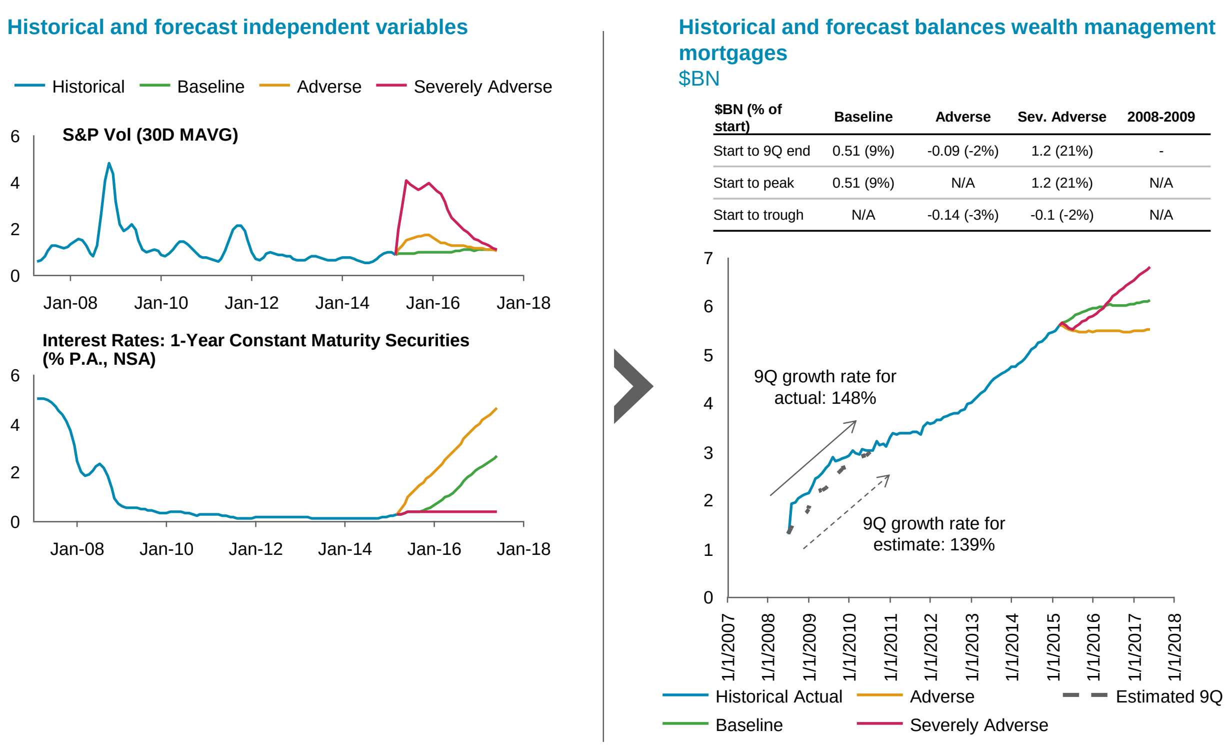
Tested independent variable	Original coefficient estimate	Sum of Coefficients	P-value of shortened period Coefficient	Conclusion
S&P Volatility (30-day moving average)	-84.598	-101.026	0.92	Statistically insignificant
1-year Treasury rate	-302.870	-130.156	0.84	Statistically insignificant
Intercept	46.156		0.91	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	1.00	Statistically insignificant

7.9.7.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 332: Final model forecast for Wealth Management mortgages



$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	0.51 (9%)	-0.09 (-2%)	1.2 (21%)	-
Start to peak	0.51 (9%)	N/A	1.2 (21%)	N/A
Start to trough	N/A	-0.14 (-3%)	-0.1 (-2%)	N/A

The Working Group considered the forecast behavior for the selected Wealth Management mortgages model as directionally reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts a small drop followed by a very sharp rise in the balances of Wealth Management mortgages during a severely adverse scenario, driven by the rise and quick fall of the market volatility. The quick recovery of the wealth of high-net-worth clients mimics the recovery seen after the 2008–2009 financial crisis. However, the growth may be overly strong and management review is still recommended. Additionally, high-net-worth clients may take additional loans immediately after a recessionary scenario to take advantage of lower priced assets during a severe recession scenario
- **Interest rate shock (Adverse) scenario**: The sudden spike in interest rates leads to more expensive loans and thus the demand for additional Wealth Management mortgages is dampened in this scenario
- **Baseline scenario**: The model predicts that balances will grow at a slow rate over the 9-quarter period. This slow growth was deemed reasonable by the line of business

7.9.8. Model limitations

As discussed, Wealth Management mortgages is a growing segment that has undergone consistent growth during the January 2008 to March 2015 time period assessed. However, this growth trend implies that purely statistically driven models may not reflect the realities of the sensitivities to macroeconomic variables, and can produce forecasts that would be more aggressive than intuitively expected if the growth eventually slows. Therefore, as additional historical data becomes available, the models will be updated and recalibrated to improve their predictive power.

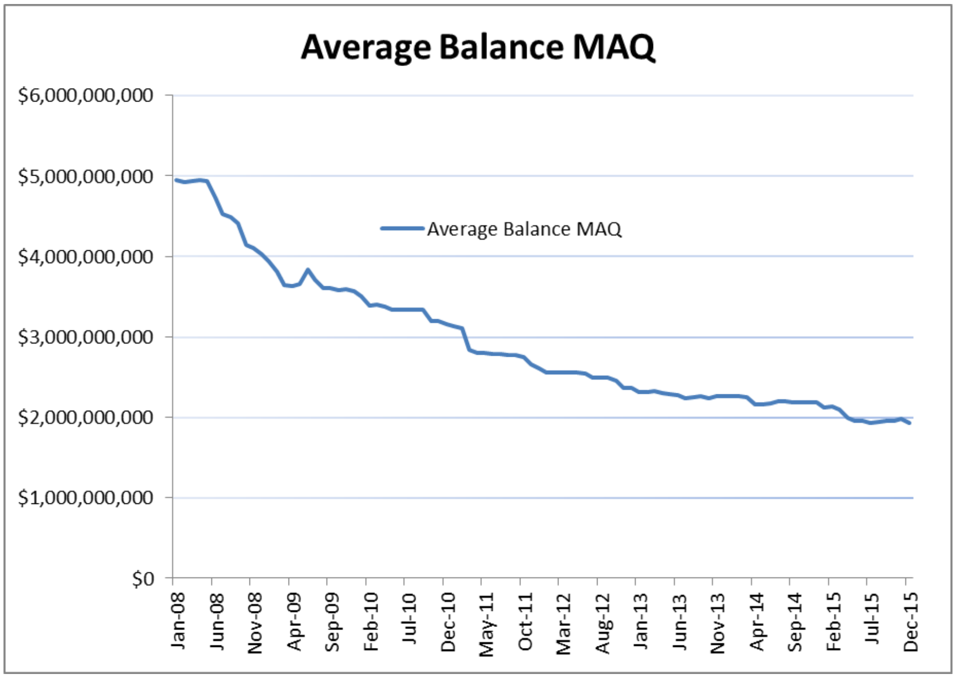
7.10. Lease financing

7.10.1. Business overview

The lease portfolio consists primarily of financing for well-diversified assets, primarily large-ticket transportation equipment. The portfolio is currently in run-off, as no new leasing business is expected to occur in the future. As a result, the portfolio balances are insensitive to changes in macroeconomic factors, and a qualitative framework is used. As of April 30, 2015, the size of this portfolio was $2.0 BN.

7.10.2. Historical data

Figure 333: Lease financing balances

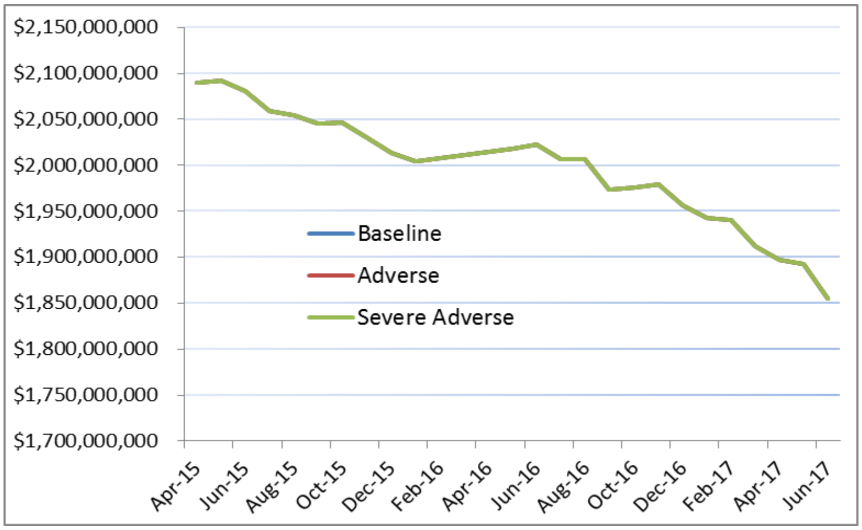


The figure above, based on data from MAQ, shows the Lease financing portfolio in a clear run-off trend. As such, the historical data was not utilized in the run-off approach.

7.10.3. Summary of approach

The lease financing portfolio is currently in run-off, and going forward no new leasing business is expected to occur. Because there are no plans to grow this business, the characteristics of all potential balances – including rate earned and the contractual terms that dictate evolution of balances – are known at the start of the scenario, eliminating the need for a predictive model. Given this, a qualitative framework is taken in which changes in balances over the forecast horizon are based on the contractual terms of individual lease finance exposures. These terms are available in QRM, which can forecast the portfolio runoff using the maturity dates of the individual exposures:

Figure 334: Dry-Run QRM Run Off for Lease Financing Balances



7.11. Other mortgage loans

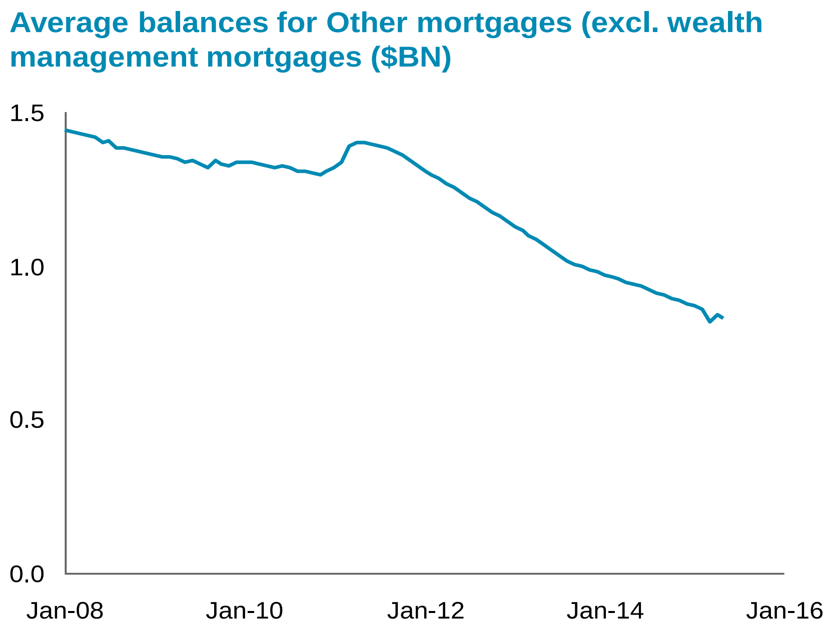
7.11.1. Business overview

The “Other mortgages” segment includes all mortgages outside of Wealth Management. It consists primarily of 15- and 30-year Fixed Rate Mortgages that were provided to employees and ex-employees of BNY Mellon. The employee mortgage program was discontinued in 2010, and therefore the existing portfolio is in run-off. Further, there are no plans to purchase incremental whole loan balances. As a result, a structural approach is appropriate. As of April 2015, the total balance for this segment was $1.2 BN.

7.11.2. Historical data

The historical balances in Figure 1 show a clear run-off trend in the Other Mortgage loans portfolio since 2011. As no new mortgages are added to this portfolio, all of the contractual terms of this portfolio, including both maturities and rates, are already known. As such, the behavior for balances and rates do not require a new and separate statistical model: they can be accommodated through the existing analytical infrastructure in QRM (balance evolution, subject to prepayments, and rate paid including any logic for floating rate loans).

Figure 335: Other mortgage loans balances



7.11.3. Summary of approach

Both of the structural approaches for the Other Mortgage Loans' balance and rate are based on run-off schedules through QRM.

The other mortgage loans portfolio is expected to run off over time based on the amortization schedule, subject to prepayment behavior linked to the interest rate environment. The prepayments are determined by a vendor model from Andrew Davidson & Co. (AD&Co) that is embedded in QRM and already validated for estimating prepayments under a range of interest rate scenarios.

7.12. HELOCs

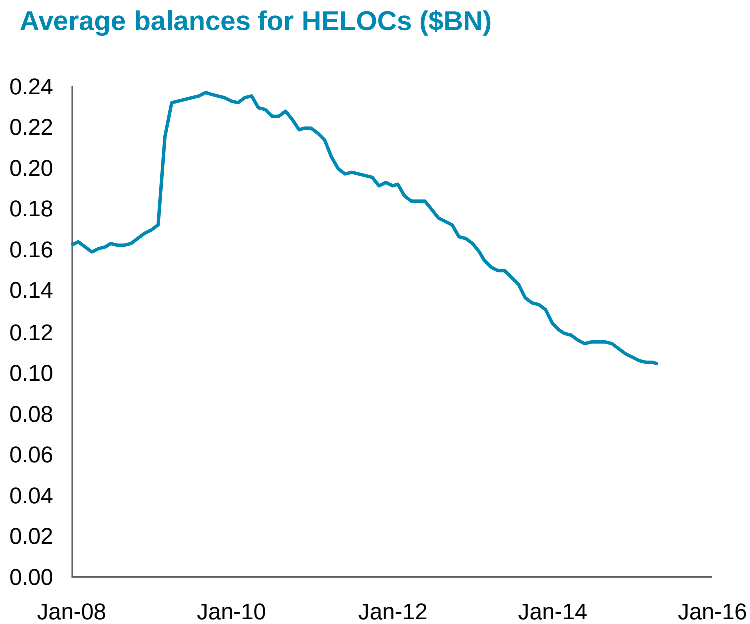
7.12.1. Business overview

Home Equity Lines of Credit (HELOCs) are revolving loans and represent a relatively small segment of BNY Mellon's total loans, with a spot balance of $95 million as of December 2015, with approximately ~$93.5 million floating & ~$1.5 million fixed. The $95 million HELOC portfolio as of Dec 2015 consists of Legacy Mellon and Legacy BNY HELOC's as well as the Private Wealth HELOC portfolio. The legacy accounts are a much older portfolio and are in run-off. However historically we have seen smaller loans originations offered to Wealth Management clients on a request basis. Balances for HELOCs from January 2008 until March 2015 can be seen in Figure 345. The overall portfolio has been in runoff since 2010, however according to the Line of Business there may be occasional HELOCs issued to Wealth Management clients on a request basis in the future. While management does not expect the Private Wealth HELOC portfolio to grow, given the request-based nature of the portfolio they cannot be certain as to how many HELOCs will be issued. Further, as the figure below shows, this segment represents a relatively small set of balances (about $95 million).

7.12.2. Historical data

Balances for HELOCs from January 2008 until March 2015 can be seen in the figure below. The portfolio has been in runoff since 2010.

Figure 336: HELOC balances



7.12.3. Summary of approach

The decision to adopt qualitative frameworkes for the HELOCs' balance and rate was discussed in several meetings with the Working Group. The HELOCs was also discussed with the business to determine potential macroeconomic drivers. As the historical data shows, the Legacy Mellon and Legacy BNY HELOC portfolios are in run off mode. However for Private Wealth HELOC portfolio we have seen smaller loans originations offered to Wealth Management clients on a request basis. A qualitative framework was therefore determined to be more appropriate for these revolving loans as opposed to a macroeconomic statistical model. Further, as Figure 1 above shows, this segment represents a small set of balances (~$95MM).

For HELOCs balances, the qualitative framework is to maintain a constant spot balance across the forecast horizon under both baseline and stress scenarios. A constant spot balance will be used because although the Private Wealth HELOCs segment is not expected to grow, due to the per-request basis of the loans originations, management cannot be certain how many loans originations to expect. So as not to understate the balances, a conservative spot-balance flat-line assumption will be used.

7.13. Iron Hound loans

7.13.1. Business overview

The Iron Hound segment is a CMBS conduit platform that began in the fourth quarter of 2014 as a joint venture between Iron Hound Capital and BNY Mellon. The loans consist of commercial real estate loans warehoused in BNY Mellon's portfolio for securitization. BNY Mellon has allocated a maximum of $500 MM of its balance sheet to the Iron Hound loan segment, and the portfolio began to onboard loans as of December 2014. As of December 31, 2015, the size of the Iron Hound loan portfolio was $401 million. The average balance of this portfolio in December 2015 was $219 million.

7.13.2. Historical data

Because Iron Hound is a new business, very limited historical data was available at the time of model development. The reason for the qualitative framework is the lack of historical data that is available for BNY Mellon's Iron Hound portfolio. Because Iron Hound loans are a new business that was initiated in 2014 and the first loans weren't on-boarded until December 2014, only 4 months of data was available at the time of model development. As a consequence, it was not possible to develop statistical models for Iron Hound balances and rates.

7.13.3. Summary of approach

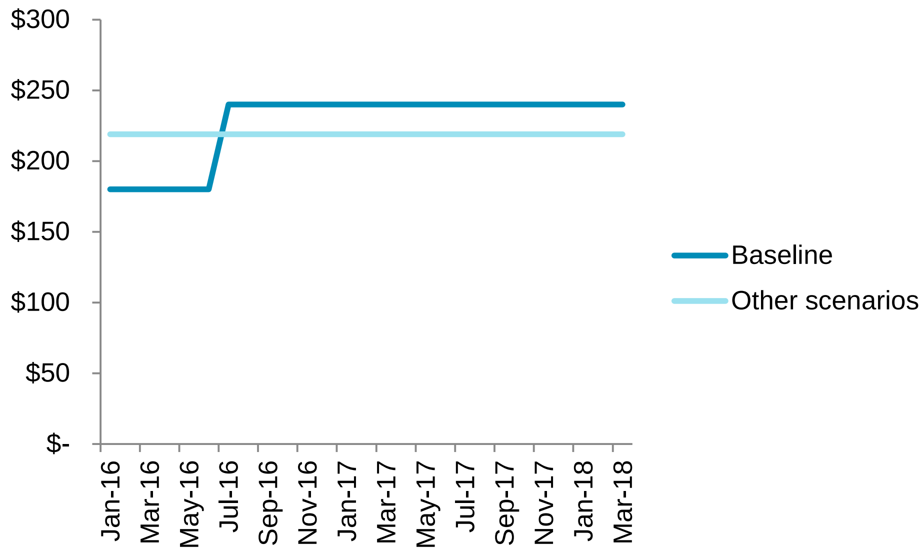
The Iron Hound business is a securitization conduit and in 'business-as-usual' scenarios largely dependent on management decisions (balance sheet/funding availability). In stress scenarios the business might be adversely impacted by disruption in securitization markets.

Therefore, in the baseline scenario, the qualitative framework is to project Iron Hound loan balances per the Company's Operating Plan. Beyond the Operating Plan horizon, balances will be held constant. Further, since these loans are subject to "fair value" accounting treatment, market value for projected balances will be calculated and reported. The Moody's projected changes in Non-Agency CMBS Subordinate Tranche spreads will be used in valuations.

In stress scenarios, the securitization markets are assumed to have been disrupted, causing loan balances as of the forecasting date (Dec 31st for CCaR) to be illiquid. BNY Mellon holds the illiquid loan balances on balance sheet over the entire nine quarter forecast horizon. Further, since these loans are subject to "fair value" accounting treatment, the stressed market value for projected balances will be calculated and reported. The Moody's projected changes in Non-Agency CMBS Subordinate Tranche spreads will be used in valuations.

Associated hedges are modelled independently in QRM and not in scope for this qualitative framework.

Figure 337: Iron Hound loan balances forecasts ($ millions)



7.13.4. Approach limitations

With all new businesses, the forecast expected by management is based on currently available information. Additional business limits, such as the maximum of $500 MM allocated from BNY Mellon's balance sheet to the Iron Hound loans, can change over time pending business circumstances, which would affect the validity of the current forecast. As the Iron Hound business continues its growth phase, the assumptions for the described qualitative framework will be closely monitored and revised if necessary to align with evolving business environment and constraints.

7.14. Reverse mortgages

7.14.1. Business overview

BNY Mellon re-entered the reverse mortgage business in 2014, in which the bank purchases, securitizes, and services reverse mortgages. The business also advises brokers, financial advisors, and asset managers on how to integrate reverse mortgages into retirement plans. As of April 30, 2015, reverse mortgages account for less than $10 MM on the BNY Mellon balance sheet and are anticipated to be less than $20 MM by the end of 2015. The business is currently focused on FHA-insured products, primarily floating Home Equity Conversion Mortgages (HECMs) in which borrowers leverage home equity for income.

7.14.2. Historical data

Because reverse mortgages are a new business, very limited historical data was available at the time of model development.

7.14.3. Summary of approach

The reverse mortgage loan segment belongs to the management-driven category of qualitative frameworkes for forecasting. Due to BNY Mellon's relatively recent re-entry into the reverse mortgage business, the anticipated trajectory of the balances requires significant management review for both baseline and stressed scenarios.

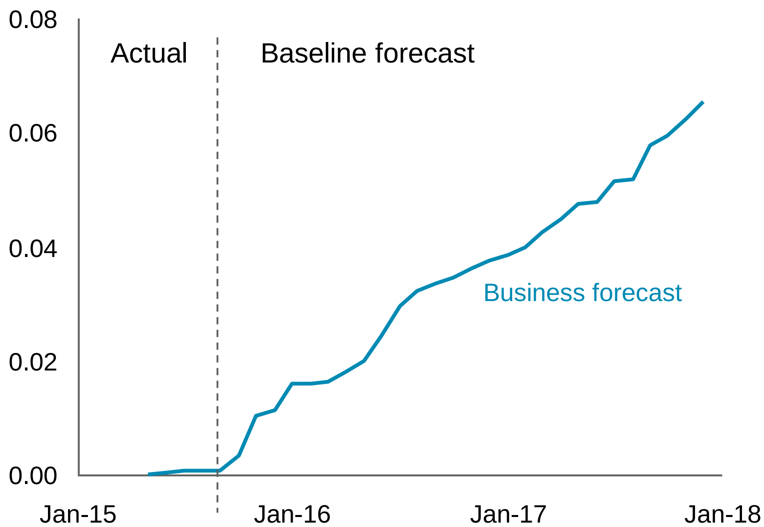
Thus, for the baseline scenario, the balance forecasting approach is based on the business plan for this segment. Beyond the Operating Plan horizon, balances will be held constant. Note that the monthly forecast for Home Equity Retirement Services (HERS) balance sheet usage through end of 2017 assumes commencement of GNMA HMBS pooling in November 2015. Further, since these loans are subject to "fair value" accounting treatment, the market value for projected balances will be calculated and reported. Per feedback from the reverse mortgage portfolio management team, in the absence of Agency HECM (Home Equity Conversion Mortgages) spread projections from Moody's, Agency CMBS spreads are the most appropriate proxy for the HECM assets. Agency CMBS spreads are to be used rather than the Agency MBS yield projections, as the HECM Arm pools are priced as a LIBOR spread product (rather than Yield or OAS) and share common characteristics and drivers to the Agency CMBS. Thus, the Moody's projected changes in Agency GNMA CMBS spreads will be used in valuations.

For stressed scenarios, the spot balance as of December 31, 2015 is held constant. Management discretion would halt activity. There would be a seizure of securitization markets--the bank would cease issuance of reverse mortgages; loan balances as of the forecasting date (December 31, 2015) are assumed to be illiquid. The seizure would persist throughout the scenario and BNY Mellon would hold the illiquid loan balances on balance sheet over the entire nine quarter forecast horizon.

The figure below shows that actual balances for the Reverse Mortgage segment are very small as of May 2015 (around $0.1 BN). The chart also shows the projected growth in balances until January 2018 according to the business forecast.

Figure 338: Reverse mortgage balance projections

Month end balances for Reverse mortgages ($BN)



7.14.4. Approach limitations

With all new businesses, the forecast expected by management is based on the best currently available assumptions. As the business matures, business drivers and constraints may change, which could affect the validity of the current forecasting approach. As the reverse mortgage business continues its growth phase, the assumptions for the described qualitative framework will be closely monitored and revised if necessary to align with evolving business environment and constraints.

7.15. Other loans

7.15.1. Business overview

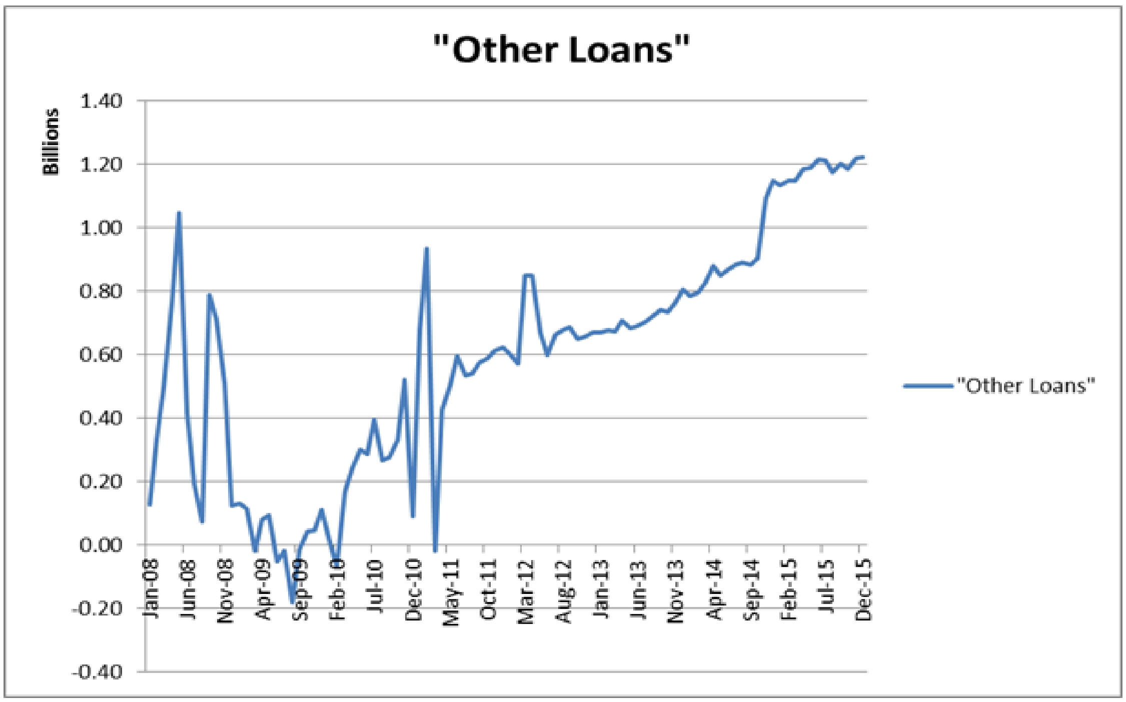
This segment contains all remaining loans that do not fall into any of the preceding loan segments. By definition, these loans are missing identifiers that would allow them to be classified in other segments. As such, they do not necessarily form an economically homogeneous segment. They consist entirely of closed-end loans.

After forecast approaches were developed, these loans were later identified as predominantly commercial loan products extended by Pershing, generally as non-purpose loans, in the most recent months of historical data. Note that the definition of commercial loan products does not completely overlap with the Commercial Loans regulatory group from the CRDW data, and therefore these loans were not included in the Commercial Loans balance segment.

7.15.2. Historical data

Balances for the Other loans segment from January 2008 until March 2015 can be seen in the figure below. In earlier years, the historical balances are very volatile due to the miscellaneous nature of this segment; loans with missing values in identifier fields are more common in the development data in these years. The data prior to 2011 is deemed unreliable as a variety of data errors were observed, such as negative loan balances, reclassifications of loans and accounting adjustments. In more recent years, the balances are better behaved as their composition becomes predominantly Pershing commercial loan product exposures. Due to this data limitation which shortens the period over which a model could have been developed, a qualitative forecasting approach is adopted.

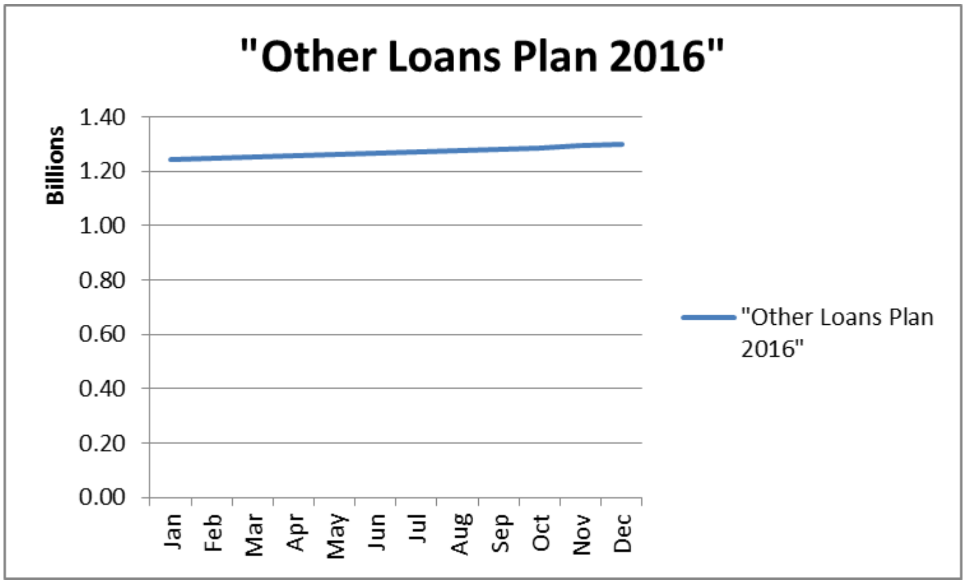
Figure 339: Other loan balances



7.15.3. Summary of approach

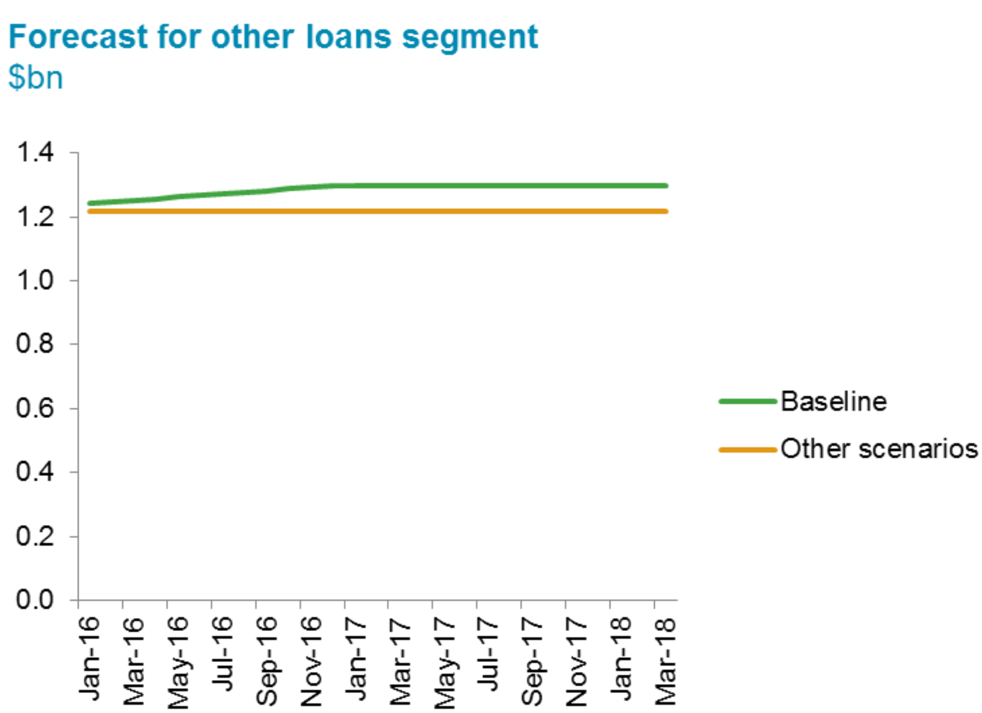
This segment uses a qualitative forecasting approach due to both its miscellaneous nature and its low materiality. Loan balances grew rapidly between 2011 and 2014, however, the recent growth rate has slowed down. Business does expect rapid growth on a go forward basis as evidenced by the Company’s 2016 operating plan projection:

Figure 340: Other Loans Plan for 2016



Thus, given the lack of future growth, for the Baseline scenario, the qualitative framework uses the Company's 2016 Operating Plan projections for the Baseline scenario, and keeping the last balance of the Operating Plan balance constant for the remaining forecasting period. For stress scenarios, the qualitative framework keeps the most recent spot balance constant:

Figure 341: Other Loans Segment Forecasted Balances



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7.15.4. Approach limitations

The historical growth rate used in the selected approach only covers a relatively uniform period of macroeconomic conditions, due to the lack of clean data in earlier years. As data quality continues to improve and these loans become more material in the future, these loans could potentially be resegmented, either into another existing segment or into a new segment.

8. Loan rates

8.1. Business overview, segmentation, and modeling approach

BNY Mellon originates and purchases loans as part of its ongoing business. The loan portfolio predominantly consists of loans to institutional borrowers, including financial institutions and non-financial corporates, as well as loans to high-net-worth individuals through BNY Mellon's Wealth Management bank. Corporate Treasury segments the loan portfolio by product; the table below lists the major loan products and provides a description for each product.

Table 314: Loan products

Product	Description	Balance as of April 2015 ($ BN)
Commercial loans	Loans primarily to financial institutions, including trade financing loans and non-purpose loans	18.5
C&I loans	Loans primarily to non-financial corporates	2.9
Margin loans	Loans primarily to broker dealer clients through Pershing, collateralized by fixed income securities and equities	11.8
Overdrafts	Short-term exposures from clients drawing from deposit accounts	6.1
Mortgage loans	Primarily mortgages to high-net-worth individuals through the Wealth Management bank; also includes other mortgage portfolios in runoff, e.g. from discontinued employee mortgage program	6.8
Broker dealer loans	Term loans made to broker dealers on a secured basis, collateralized by fixed-income and equity securities	3.2
CRE loans	Commercial real estate loans, including mostly secured loans to experienced developers and long-term holders of real estate assets	1.8
Leases	Lease financing exposures, predominantly for large-ticket non-aircraft transportation equipment; currently planning to run off existing portfolio with no active plans for new originations	2.0
HELOCs	Home Equity Lines of Credit offered to Wealth Management clients; currently planning to run off existing portfolio with no active plans for new originations	0.1
Reverse mortgages	Re-entered business in 2014; predominantly FHA-insured HECMs	0.0
Iron Hound loans	CRE loans held on BNY Mellon's balance sheet for securitization through IH Capital, a joint venture conduit shop between BNY Mellon and Iron Hound Management started in 2014	0.0

As discussed in Section 3.1.3 on loan segmentation, the segmentation by product used for loan rates differs from the segmentation used for loan balances due to data constraints. The loan balance segmentation is based on CRDW data, which does not contain the required data needed to develop models for rates. The loan rate segmentation therefore uses MAQ data, which does not contain the identifiers used in the loan balance segmentation. The Working Group therefore decided to apply a separate segmentation by product to loan rates, which the MAQ data is able to support.

The rates charged to customers on these loans are based on reference rates such as LIBOR or Fed funds rates, and for certain products they may be fixed or floating. When there are movements in the reference rates, the overall blended rate across an entire segment shifts due to two effects:

- Floating rate loans by definition move with the reference rates
- Due to changes in the rate and spread environment, the pricing terms for new loan originations may differ from the pricing terms for maturing or prepaid loans (e.g. higher spreads if interest rates rise), leading to a shift in the portfolio mix

The selected loan rate modeling approach forecasts blended rates across the entire balance for each product segment, including both existing volumes and new originations. The choice of approach was constrained by data availability; for most segments, data on new originations and their rates was not readily available, so modeling new originations and their rates was not a viable option. Therefore, the rates forecasted by the loan rate models are weighted average of rates for all loans in each segment at any given point in time, including both new originations and existing loans that have not yet matured.

Leases, other mortgage loans (excluding Wealth Management), HELOCs, reverse mortgages, and Iron Hound loans use qualitative frameworkes for rates. In the case of Leases and HELOCs, since the portfolios are in run-off, rates will be based on the contractual rates of loans that already exist in the respective portfolios. Reverse mortgages and Iron Hound loans have very limited historical data given how new these portfolios are, and therefore rates are forecast based on identified reference rates, but not modeled statistically.

8.2. Hypotheses and independent variable identification

As discussed in Section 3.5 on Methodology, reference rates were identified for each of the loan rate modeling segments, and relationships between the reference rates and the corresponding customer loan rates are estimated. The reference rates represent the interest rates that BNY Mellon uses as benchmarks to price the different types of loans that it extends to clients, generally with a spread to the reference rate. The table below contains the reference rates for each segment.

Table 315: Loan rates segments and identified reference rates

Segment	Reference rates
Commercial C&I	USD 1-month LIBOR USD 3-month LIBOR USD 5-year swap rate GBP 1-month LIBOR GBP 3-month LIBOR EUR 3-month LIBOR
Margin	Fed funds target rate
Overdrafts	Fed funds target rate GBP target rate EUR target rate 1-month respective LIBOR rates for other currencies

Segment	Reference rates
Mortgage	USD 1-month LIBOR USD 6-month LIBOR USD 1-year LIBOR USD 3-year swap rate USD 5-year swap rate USD 10-year swap rate
Broker dealer	Fed funds target rate
CRE	USD 1-month LIBOR USD 5-year swap rate

Since the lines of business use the reference rates to price their loans, the ingoing assumption was that changes in reference rates should be strongly correlated with changes in blended overall customer rates. Lags were allowed in order to capture the effect of delayed changes in customer rates following movements in reference rates.

In addition to the reference rate variables, market volatility, credit spreads, and yield spreads were also included as potential independent variables. While changes in the underlying reference rate were hypothesized to partially explain changes in the spread component of customer rates (e.g. higher spreads at higher rates), these additional variables were hypothesized to provide further explanatory power. The table below lists the additional variables used as candidate independent variables, in addition to the reference rates.

Table 316: Additional variables used as candidate independent variables

Category	Candidate independent variables
Market volatility/uncertainty	S&P Volatility (30-day moving average of VIX) Market Volatility (period maximum end-of-day value of VIX) 10-year US T-Note Volatility Index
Credit spreads	Baa to Treasury spread Overnight LIBOR 1-week OIS spread 1-week LIBOR 1-week OIS spread TED spread
Yield spreads	3-month to 5-year Treasury spread 3-month to 10-year Treasury spread

8.3. Overview of models

The summary of the loan rates models is illustrated in the table below, showing the independent variables used and their categories. The methodology used for modeling is described in Section 3.5.

Table 317: Summary of loan rate models

Product	Variable 1	Variable 2	Variable 3
Commercial Loans	USD 1-month Libor (diff QoQ)	USD 1-month Libor (diff MoM, lag 1)	1-week Libor 1-week OIS spread (diff YoY)
C&I Loans	USD 1-month Libor (diff MoM, lag 1)		
Margin Loans	Fed funds target rate (diff MoM)	Fed funds target rate (diff MoM, lag 1)	
Overdrafts	Fed funds target rate (diff MoM, lag 3)		
Mortgage Loans	USD 6-month Libor (diff MoM)		
Broker Dealer Loans	Fed funds target rate (diff MoM, lag 1)	Fed funds target rate (diff QoQ)	Baa to treasury spread (diff YoY)
CRE Loans	USD 1-month Libor (diff MoM, lag 1)	USD 1-month Libor (diff QoQ, lag 1)	

Reference rate for pricing Credit spread

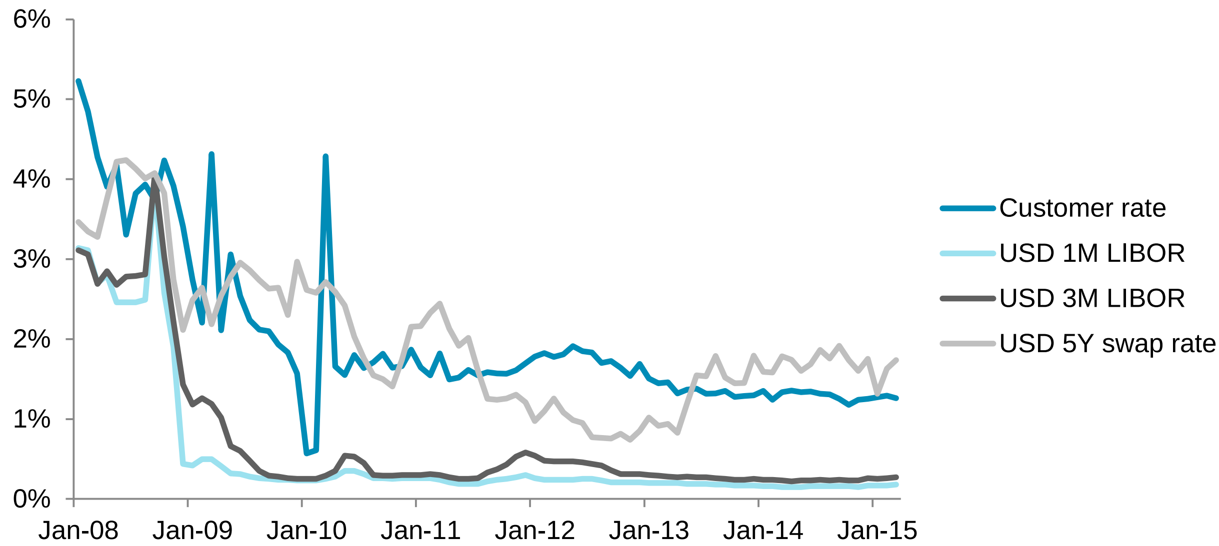
The following sections provide further details on each of the loan rate models.

8.4. Commercial loan rates

8.4.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with the USD reference rates. The historical Commercial loan rate data is noisy due to accounting adjustments and variations in portfolio mix, but generally follows the directional movement of the reference rates.

Figure 342: Historical rates for overall Commercial loan portfolio



8.4.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Commercial loan rates segment. However, given the volatile nature of the historical dependent variable time series, which is partially due to the longer duration of this loan product, management scrutiny is recommended.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is determined to be stationary through manual review
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 318: Coefficient estimates for the Commercial loan rates model

	Commercial loan rates (in %) – Selected model			
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
USD 1-month LIBOR	First difference – QoQ	%	0.138	0.123
USD 1-month LIBOR	First difference – MoM, 1-month lag	%	0.192	0.095
1-week LIBOR 1-week OIS spread	First difference – YoY	%	0.174	0.105
Intercept	None (level)	%	-0.012	N/A

The model uses three factors: two transformations of the USD 1-month LIBOR and a credit spread. All three variables have a positive coefficient. The Working Group confirmed the intuition of these variables and their signs.

- For the reference rate variables, a positive coefficient was required to match business intuition that the blended overall customer rate should be positively correlated with the reference rates
- For the credit spread variable, a positive coefficient indicates that as credit spreads widen, so do customer spreads, independent of the level of the rates

8.4.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

8.4.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 319: Unit root tests and stationarity tests including a trend variable on balances

Commercial loan rates (in %) – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	11	-4.7	<0.01	Reject unit root
Phillips-Perron	1	-3.9	<0.01	Reject unit root
KPSS	5	1.1	<0.01	Reject stationarity

Table 320: Unit root tests and stationarity tests including a constant on first differences

Commercial loan rates (in %) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	11	-1.9	0.32	Fail to Reject unit root
Phillips-Perron	1	-16	<0.01	Reject unit root
KPSS	0	0.06	0.81	Fail to Reject stationarity

Stationarity tests for Commercial loans rates yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non-stationary. For the monthly first difference the ADF test fails to reject the unit root while the PP rejects the unit root and the KPSS test does not reject stationarity. Since the KPSS test is the primary test reviewed for first differences, the Commercial loan rates on first differences is determined to be stationary.

However, because it failed the ADF test, the modeling team reviewed the data manually. It was assessed that because the loans data spanned less than a full rate segment the stationarity results may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable does not show stationary behavior for first differences for the ADF test, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables on levels and stationary on first differences.[36] Thus, manual review, a review of academic literature, and the results of the KPSS test on first differences provided sufficient evidence of stationarity for the application of OLS on first differences.

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.4.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Commercial loan rates data showed significant noise, in part due to accounting adjustments. However, to preserve the integrity of the data, no changes were made to the underlying data to reverse accounting adjustments. Model results showed that the candidate independent variables generally were not able to pick up the observed noise anyway, and therefore the model parameters are not strongly sensitive to the noise.

8.4.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold

[36] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Commercial loan rates model are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 321: Statistical significance tests of model and variables for Commercial loan rates

Commercial loan rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	<1%	10%	Statistically significant
USD 1-month LIBOR	First difference – QoQ	0.138	3%	10%	Statistically significant
USD 1-month LIBOR	First difference – MoM, 1-month lag	0.192	7%	10%	Statistically significant
1-week LIBOR 1-week OIS spread	First difference – YoY	0.174	9%	10%	Statistically significant
Intercept	None (level)	-0.012	70%	10%	Statistically not significant

8.4.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted

were highlighted and investigated to ensure the modeling team understood the reason for the deviation

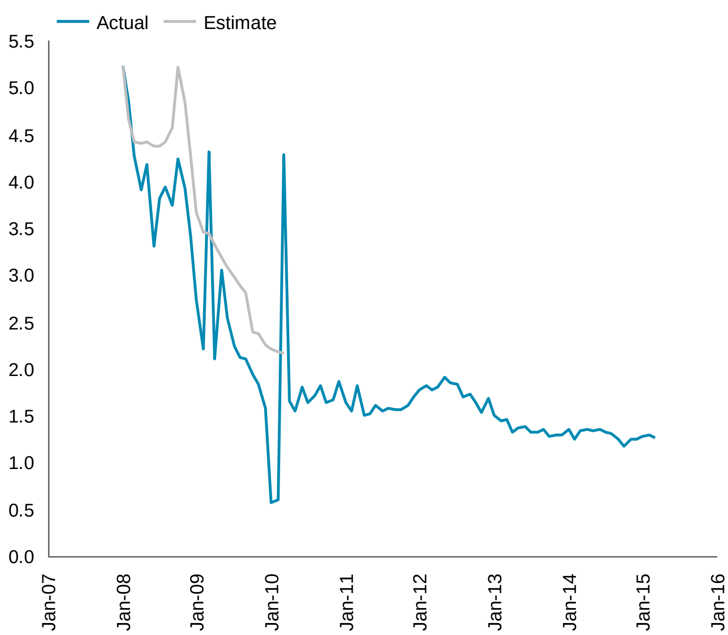
The results for the diagnostic tests reviewed are exhibited below.

Table 322: Commercial loan rate model diagnostics

Commercial loan rates – Model diagnostics

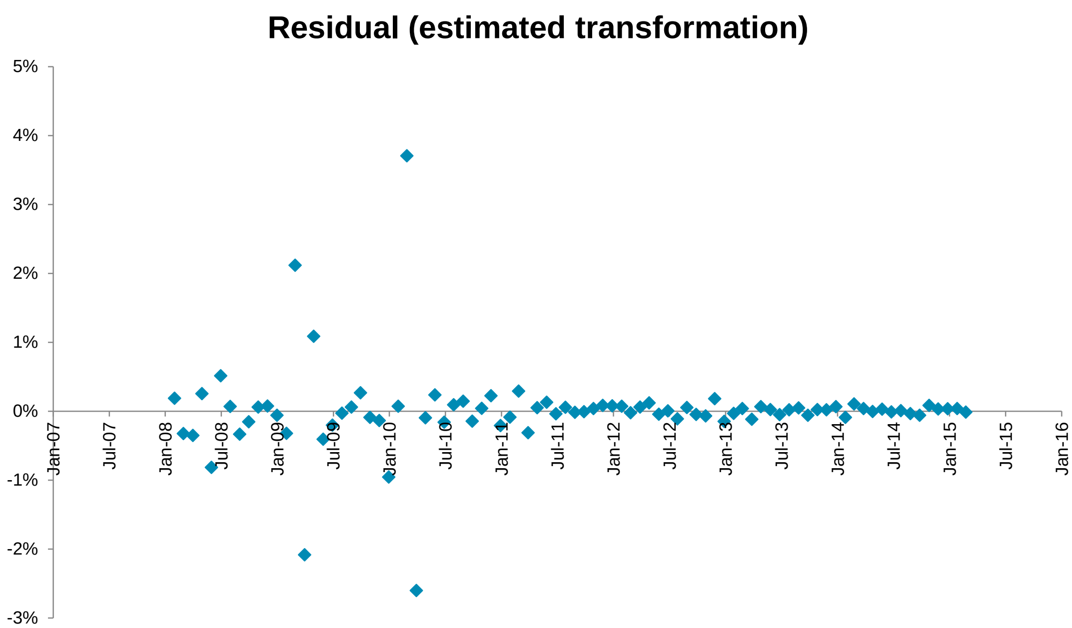
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	5%	-	-
	Adjusted R-squared	2%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	83%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.81	5	No multicollinearity
Linearity	RESET test	97%	10%	Linear specification appropriate

Figure 343: Commercial loan rate 9Q in-sample prediction (%)



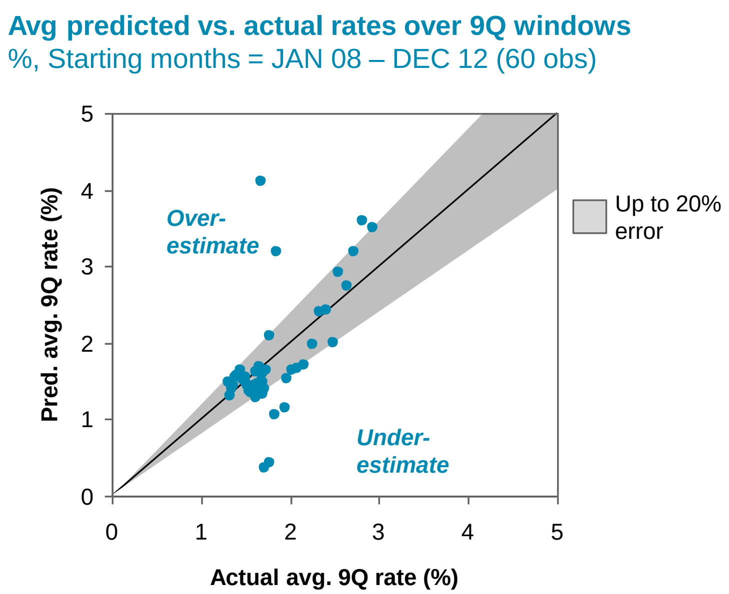
In the select 9Q in-sample prediction, the model captures most of the directional movements of the historical data. However, it does not capture the full magnitude of the decline in the blended overall customer rate from the beginning to the middle of 2008, which causes overestimation in the remaining months.

Figure 344: Commercial loan rate residual plot (%)



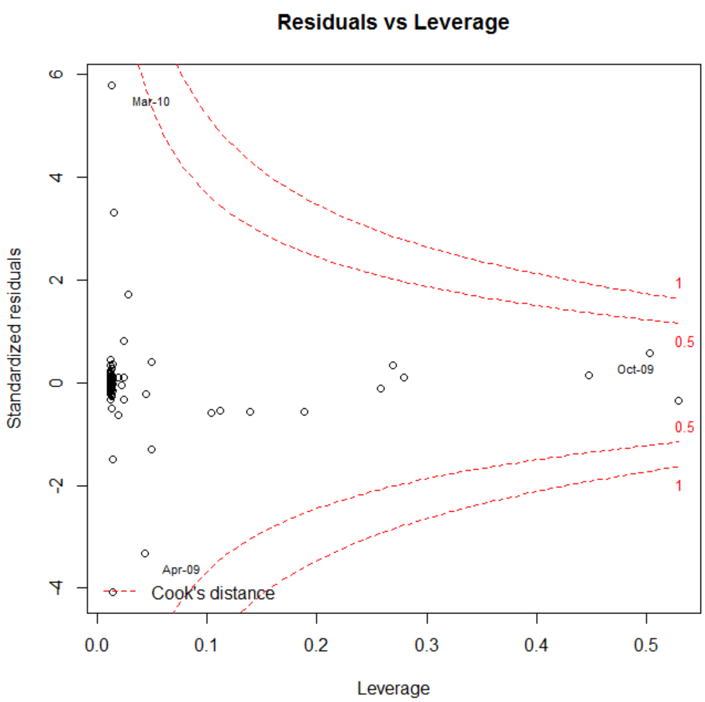
As seen in the figure above, the residuals are randomly distributed around the horizontal axis until 2011, when the residuals become much closer to zero due to the more stable rate environment in that period.

Figure 345: Commercial loan rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels generally track closely with actual average 9-quarter levels for different 9-quarter forecast windows. A few outliers exist due to noise in the data; when the starting month that is used corresponds to one of the spikes or dips in the historical data that the model does not pick up, all of the estimates for the 9-quarter window are offset by the magnitude of the spike or dip since the rates are estimated on first differences. Therefore, in these cases, estimated levels are consistently and overestimated or underestimated by a large amount.

Figure 346: Influential points for Commercial rates



The segment has no highly influential points.

8.4.6. Model sensitivity

8.4.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 323: Sensitivity to changes to independent variables for Commercial loan rates

Commercial loan rates – model sensitivity				
Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable

USD 1-month LIBOR	First difference – QoQ	%	0.123	0.80
USD 1-month LIBOR	First difference – MoM, 1-month lag	%	0.095	0.32
1-week LIBOR 1-week OIS spread	First difference – YoY	%	0.105	0.39
Intercept	None (level)	%	N/A	N/A

8.4.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

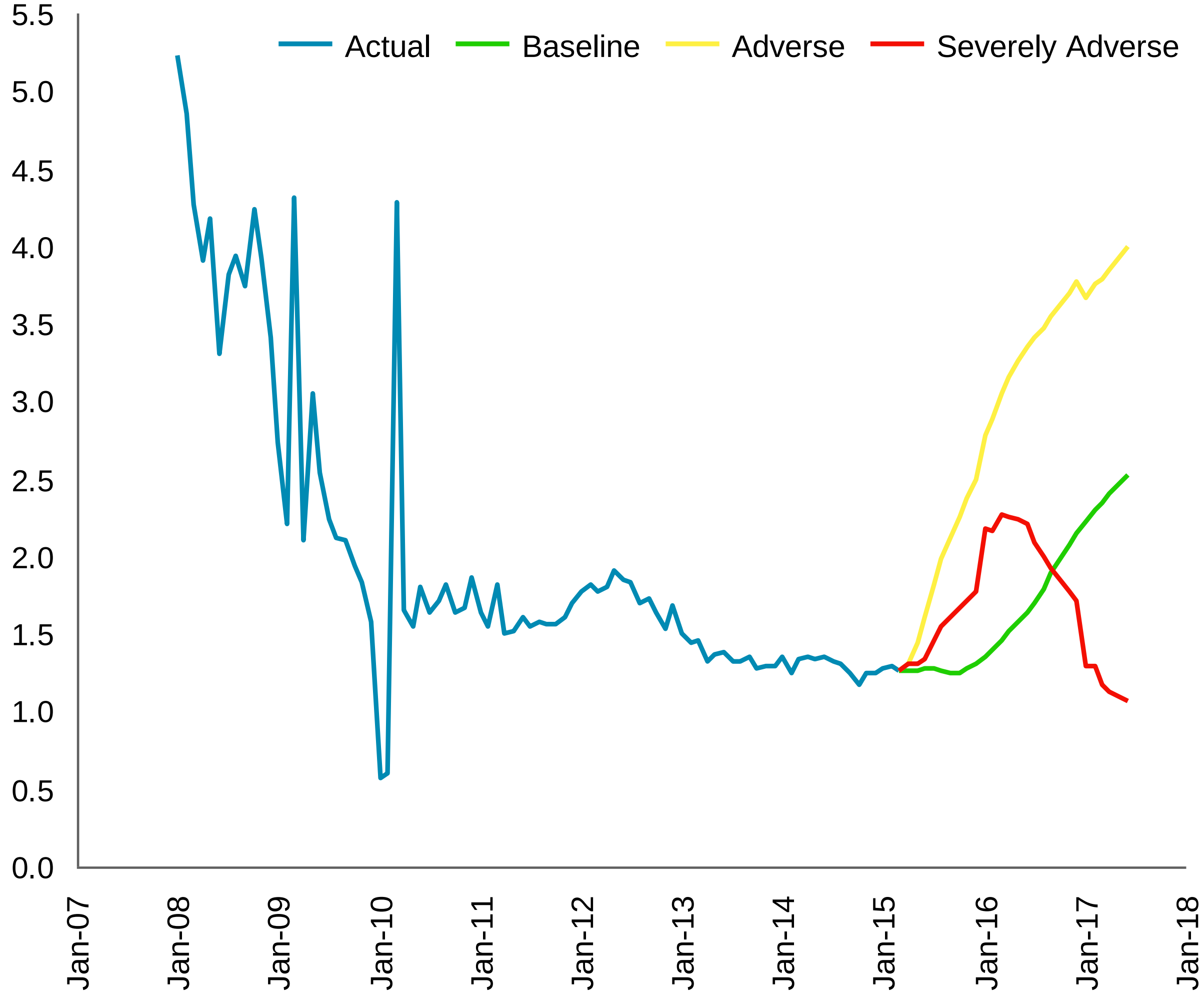
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.4.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 347: Commercial loan rates model forecast (%)



The Working Group considered the forecast behavior for the selected Commercial loan model as requiring high scrutiny during management review, due to the relatively weak historical fit of the model. However, the model forecasts for the scenarios are in line with the rate and spread environment of the scenarios.

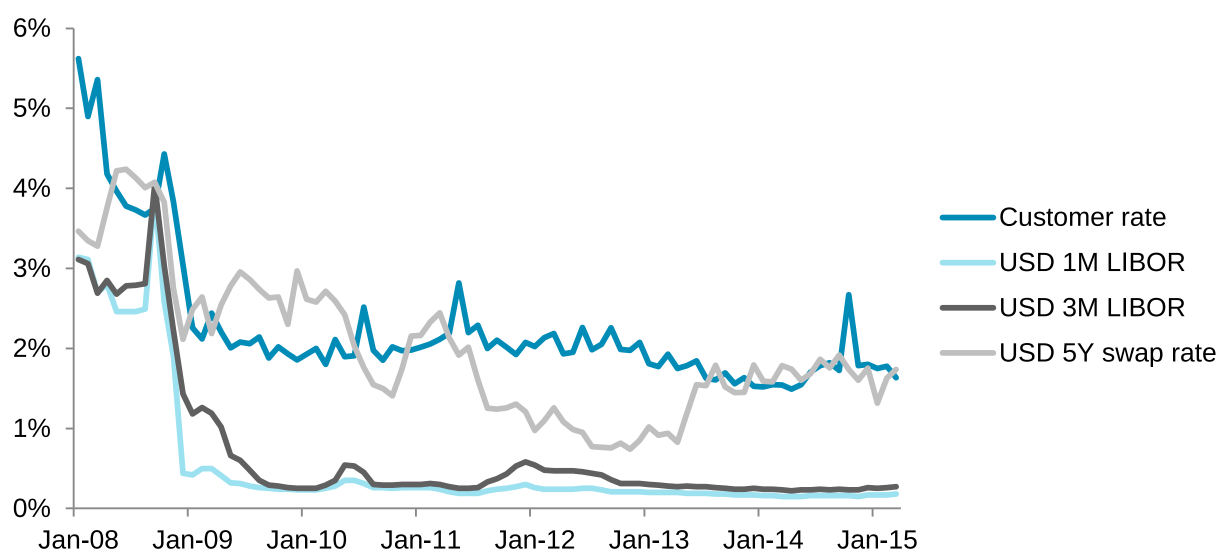
- **Severe recession (Severely Adverse) scenario:** The model predicts a rise in blended overall customer rates driven by widening credit spreads, peaking in the middle of the forecast window before declining back to starting levels. Some management review may be warranted to determine whether the impact of changing spreads is accurately reflected in the forecast behavior
- **Interest rate shock (Adverse) scenario**: The model predicts a rapid rise in blended overall customer rates, to levels similar to those before the 2008–2009 financial crisis
- **Baseline scenario**: The model predicts a gradual increase in blended overall customer rates in line with the expected baseline rise in interest rates

8.5. C&I loan rates

8.5.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with the USD reference rates. The historical C&I loan rate data has some noise due to variations in portfolio mix over time, but is generally well behaved and follows the directional movement of the reference rates.

Figure 348: Historical rates for overall C&I loan portfolio



8.5.2. Model summary

A statistically sound model that is consistent with business intuition was found for the C&I loan rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which, upon manual review, is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 324: Coefficient estimates for the C&I loan rates model

C&I loan rates (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
USD 1-month LIBOR	First difference – MoM, 1-month lag	%	0.561	0.564
Intercept	None (level)	%	-0.018	N/A

The model uses a single factor: a transformation of the USD 1-month LIBOR, which is one of the reference rates for this segment. This variable has a positive coefficient, matching business intuition that the blended overall customer rate should be positively correlated with the reference rates. The Working Group confirmed the intuition of the variable and its sign. No better models were found that used variables other than reference rates, such as market volatility, yield spread, or credit spread variables.

8.5.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

8.5.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 325: Unit root tests and stationarity tests including a trend variable on balances

C&I loan rates (in %) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-5	<0.01	Reject unit root
Phillips-Perron	1	-4.5	<0.01	Reject unit root
KPSS	5	0.87	<0.01	Reject stationarity

Table 326: Unit root tests and stationarity tests including a constant on first differences

C&I loan rates (in %) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-7.1	<0.01	Reject unit root
Phillips-Perron	1	-12	<0.01	Reject unit root
KPSS	2	0.43	0.06	Reject stationarity

Stationarity tests for C&I loans rates yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non-stationary. The monthly first difference series has similar results to the levels. Because the first difference failed the KPSS test, the modeling team reviewed the data manually. It was assessed that because the loans data spanned less than a full rate segment the stationarity results may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable does not show stationary behavior for differences for the KPSS test, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables at levels, but stationary for first differences.[37] Thus, manual review in addition to a review of academic literature provided sufficient evidence of stationarity for the application of OLS at first differences.

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.5.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

A low level of volatility was observed in historical levels, for C&I loan rates, but this was accepted for model development; no adjustments to data were made.

[37] “Real Interest Rate Persistence: Evidence and Implications” Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

8.5.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the C&I loan rates model are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 327: Statistical significance tests of model and variables for C&I loan rates

C&I loan rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	<1%	10%	Statistically significant
USD 1-month LIBOR	First difference – MoM, 1-month lag	0.561	<1%	10%	Statistically significant
Intercept	None (level)	-0.018	55%	10%	Statistically not significant

8.5.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

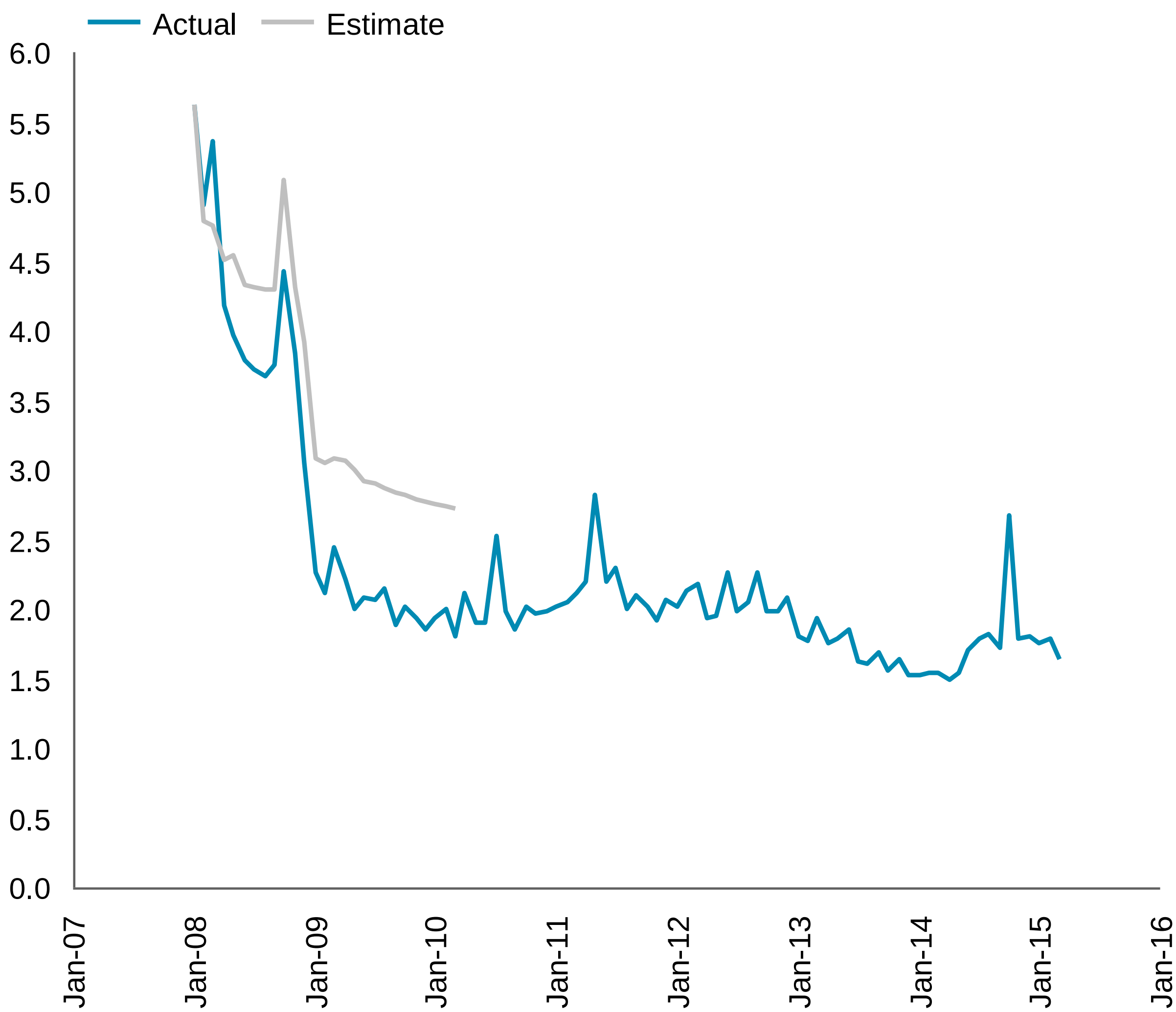
The results for the diagnostic tests reviewed are exhibited below.

Table 328: C&I loan rate model diagnostics

C&I loan rates – Model diagnostics

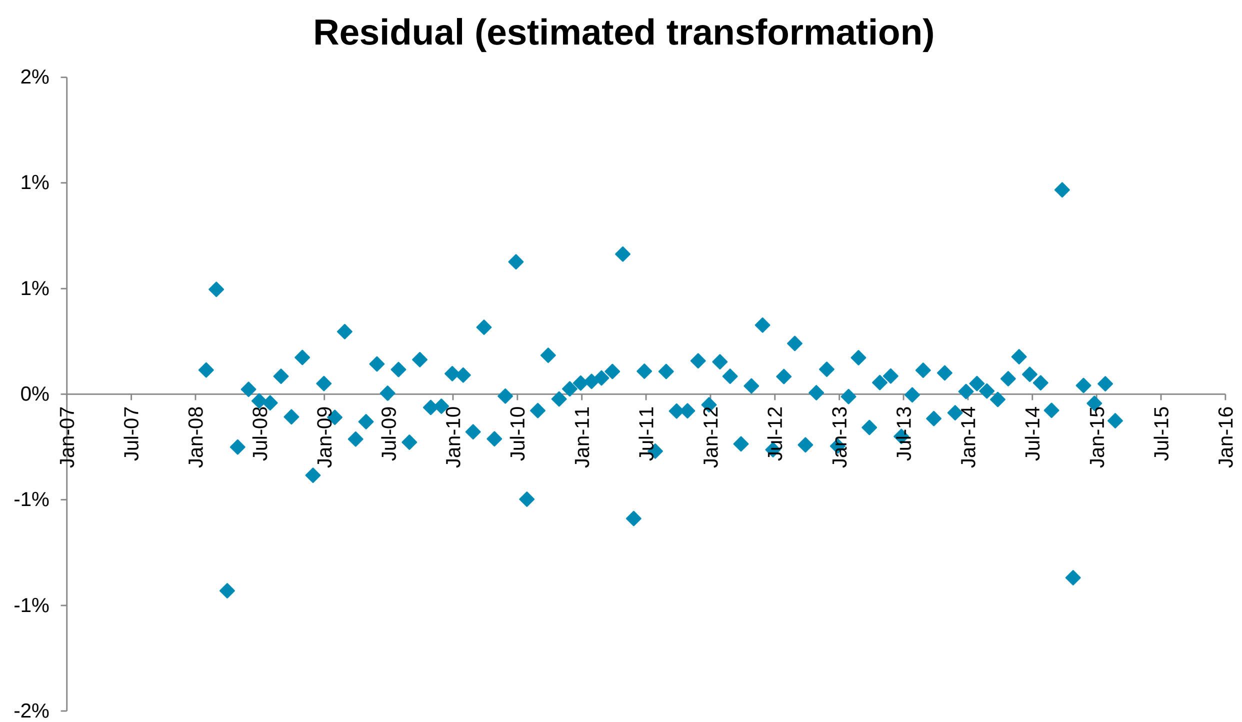
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	32%	-	-
	Adjusted R-squared	31%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	65%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	92%	10%	Linear specification appropriate

Figure 349: C&I loan rate 9Q in-sample prediction (%)



In the select 9Q in-sample prediction, the model captures most of the directional movements of the historical data. However, it does not capture the full magnitude of the decline in the blended overall customer rate from the beginning to the middle of 2008, which causes overestimation in the remaining months.

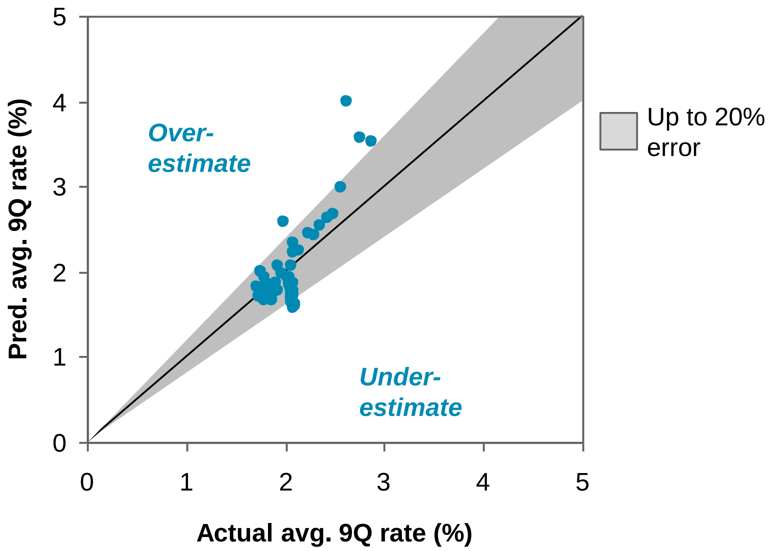
Figure 350: C&I loan rate residual plot (%)



As seen in the figure above, the residuals are randomly distributed around the horizontal axis, as expected.

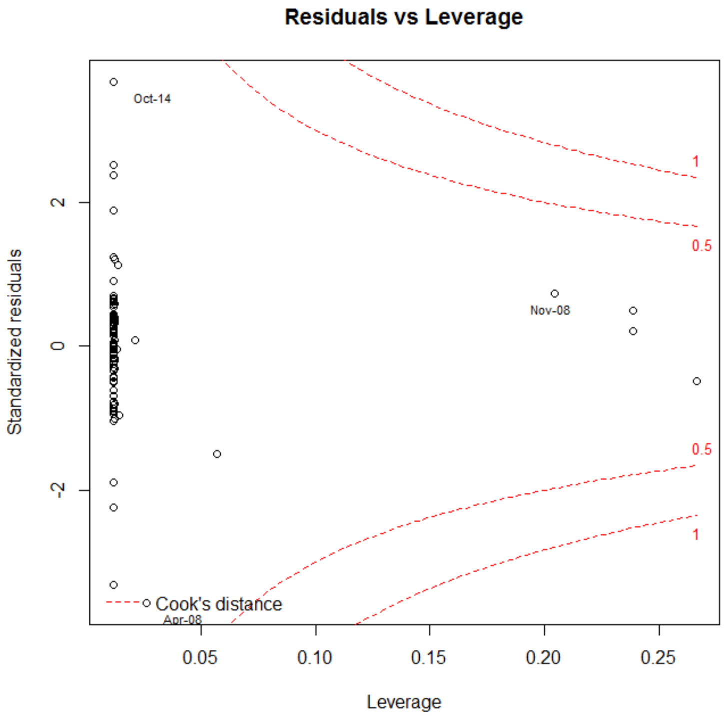
Figure 351: C&I loan rate estimation scatterplot

Avg predicted vs. actual rates over 9Q windows
%, Starting months = JAN 08 – DEC 12 (60 obs)



As seen in the figure above, estimated average 9-quarter levels generally track closely with actual average 9-quarter levels for different 9-quarter forecast windows, with most of the estimated average values falling within 20% of actual average values.

Figure 352: Influential points for C&I loan rates



The segment has no highly influential points.

8.5.6. Model sensitivity

8.5.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 329: Sensitivity to changes to independent variables for C&I loan rates

C&I loan rates – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
USD 1-month LIBOR	First difference – MoM, 1-month lag	%	0.564	.0322
Intercept	None (level)	%	N/A	N/A

8.5.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

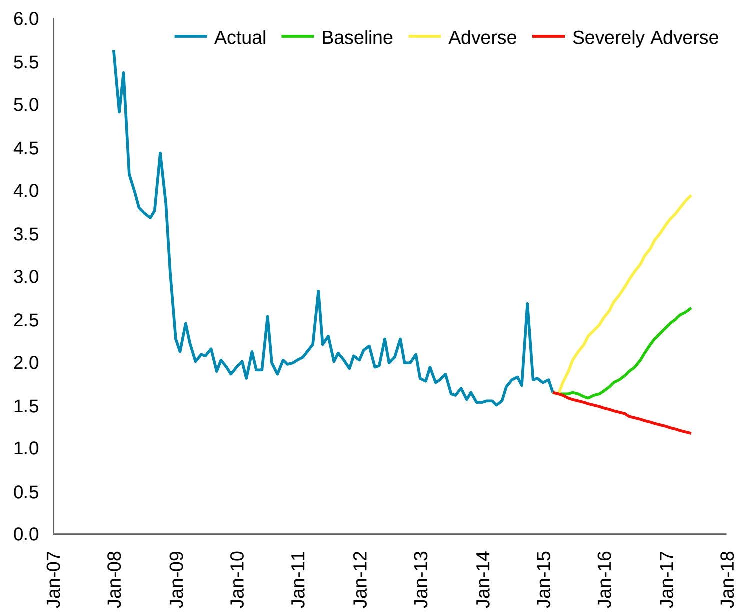
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.5.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 353: C&I loan rates model forecast (%)



The Working Group considered the forecast behavior for the selected C&I loan model as generally reasonable and intuitive. The model forecasts for the scenarios are in line with the rate environment of the scenarios.

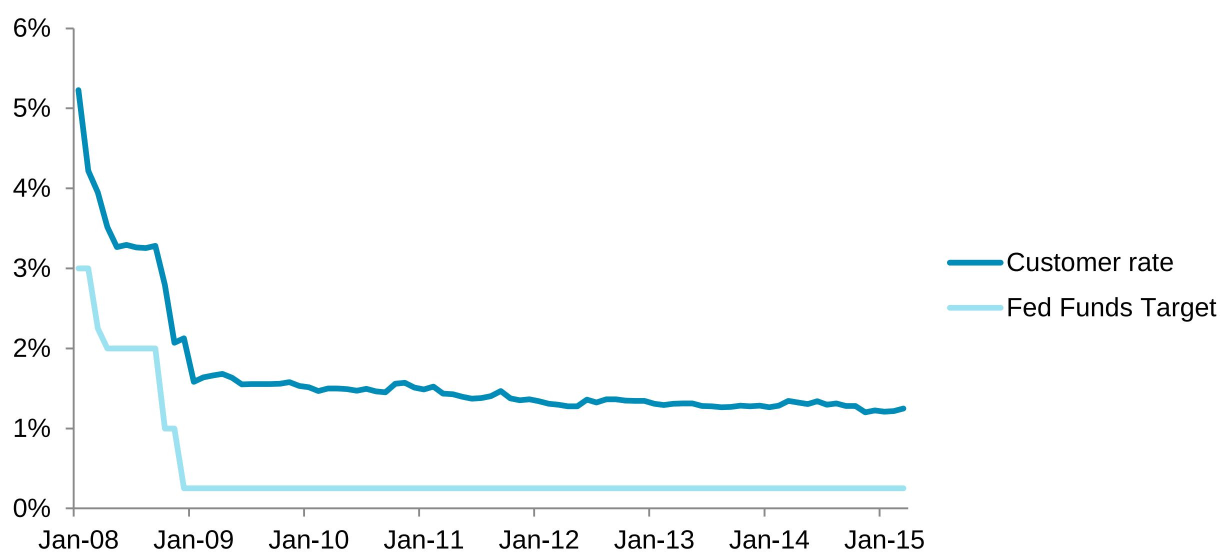
- **Severe recession (Severely Adverse) scenario:** The model predicts a small decline in blended overall customer rates, which could be reasonable as the portfolio evolves and older loans originated under higher interest rate and spread environments mature. Some management review may be needed to ensure that the magnitude of decline is within expectations
- **Interest rate shock (Adverse) scenario**: The model predicts a rapid rise in blended overall customer rates, to levels similar to those before the 2008–2009 financial crisis
- **Baseline scenario**: The model predicts a gradual increase in blended overall customer rates in line with the expected baseline rise in interest rates

8.6. Margin loan rates

8.6.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with the reference rate. The historical Margin loan rate data is clean compared to the data in other segments, due to the short-term nature of these loans. The historical blended overall customer rate tracks very closely with movements in the reference rate.

Figure 354: Historical rates for overall Margin loan portfolio



8.6.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Commercial loan rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which upon manual review is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests other than the reset test for linearity described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 330: Coefficient estimates for the Margin loan rates model

Margin loan rates (in %) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Fed funds target rate	First difference – MoM	%	0.282	0.268
Fed funds target rate	First difference – MoM, 1-month lag	%	0.722	0.897
Intercept	None (level)	%	-0.004	N/A

The model uses two transformations of the Fed funds target rate, one as a 1-month lag of the other. Both variables have a positive coefficient, matching business intuition that the blended overall customer rate should be positively correlated with the reference rates. The use of a reference rate variable and its 1-month lag is reasonable, indicating a slight delay in adjustments to customer rates for some margin loans when the underlying reference rate changes.

The Working Group confirmed the intuition of the variables and their signs. No better models were found that used variables other than reference rates, such as market volatility, yield spread, or credit spread variables.

8.6.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

8.6.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 331: Unit root tests and stationarity tests including a trend variable on balances

Margin loan rates (in %) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	5	-6.7	<0.01	Reject unit root
Phillips-Perron	1	-8.9	<0.01	Reject unit root
KPSS	5	0.87	<0.01	Reject stationarity

Table 332: Unit root tests and stationarity tests including a constant on first differences

Margin loan rates (in %) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	10	-6	<0.01	Reject unit root
Phillips-Perron	1	-9.5	<0.01	Reject unit root
KPSS	4	0.75	<0.01	Reject stationarity

Stationarity tests for Margin loans rates yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non-stationary. The monthly first difference series has similar results to the levels. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that because the loans data spanned less than a full rate segment the stationarity results may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable does not show stationary behavior, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[38].

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.6.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No issues were noted in the historical data for Margin loan rates, and therefore no adjustments were made to the data.

[38] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

8.6.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Margin loan rates model are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 333: Statistical significance tests of model and variables for Margin loan rates

Margin loan rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	<1%	10%	Statistically significant
Fed funds target rate	First difference – MoM	0.282	<1%	10%	Statistically significant
Fed funds target rate	First difference – MoM, 1-month lag	0.722	<1%	10%	Statistically significant
Intercept	None (level)	-0.004	28%	10%	Statistically not significant

8.6.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

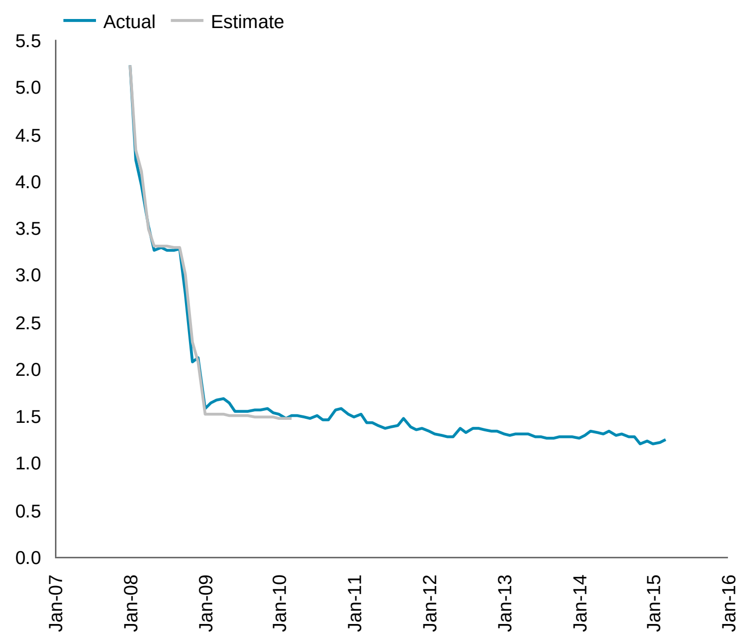
The results for the diagnostic tests reviewed are exhibited below.

Table 334: Margin loan rate model diagnostics

Margin loan rates – Model diagnostics

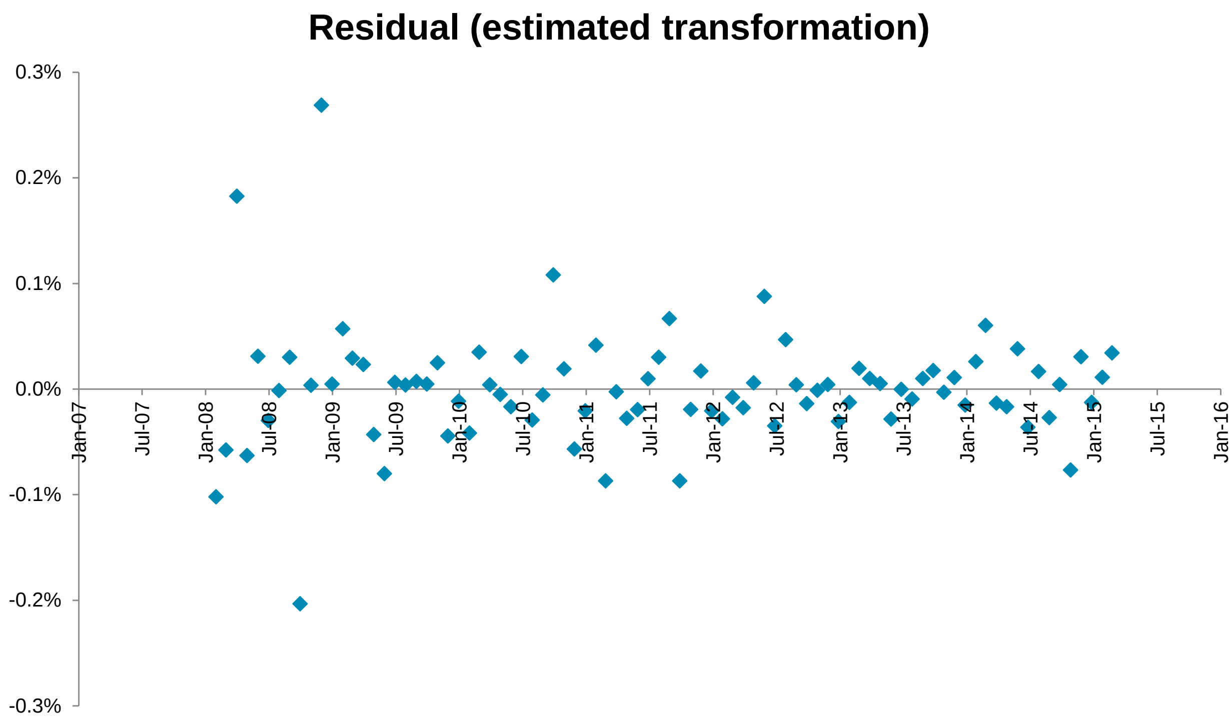
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	89%	-	-
	Adjusted R-squared	88%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	3%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	8%	10%	Linear specification inappropriate

Figure 355: Margin loan rate 9Q in-sample prediction (%)



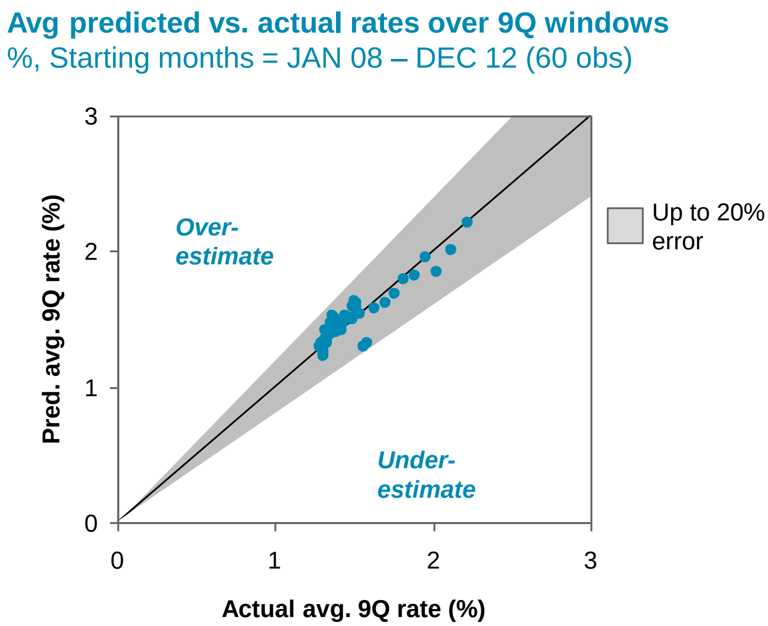
In the select 9Q in-sample prediction, the model captures both the directional changes and their magnitudes very closely.

Figure 356: Margin loan rate residual plot (%)



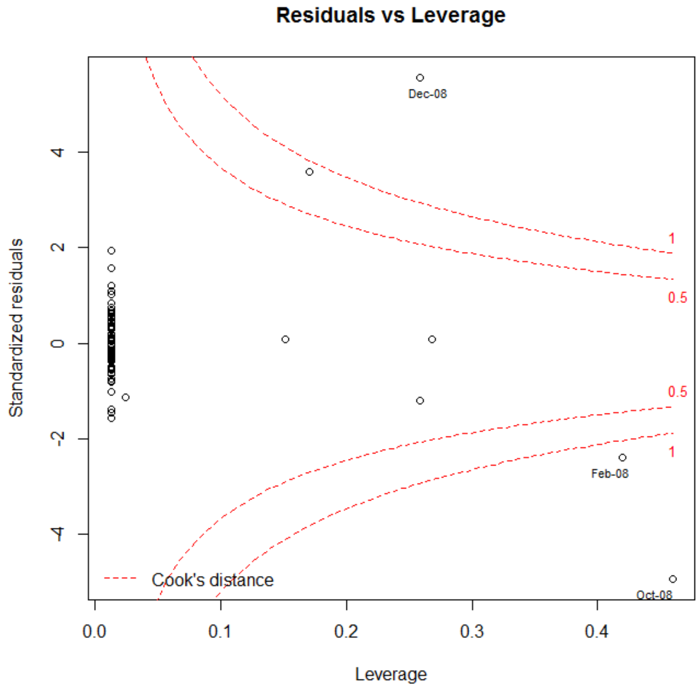
As seen in the figure above, the residuals are randomly distributed around the horizontal axis, as expected.

Figure 357: Margin loan rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels track closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all of the estimated average values falling within 20% of actual average values.

Figure 358: Influential points for Margin Loan rates



For this segment February, October and December are highly influential points. However, this is not surprising because the financial crisis caused rates to spike and does not invalidate the model.

8.6.6. Model sensitivity

8.6.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 335: Sensitivity to changes to independent variables for Margin loan rates

Margin loan rates – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
Fed funds target rate	First difference – MoM	%	0.268	0.200
Fed funds target rate	First difference – MoM, 1-month lag	%	0.897	0.20
Intercept	None (level)	%	N/A	N/A

8.6.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

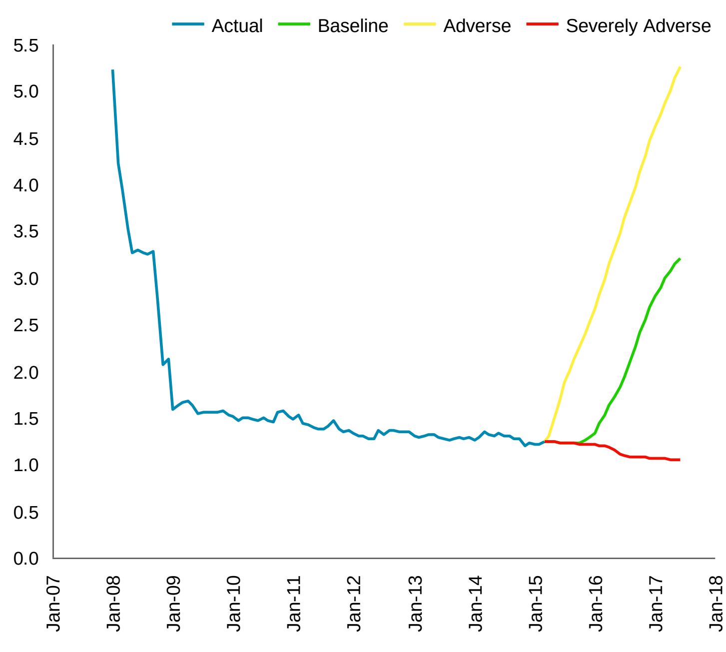
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.6.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 359: Margin loan rates model forecast (%)



The Working Group considered the forecast behavior for the selected Margin loan model as generally reasonable and intuitive. The model forecasts for the scenarios are in line with the rate environment of the scenarios.

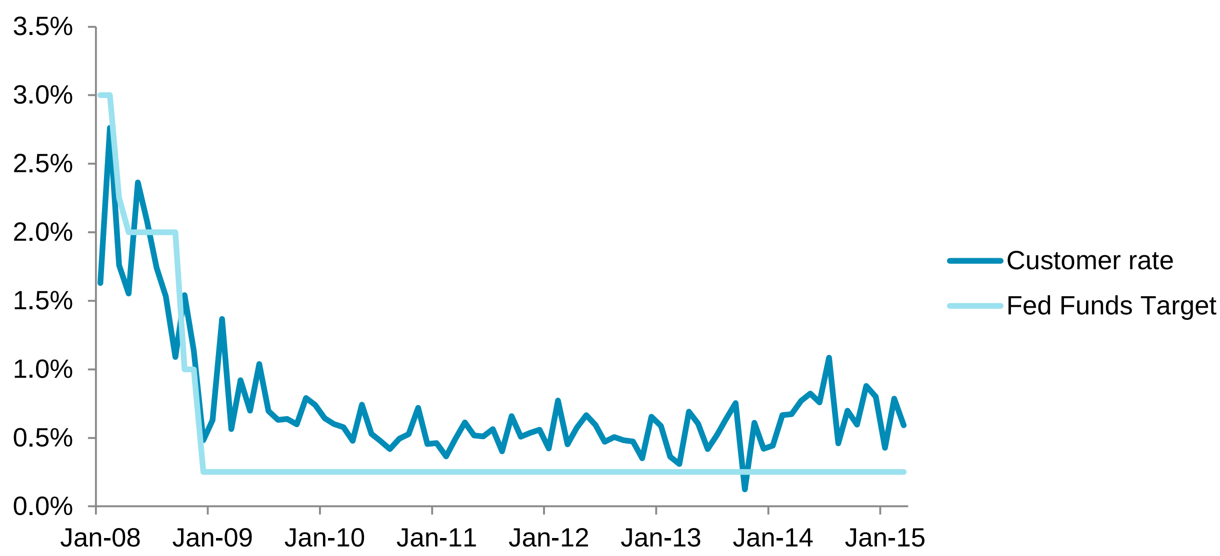
- **Severe recession (Severely Adverse) scenario:** The model predicts that blended overall customer rates will remain flat or decline very slightly, which is consistent with a continued low interest rate environment
- **Interest rate shock (Adverse) scenario**: The model predicts a rapid rise in blended overall customer rates, to levels similar to those before the 2008–2009 financial crisis
- **Baseline scenario**: The model predicts a gradual increase in blended overall customer rates in line with the expected baseline rise in interest rates

8.7. Overdraft rates

8.7.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with the USD reference rate. The historical Overdraft rate data is noisy because overdrafts are typically very short-term exposures, but different clients are offered different pricing terms. Therefore, the overall rate for the portfolio depends on which clients have overdrafts at any point in time. Generally, the overall customer rate follows the directional movement of the reference rate.

Figure 360: Historical rates for overall Overdraft portfolio



8.7.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Commercial loan rates segment. However, historical fit for this model is poor, given the volatile nature of the historical dependent variable time series. Therefore, management scrutiny is highly recommended for the outputs of this model.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests other than the RESET test for linearity described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 336: Coefficient estimates for the Overdrafts rates model

Overdraft rates (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Fed funds target rate	First difference – MoM, 3-month lag	%	0.336	0.217
Intercept	None (level)	%	0.005	N/A

The model uses a single factor: a transformation of the Fed funds target rate, which is one of the reference rates for this segment. This variable has a positive coefficient, matching business intuition that the blended overall customer rate should be positively correlated with the reference rates. Given that overdraft volumes are predominantly USD, the Fed funds target rate was preferred by the Working Group over GBP or EUR equivalents.

The Working Group confirmed the intuition of the variable and its sign. No better models were found that used variables other than reference rates, such as market volatility, yield spread, or credit spread variables.

8.7.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

8.7.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 337: Unit root tests and stationarity tests including a trend variable on balances

Overdraft rates (in %) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	4	-5.1	<0.01	Reject unit root
Phillips-Perron	1	-3.4	0.01	Reject unit root
KPSS	5	0.69	0.01	Reject stationarity

Table 338: Unit root tests and stationarity tests including a constant on first differences

Overdraft rates (in %) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-8.8	<0.01	Reject unit root
Phillips-Perron	1	-17	<0.01	Reject unit root
KPSS	0	0.03	0.96	Fail to Reject stationarity

Stationarity tests for Overdraft rates yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non-stationary. The monthly first difference series however, passes stationarity across all three tests. This suggests that it is stationary.

There is, however, a limitation to these tests. The loan rates data spans less than one full rate cycle. Therefore, tests on stationarity may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable shows stationary behavior, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[39].

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.7.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Overdraft rates data showed significant noise, due to the variations in pricing offered to different clients and the churn in which clients have overdrafts at any given point in time. Since this volatility is an expected characteristic of the historical rates, no adjustments were made to the data.

[39] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

8.7.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Overdraft rates model are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 339: Statistical significance tests of model and variables for Overdraft rates

Overdraft rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	<1%	10%	Statistically significant
Fed funds target rate	First difference – MoM, 3-month lag	0.336	<1%	10%	Statistically significant
Intercept	None (level)	0.005	82%	10%	Statistically not significant

8.7.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

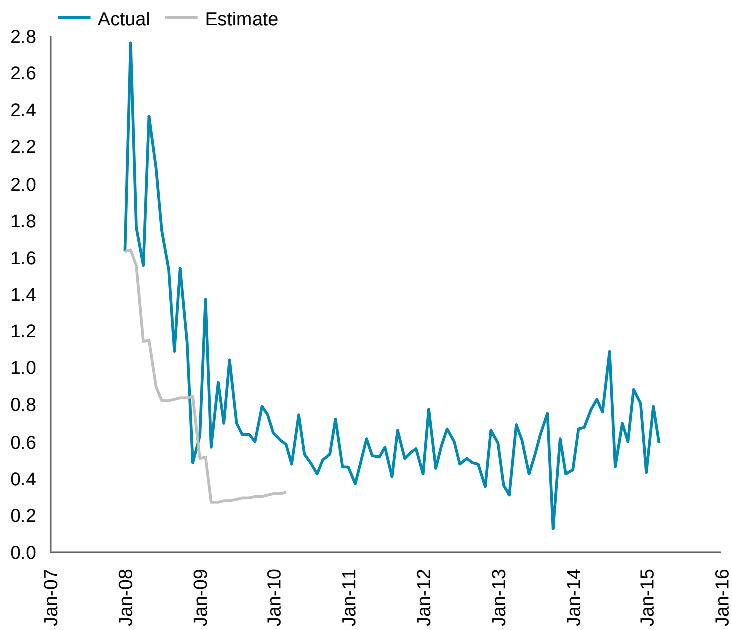
The results for the diagnostic tests reviewed are exhibited below.

Table 340: Overdraft rate model diagnostics

Commercial loan rates – Model diagnostics

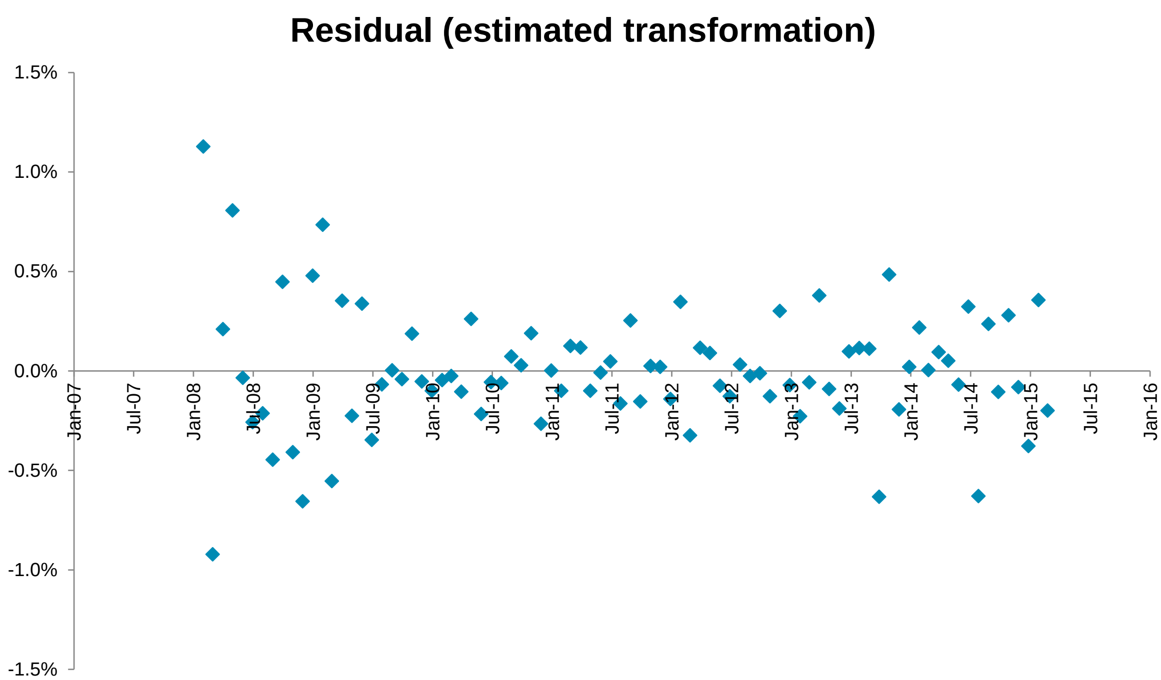
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	5%	-	-
	Adjusted R-squared	4%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	36%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	1%	10%	Linear specification inappropriate

Figure 361: Overdraft rate 9Q in-sample prediction (%)



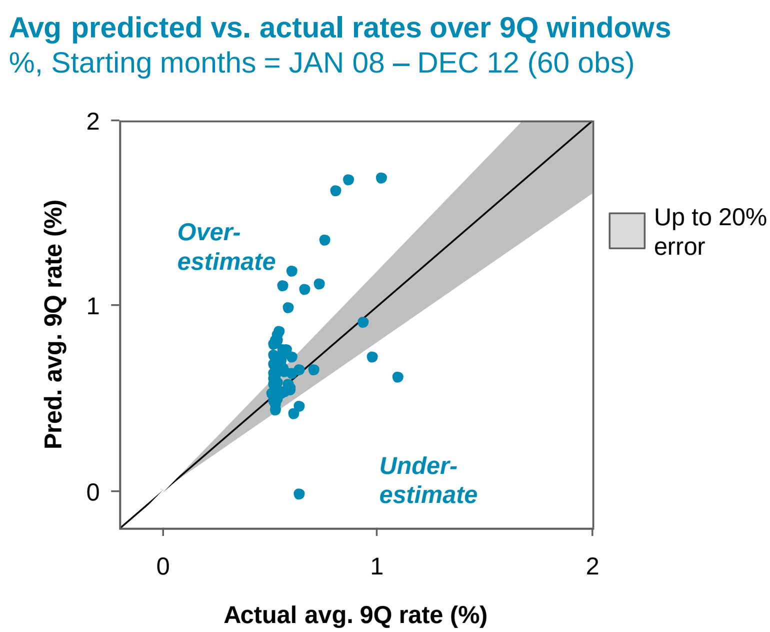
In the select 9Q in-sample prediction, the model fails to capture the volatility in the historical time series, which is expected because a significant portion of the volatility arises from BNY Mellon's variations in pricing terms for overdrafts. The model captures the sharp downward movement of blended overall customer rates over the forecast window, but notably does not capture several upward spikes in the beginning of the forecast window, leading to consistent underestimation of actual rates.

Figure 362: Overdraft rate residual plot (%)



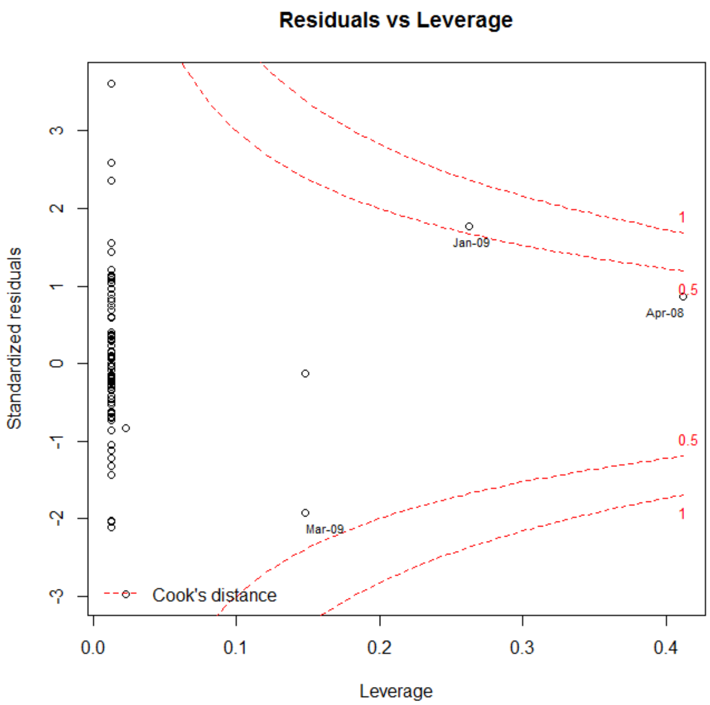
As seen in the figure above, despite their relatively large magnitude due to the model's poor historical fit, the residuals are randomly distributed around the horizontal axis, as expected.

Figure 363: Overdraft rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels do not always track closely with actual average 9-quarter levels for different 9-quarter forecast windows. The cause of this is the high volatility in the historical data series, which the model cannot pick up. When the starting month that is used corresponds to one of the spikes or dips in the historical data that the model does not pick up, all of the estimates for the 9-quarter window are offset by the magnitude of the spike or dip since the rates are estimated on first differences. Therefore, in these cases, estimated levels are consistently and overestimated or underestimated by a large amount.

Figure 364: Influential points for Overdraft Rates



The segment does not have any highly influential points.

8.7.6. Model sensitivity

8.7.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 341: Sensitivity to changes to independent variables for Overdraft rates

Overdraft rates – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
Fed funds target rate	First difference – MoM, 3-month lag	%	0.217	0.202

Intercept	None (level)	%	N/A	N/A

8.7.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

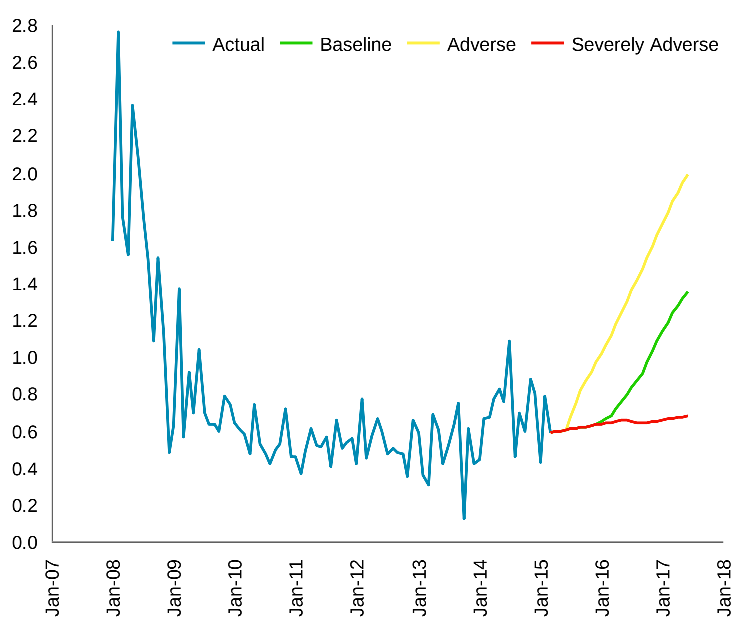
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.7.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 365: Overdraft rates model forecast (%)



The Working Group considered the forecast behavior for the selected Commercial loan model as requiring high scrutiny during management review, due to the weak historical fit of the model. However, the model forecasts for the scenarios are in line with the rate environment of the scenarios.

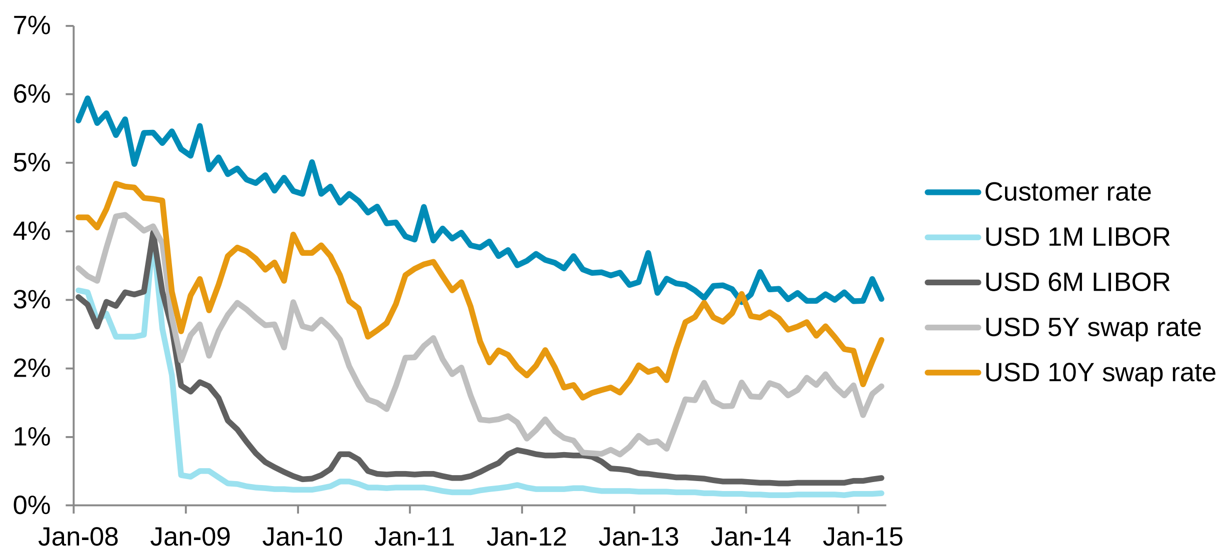
- **Severe recession (Severely Adverse) scenario:** The model predicts a very slight increase in blended overall customer rates, consistent with a continued low interest rate environment
- **Interest rate shock (Adverse) scenario**: The model predicts a rapid rise in blended overall customer rates, to levels similar to those before the 2008–2009 financial crisis
- **Baseline scenario**: The model predicts a gradual increase in blended overall customer rates in line with the expected baseline rise in interest rates

8.8. Mortgage loan rates

8.8.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with select reference rates. The historical Mortgage loan rate data shows a small amount of noise due to variations in portfolio mix, with a gradual decline following the general directional movement of the reference rates. The gradual nature of this decline is consistent with the longer duration of the loans in this portfolio, which means that the overall blended rate is slower to react as a relatively small proportion of the loans in the portfolio mature or are paid off in any given month.

Figure 366: Historical rates for overall Mortgage loan portfolio



8.8.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Mortgage loan rates segment. The model is unable to capture the short-term volatility observed in the historical blended overall customer rates, but does capture the general historical trend. Management scrutiny is recommended to ensure alignment with expectations.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which, upon manual review by the modeling team, is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 342: Coefficient estimates for the Mortgage loan rates model

Mortgage loan rates (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
USD 6-month LIBOR	First difference – MoM	%	0.183	0.151
Intercept	None (level)	%	-0.025	N/A

The model uses a single factor: a transformation of the USD 6-month LIBOR, which is one of the reference rates for this segment. This variable has a positive coefficient, matching business intuition that the blended overall customer rate should be positively correlated with the reference rates.

The Working Group confirmed the intuition of the variable and its sign. No better models were found that used variables other than reference rates, such as market volatility, yield spread, or credit spread variables.

8.8.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

8.8.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 343: Unit root tests and stationarity tests including a trend variable on balances

Mortgage loan rates (in %) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	11	-5.3	<0.01	Reject unit root
Phillips-Perron	1	-1.5	0.54	Fail to Reject unit root

KPSS	5	1.5	<0.01	Reject stationarity

Table 344: Unit root tests and stationarity tests including a constant on first differences

Mortgage loan rates (in %) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	11	-2.2	0.21	Fail to Reject unit root
Phillips-Perron	1	-22	<0.01	Reject unit root
KPSS	12	0.27	0.17	Reject stationarity

The mortgage loan rates levels yield mixed results. The ADF test rejects the unit root while the PP and KPSS tests fail to reject a unit root and reject stationarity. This implies that the levels are not stationarity. Because of this the modeling team looked at the first differences. These results were also mixed in that the ADF test and KPSS failed for stationarity while the PP test passed. Because it failed the ADF and KPSS tests, the modeling team reviewed the data manually. It was assessed that because the loans data spanned less than a full rate segment the stationarity results may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable does not show stationary behavior, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[40].

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.8.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Mortgage loan rates data showed a small level of volatility. Since this volatility is an expected characteristic of the historical rates, no adjustments were made to the data.

8.8.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are

[40] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold.

- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%.

The table below reports the results of the significance tests. All of the coefficient estimates in the Commercial loan rates model are statistically significant. The intercept is found to be statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 345: Statistical significance tests of model and variables for Mortgage loan rates

Mortgage loan rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	2%	10%	Statistically significant
USD 6-month LIBOR	First difference – MoM	0.183	2%	10%	Statistically significant
Intercept	None (level)	-0.025	2%	10%	Statistically significant

In this model, the intercept is statistically significant, which is expected given the steady declining trend in the observed historical rates.

8.8.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted

were highlighted and investigated to ensure the modeling team understood the reason for the deviation

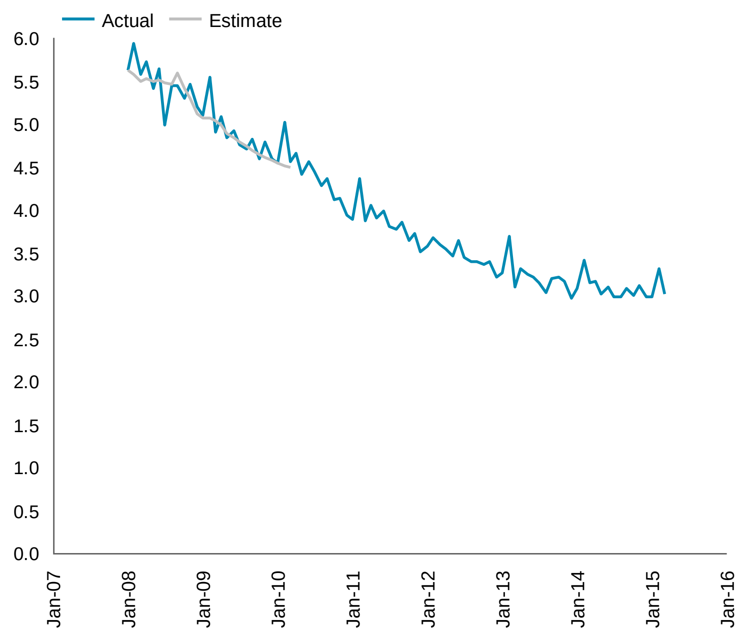
The results for the diagnostic tests reviewed are exhibited below.

Table 346: Mortgage loan rate model diagnostics

Mortgage loan rates – Model diagnostics

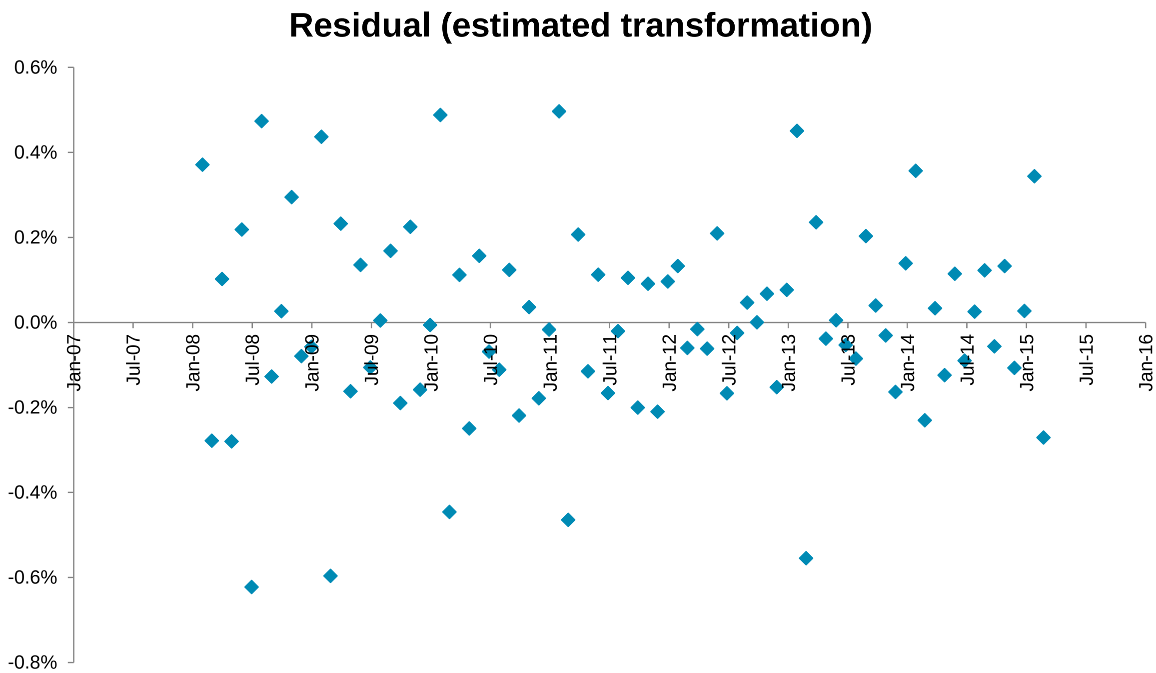
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	2%	-	-
	Adjusted R-squared	1%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	68%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	80%	10%	Linear specification appropriate

Figure 367: Mortgage loan rate 9Q in-sample prediction (%)



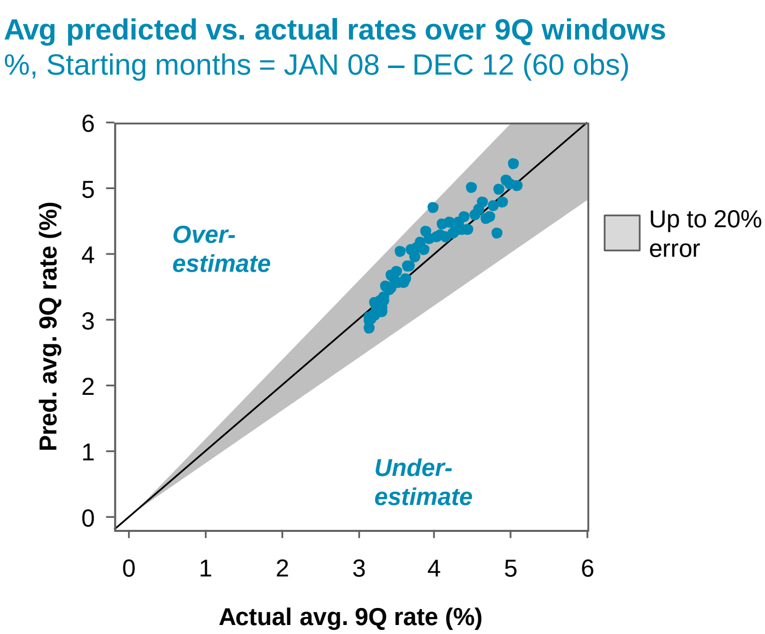
In the select 9Q in-sample prediction, the model captures most of the overall directional movements of the historical data and their magnitudes. It fails to pick up most of the short-term volatility, which can be partially attributable to changes in the mix of mortgages in the portfolio in terms of pricing and duration, which would not be explainable by underlying reference rates.

Figure 368: Mortgage loan rate residual plot (%)



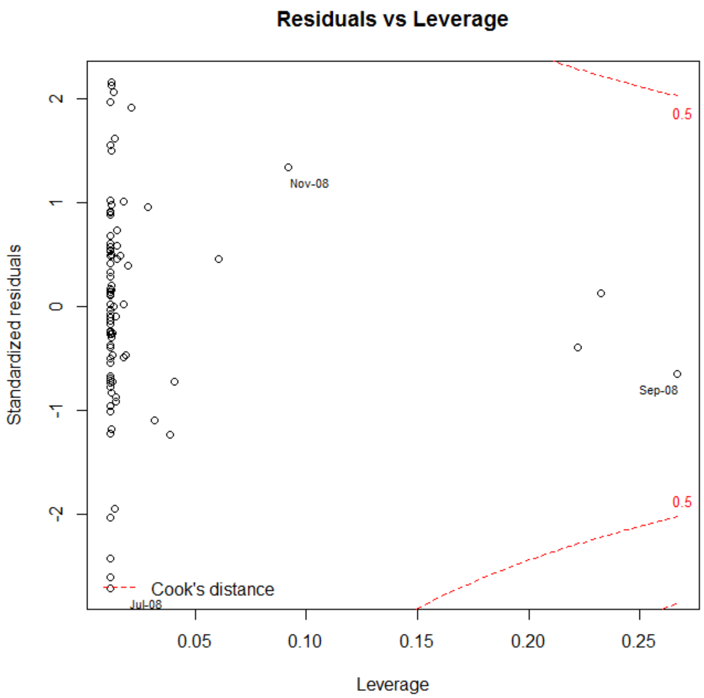
As seen in the figure above, the residuals are randomly distributed around the horizontal axis, as expected.

Figure 369: Mortgage loan rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels track closely with actual average 9-quarter levels for different 9-quarter forecast windows, with all of the estimated average values falling within 20% of actual average values.

Figure 370: Influential points for Mortgage loan rates



The segment does not have any highly influential points.

8.8.6. Model sensitivity

8.8.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 347: Sensitivity to changes to independent variables for Mortgage loan rates

Mortgage loan rates – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
USD 6-month LIBOR	First difference – MoM	%	0.15	0.245
Intercept	None (level)	%	N/A	N/A

8.8.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

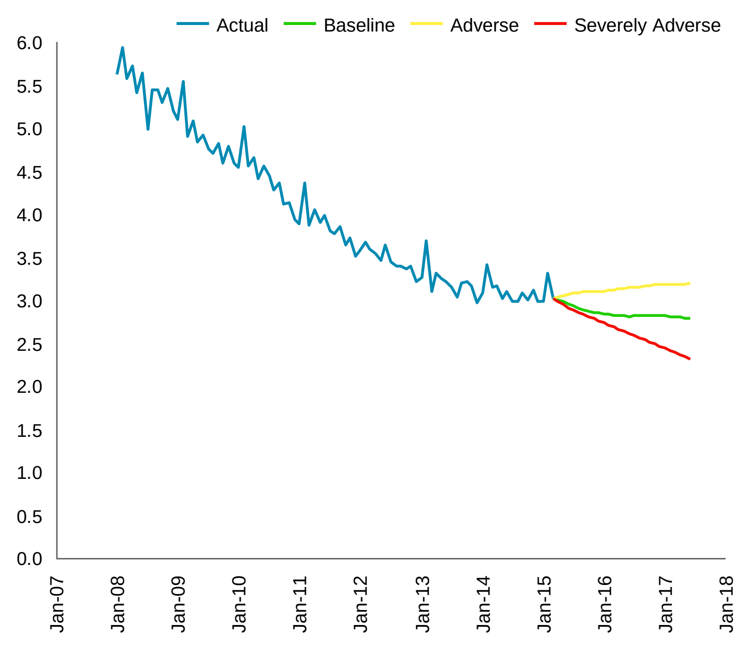
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.8.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 371: Mortgage loan rates model forecast (%)



The Working Group considered the forecast behavior for the selected Commercial loan model as requiring scrutiny during management review, due to the strong impact of the model's intercept on the forecasts.

- **Severe recession (Severely Adverse) scenario:** The model predicts a continued decline in overall blended customer rates, driven by the intercept of the model. This forecast may lead to rates that are lower than would be expected, since the historical blended overall customer rate shows signs of leveling off in recent years. Therefore, management scrutiny is recommended for this model's forecasts

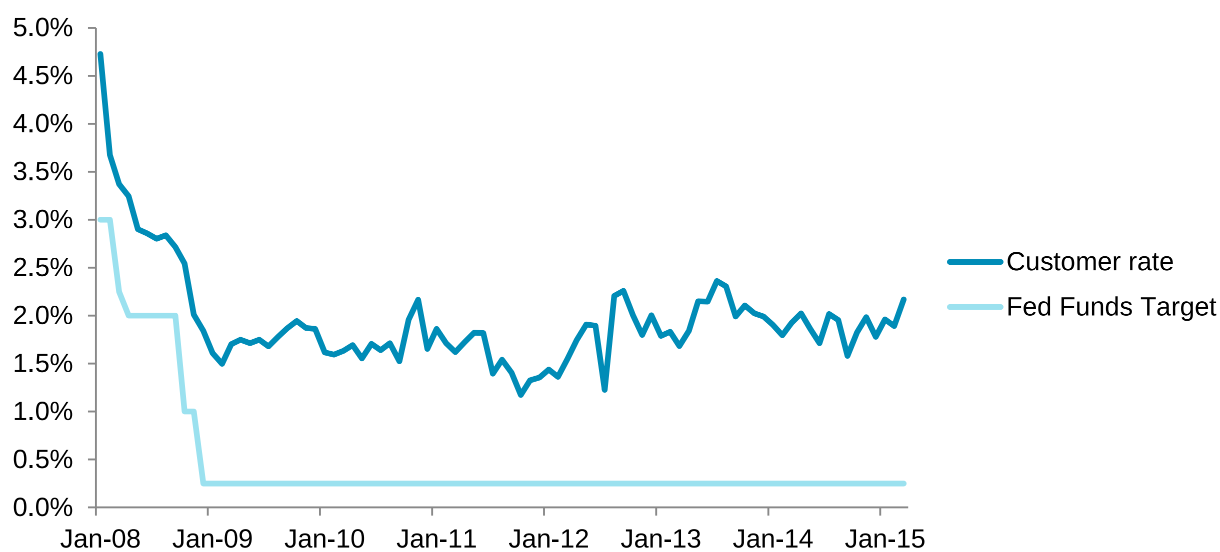
- **Interest rate shock (Adverse) scenario**: The model predicts a slight rise in blended overall customer rates. This forecast may lead to rates that are lower than would be expected, due to the effect of the model's negative intercept
- **Baseline scenario**: The model predicts a slight decrease in blended overall customer rates, which again may lead to rates that are lower than would be expected

8.9. Broker dealer loan rates

8.9.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with the reference rate. The historical Broker Dealer loan rate data generally follows the directional movement of the reference rate, with some additional volatility.

Figure 372: Historical rates for overall Broker Dealer loan portfolio



8.9.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Broker Dealer loan rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary upon manual review

- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 348: Coefficient estimates for the Broker Dealer loan rates model

Broker Dealer loan rates (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Fed funds target rate	First difference – MoM, 1-month lag	%	0.436	0.354
Fed funds target rate	First difference – QoQ	%	0.185	0.287
Baa to Treasury spread	First difference – YoY	%	0.021	0.111
Intercept	None (level)	%	0.013	N/A

The model uses three factors: two transformations of the Fed funds target rate and a credit spread. All three variables have a positive coefficient. The Working Group confirmed the intuition of these variables and their signs.

- For the reference rate variables, a positive coefficient was required to match business intuition that the blended overall customer rate should be positively correlated with the reference rates
- For the credit spread variable, a positive coefficient indicates that as credit spreads widen, so do customer spreads, independent of the level of the rates

8.9.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

8.9.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 349: Unit root tests and stationarity tests including a trend variable on balances

Broker Dealer loan rates (in %) – Unit root test with trend on balance series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-4.4	<0.01	Reject unit root
Phillips-Perron	1	-6.5	<0.01	Reject unit root
KPSS	5	0.4	0.07	Reject stationarity

Table 350: Unit root tests and stationarity tests including a constant on first differences

Broker Dealer loan rates (in %) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-8.4	<0.01	Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	3	0.61	0.02	Reject stationarity

Stationarity tests for broker dealer loan rates yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non stationary. The monthly first difference series has similar results to the levels. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that because the loans data spanned less than a full rate segment the stationarity results may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable does not show stationary behavior for differences for the KPSS test, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables for levels but stationary for first differences.[41] Thus, manual review in addition to a review of academic literature provided sufficient evidence of stationarity for the application of OLS at first differences.

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.9.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Broker Dealer loan rates data showed a small level of volatility. Since this volatility is an expected characteristic of the historical rates, no adjustments were made to the data.

[41] “Real Interest Rate Persistence: Evidence and Implications” Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

8.9.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Commercial loan rates model are statistically significant. The intercept was found to be statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 351: Statistical significance tests of model and variables for Broker Dealer loan rates

Broker Dealer loan rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	<1%	10%	Statistically significant
Fed funds target rate	First difference – MoM, 1-month lag	0.436	<1%	10%	Statistically significant
Fed funds target rate	First difference – QoQ	0.185	<1%	10%	Statistically significant
Baa to Treasury spread	First difference – YoY	0.021	4%	10%	Statistically significant
Intercept	None (level)	0.013	42%	10%	Statistically not significant

8.9.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics

- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

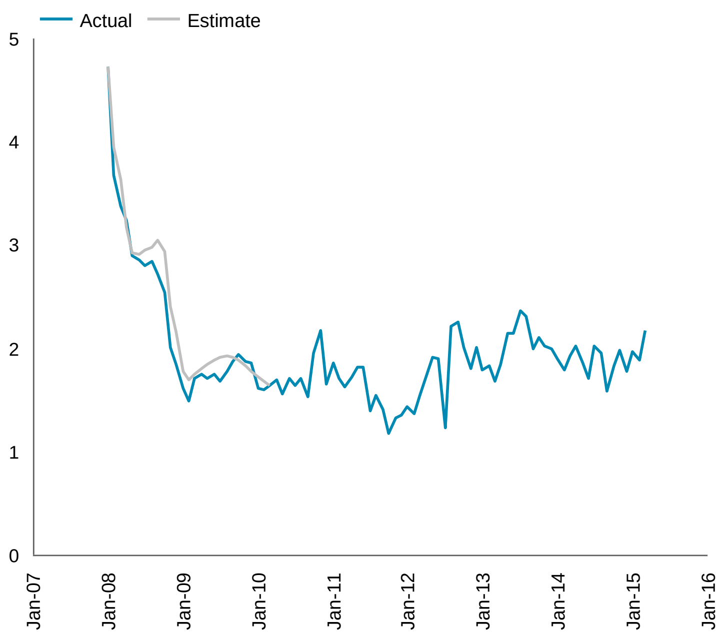
The results for the diagnostic tests reviewed are exhibited below.

Table 352: Broker Dealer loan rate model diagnostics

Broker Dealer loan rates – Model diagnostics

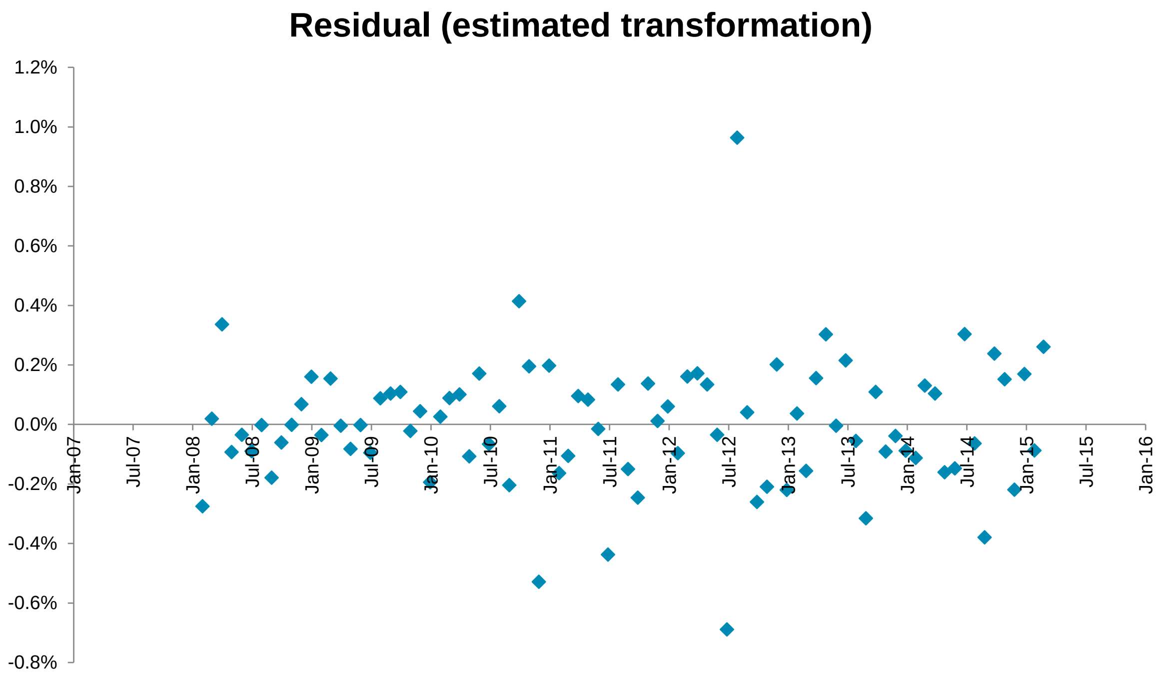
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	27%	-	-
	Adjusted R-squared	24%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	84%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.88	5	No multicollinearity
Linearity	RESET test	12%	10%	Linear specification appropriate

Figure 373: Broker Dealer loan rate 9Q in-sample prediction (%)



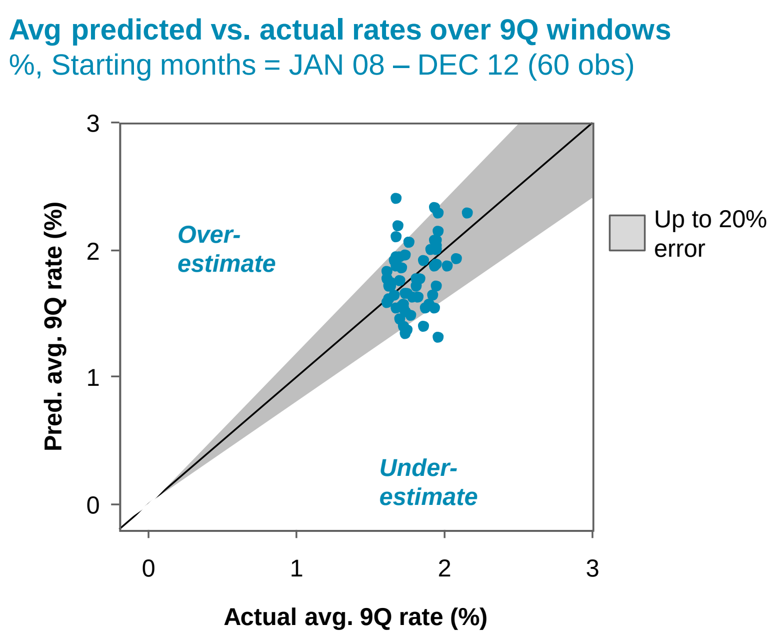
In the select 9Q in-sample prediction, the model captures both the directional changes and their magnitudes very closely.

Figure 374: Broker Dealer loan rate residual plot (%)



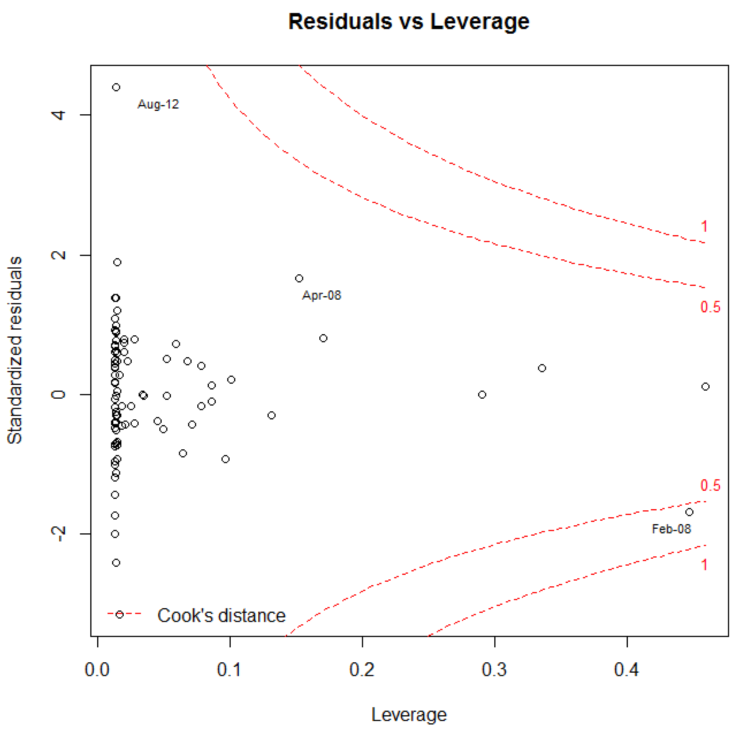
As seen in the figure above, the residuals are randomly distributed around the horizontal axis, as expected.

Figure 375: Broker Dealer loan rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels generally track closely with actual average 9-quarter levels for different 9-quarter forecast windows, with most of the estimated average values falling within 20% of actual average values. A few outliers exist due to noise in the data; when the starting month that is used corresponds to one of the spikes or dips in the historical data that the model does not pick up, all of the estimates for the 9-quarter window are offset by the magnitude of the spike or dip since the rates are estimated on first differences. Therefore, in these cases, estimated levels are consistently and overestimated or underestimated.

Figure 376: Influential points for Broker Dealer loan rates



The segment does not contain any highly influential points.

8.9.6. Model sensitivity

8.9.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 353: Sensitivity to changes to independent variables for Broker Dealer loan rates

Broker Dealer loan rates – model sensitivity				
Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable

Fed funds target rate	First difference – MoM, 1-month lag	%	0.35	0.200
Fed funds target rate	First difference – QoQ	%	0.29	0.68
Baa to Treasury spread	First difference – YoY	%	0.11	1.31
Intercept	None (level)	%	N/A	N/A

8.9.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

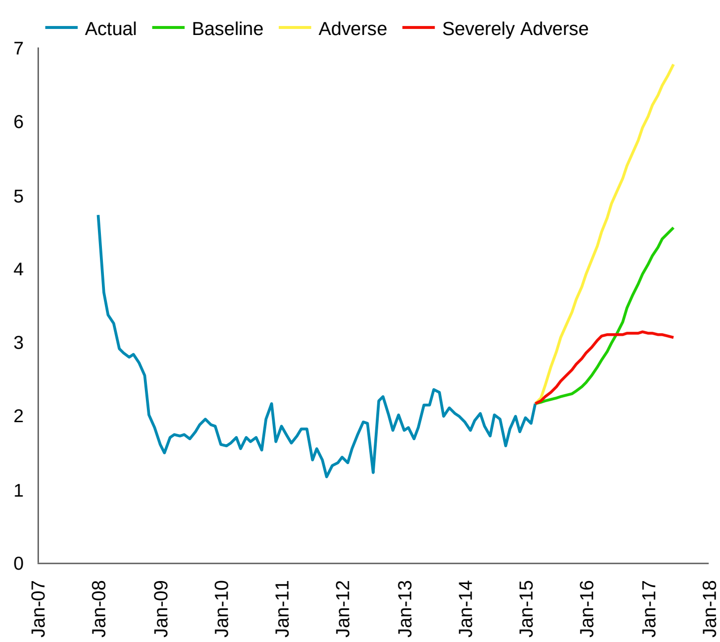
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.9.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 377: Broker Dealer loan rates model forecast (%)



The Working Group considered the forecast behavior for the selected Commercial loan model as generally reasonable. Management review should be applied to determine if the magnitudes of the forecast rate increases are within expectations.

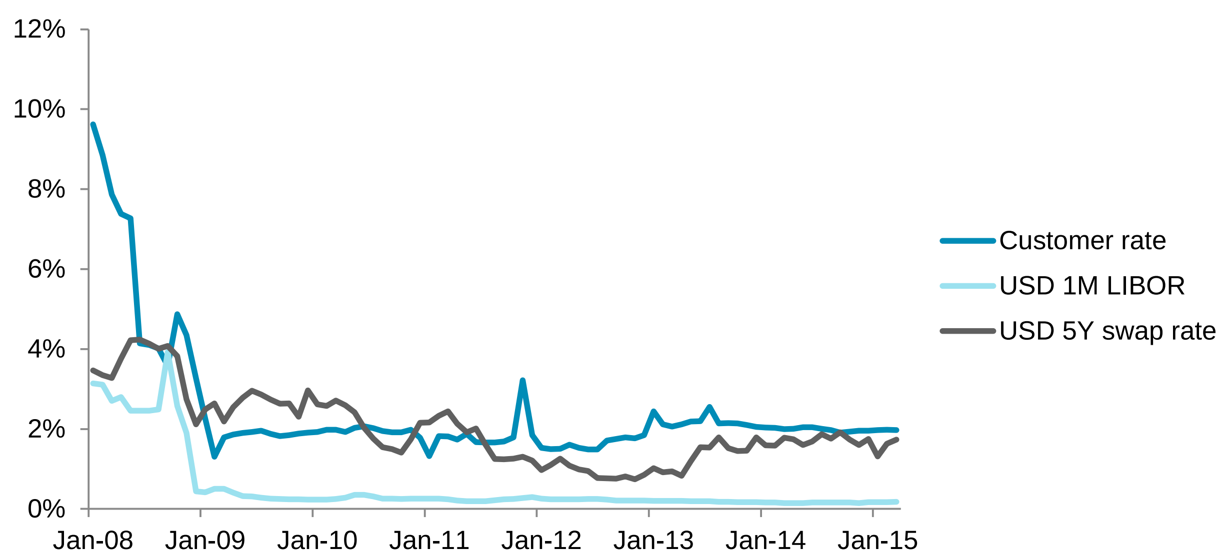
- **Severe recession (Severely Adverse) scenario:** The model predicts a rise in blended overall customer rates driven by widening credit spreads, peaking in the middle of the forecast window before leveling off. Some management review may be warranted to determine whether the impact of changing spreads is accurately reflected in the forecast behavior
- **Interest rate shock (Adverse) scenario**: The model predicts a rapid rise in blended overall customer rates. The levels surpass those observed in the period immediately before the 2008–2009 financial crisis, so management review may also be necessary under such a scenario
- **Baseline scenario**: The model predicts a gradual increase in blended overall customer rates in line with the expected baseline rise in interest rates

8.10. CRE loan rates

8.10.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with the reference rates. The historical CRE loan rate data has some noise, and but it follows the directional movement of the reference rates, particularly the USD 1-month LIBOR.

Figure 378: Historical rates for overall CRE loan portfolio



8.10.2. Model summary

A statistically sound model that is consistent with business intuition was found for the CRE loan rates segment. However, the model is unable to capture full magnitude of the large historical decline in the dependent variable time series from 2008 to 2009, which is partially due to the more bespoke nature of pricing for CRE loans. Management scrutiny is therefore highly recommended for this model's outputs.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary upon manual review
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 354: Coefficient estimates for the CRE loan rates model

CRE loan rates (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
USD 1-month LIBOR	First difference – MoM, 1-month lag	%	0.501	0.316
USD 1-month LIBOR	First difference – QoQ, 1-month lag	%	0.244	0.288
Intercept	None (level)	%	-0.023	N/A

The model uses two transformations of the USD 1-month LIBOR. Both variables have a positive coefficient, matching business intuition that the blended overall customer rate should be positively correlated with the reference rates. The Working Group confirmed the intuition of the variables and their signs. No better models were found that used variables other than reference rates, such as market volatility, yield spread, or credit spread variables.

8.10.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

8.10.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the loan rates using the same methodology as for the loan balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 355: Unit root tests and stationarity tests including a trend variable on balances

CRE loan rates (in %) – Unit root test with trend on balance series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-5.9	<0.01	Reject unit root
Phillips-Perron	1	-6.2	<0.01	Reject unit root
KPSS	5	0.59	0.02	Reject stationarity

Table 356: Unit root tests and stationarity tests including a constant on first differences

CRE loan rates (in %) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	0	-9.1	<0.01	Reject unit root
Phillips-Perron	1	-9.1	<0.01	Reject unit root
KPSS	1	0.69	0.01	Reject stationarity

Stationarity tests for CRE loan rates yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non-stationary. The monthly first difference series has similar results to the levels. Because it failed the KPSS test, the modeling team reviewed the data manually. It was assessed that because the loans data spanned less than a full rate segment the stationarity results may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable does not show stationary behavior for differences for the KPSS test, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables for levels, but stationary for first differences.[42] Thus, manual review in addition to a review of academic literature provided sufficient evidence of stationarity for the application of OLS on first differences.

Therefore, the modeling team uses first difference transformations for the loan rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

8.10.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The CRE loan rates data showed a small amount of noise, but to preserve the integrity of the data, no changes were made to the underlying data.

[42] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

8.10.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Commercial loan rates model are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 357: Statistical significance tests of model and variables for CRE loan rates

CRE loan rates (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Transformation	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	N/A	-	<1%	10%	Statistically significant
USD 1-month LIBOR	First difference – MoM, 1-month lag	0.501	<1%	10%	Statistically significant
USD 1-month LIBOR	First difference – QoQ, 1-month lag	0.244	<1%	10%	Statistically significant
Intercept	None (level)	-0.023	47%	10%	Statistically not significant

8.10.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

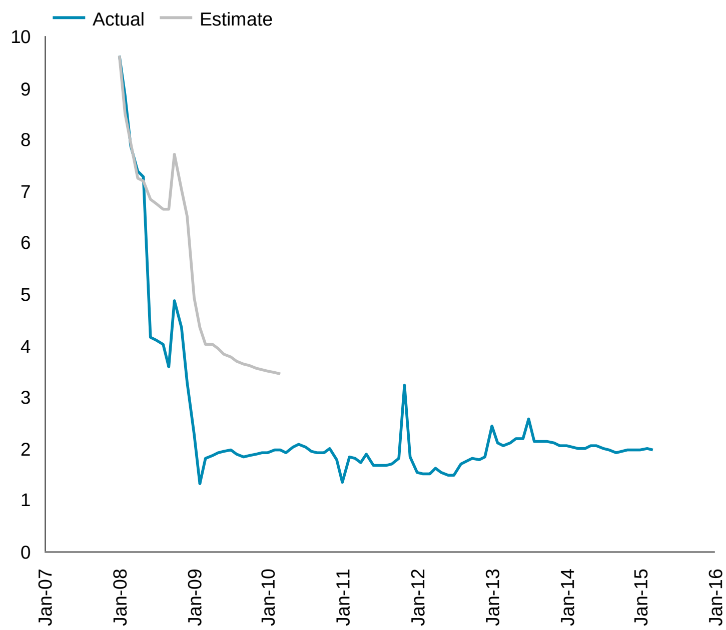
The results for the diagnostic tests reviewed are exhibited below.

Table 358: CRE loan rate model diagnostics

CRE loan rates – Model diagnostics

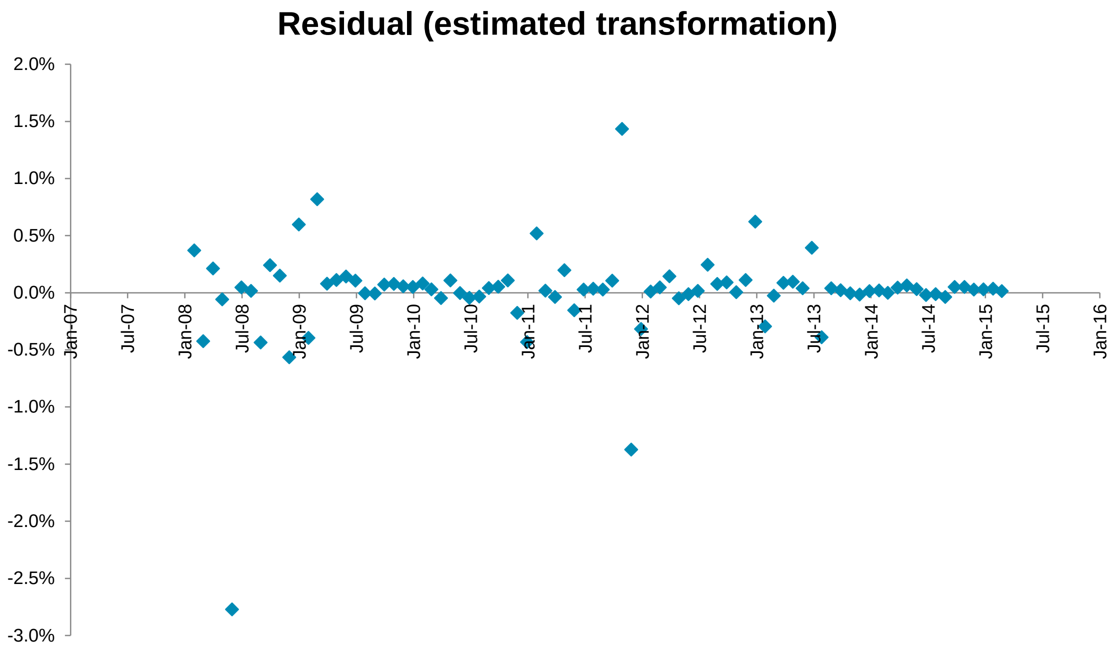
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	29%	-	-
	Adjusted R-squared	28%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	48%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	8%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.61	5	No multicollinearity
Linearity	RESET test	8%	10%	Linear specification inappropriate

Figure 379: CRE loan rate 9Q in-sample prediction (%)



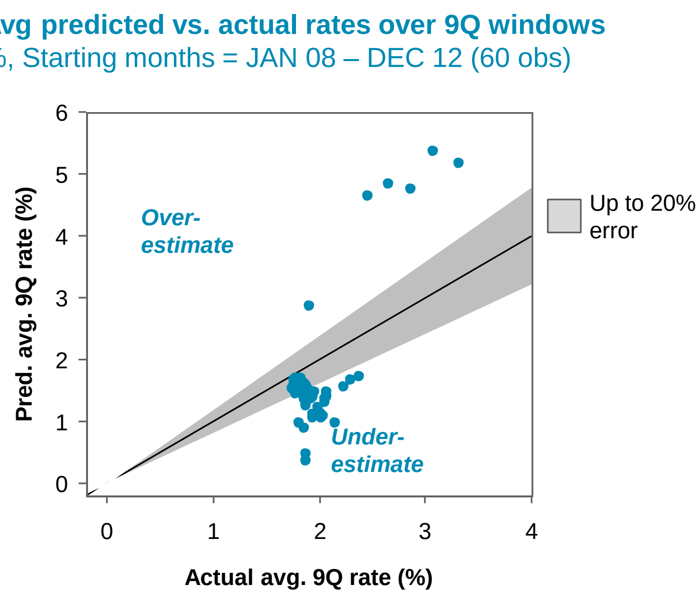
In the select 9Q in-sample prediction, the model captures most of the directional movements of the historical data. However, it does not capture the full magnitude of the decline in the blended overall customer rate from the beginning to the middle of 2008, which causes significant overestimation in the remaining months.

Figure 380: CRE loan rate residual plot (%)



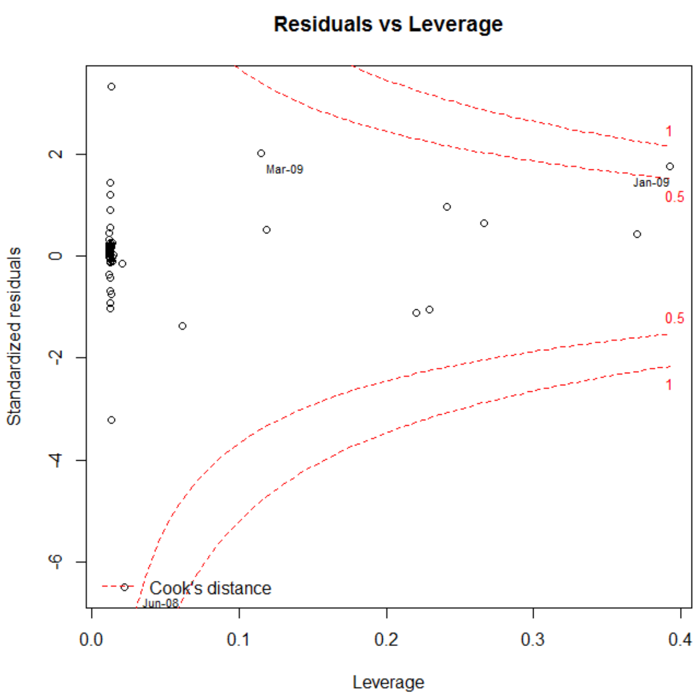
As seen in the figure above, most of the residuals are relatively small and randomly distributed around the horizontal axis. However, in the 2008–2009 and 2011–2013 periods, there are residuals that are larger in magnitude, due to the greater volatility during those periods that the model is unable to explain.

Figure 381: CRE loan rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels do not track very closely with actual average 9-quarter levels for different 9-quarter forecast windows. The small number of overestimated averages come from starting points such as in the in-sample back test shown in the figure above, where the model is unable to pick up large declines in the actual historical customer rates. The large number of underestimated averages is due to the large negative intercept being applied in many different forecast windows where the actual historical customer rates were relatively flat, leading to forecasts of rates that were consistently too low, especially towards the end of the forecast windows.

Figure 382: Influential points for CRE Rates



The segment does not contain any higly influential points.

8.10.6. Model sensitivity

8.10.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 359: Sensitivity to changes to independent variables for CRE loan rates

CRE loan rates – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable
USD 1-month LIBOR	First difference – MoM, 1-month lag	%	0.316	0.322

USD 1-month LIBOR	First difference – QoQ, 1-month lag	%	0.288	0.79
Intercept	None (level)	%	N/A	N/A

8.10.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

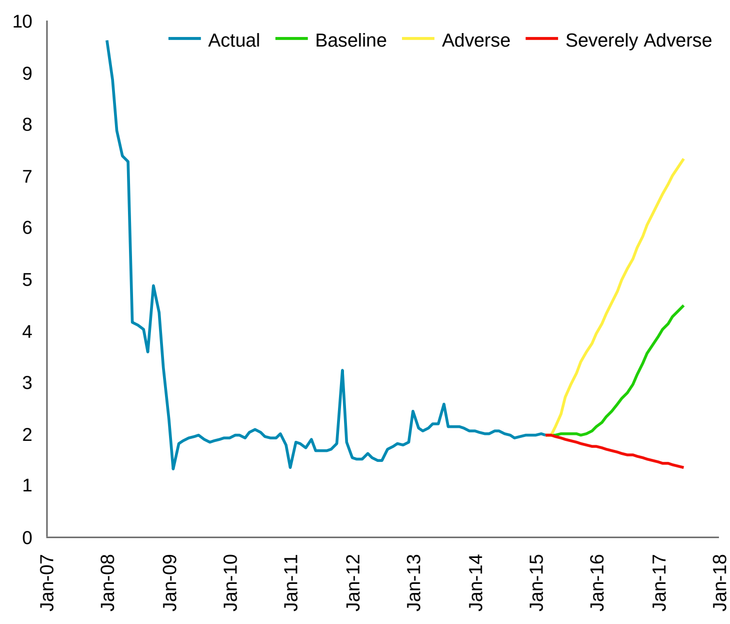
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

8.10.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 383: CRE loan rates model forecast (%)



The Working Group considered the forecast behavior for the selected Commercial loan model as requiring high scrutiny during management review, due to the weak historical fit of the model. Additionally, the intercept of the model has a strong impact on the forecasts, which may not align with management expectations.

- **Severe recession (Severely Adverse) scenario:** The model predicts a steady decline in blended overall customer rates, which is driven by the negative intercept in the model.
- **Interest rate shock (Adverse) scenario**: The model predicts a rapid rise in blended overall customer rates, to levels in line with those before the 2008–2009 financial crisis.Management review should consider whether these rates are understated as a result of the model's negative intercept
- **Baseline scenario**: The model predicts a gradual increase in blended overall customer rates. Management review should consider whether these rates are understated as a result of the model's negative intercept

8.11. Lease financing rates

8.11.1. Historical data

The lease portfolio consists primarily of financing for equipment. As of April 30, 2015, the size of this portfolio was $2.0 BN. The portfolio is currently in run-off, as no new leasing business is expected to occur in the future. As no new balances are expected, the contractual terms for all balances are known, including both balance evolution and rate earned. Given this, a qualitative framework is taken in which rate earned is based on the lease-specific terms. The graph below, based on data from MAQ, shows the Lease financing portfolio in a clear run-off trend.

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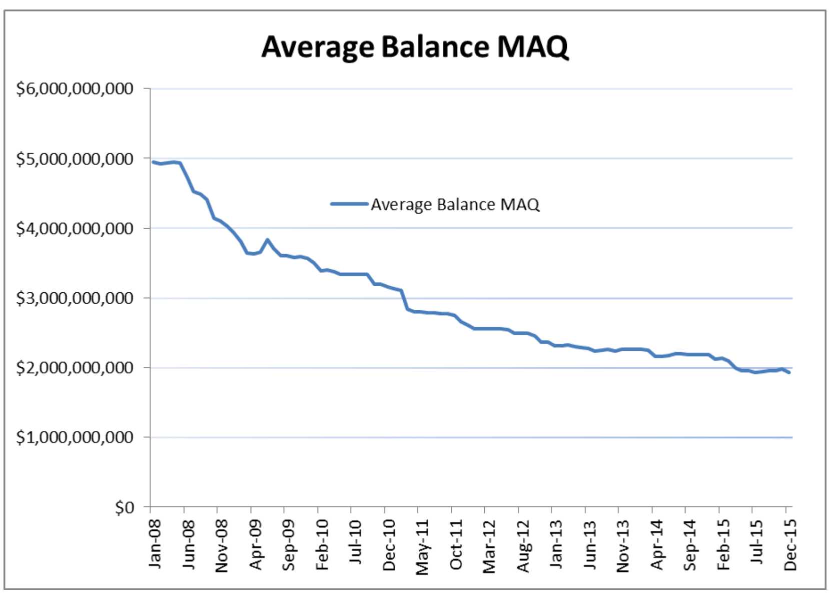
Figure 384: Historical Lease Financing Balances



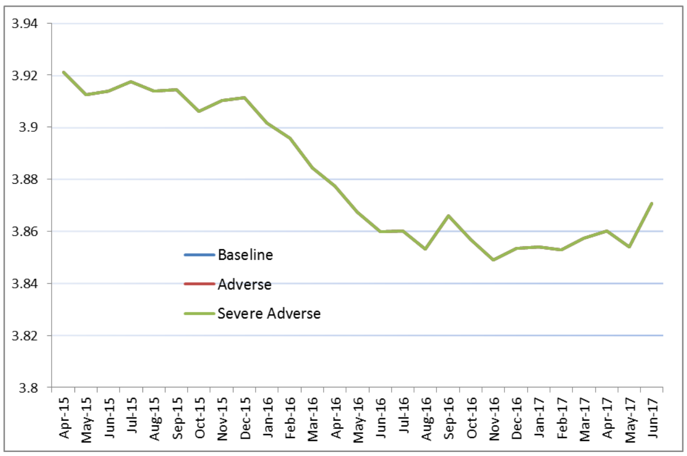
8.11.2. General data issues

Historical data was not used for the qualitative framework for this segment.

8.11.3. Summary of approach

The lease financing portfolio is currently in run-off, and going forward no new leasing business is expected to occur. Because there are no plans to grow this business, the characteristics of all potential balances – including rate earned and the contractual terms that dictate evolution of balances – are known at the start of the scenario, eliminating the need for a predictive model. Given this, a qualitative framework is taken in which rate earned is based on the lease-specific terms, per contractual schedule.

Figure 385: Dry-Run QRM Run Off for Lease Financing Rates

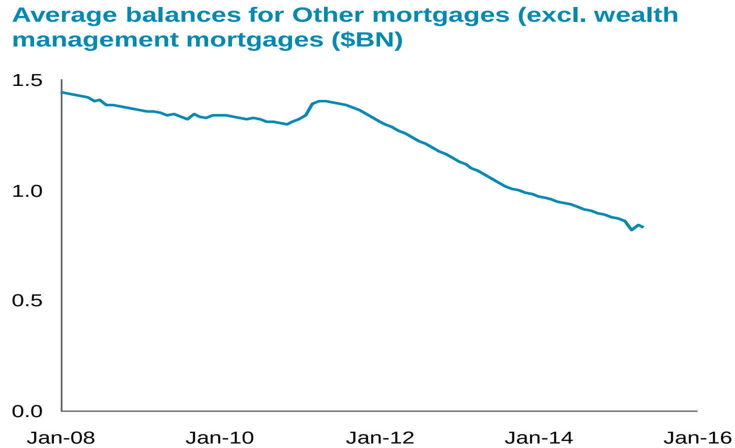


8.12. Other mortgage loan rates (excluding Wealth Management)

8.12.1. Historical data

The Other Mortgages Loans includes all mortgages outside of Wealth Management. It consists primarily of 15- and 30-year Fixed Rate Mortgages that were provided to employees and ex-employees of BNY Mellon, and Hybrid ARMs bought from Countrywide/Bank of America. The employee mortgage program was discontinued in 2011, and therefore the existing portfolio is in run-off – there are no plans to add additional balances to this segment. Further, there are no plans to purchase incremental whole loan balances. The historical balances in Figure 1 show a clear run-off trend in the Other Mortgage loans portfolio since 2011. As a result, all of the contractual terms for this portfolio, including both maturities and rates, are already known. As such, the behavior for balances and rates do not require a new and separate statistical model: they can be accommodated through the existing analytical infrastructure in QRM (balance evolution, subject to prepayments, and rate paid including any logic for floating rate loans).

Figure 386: Historical data for Other Mortgage Loans



8.12.2. General data issues

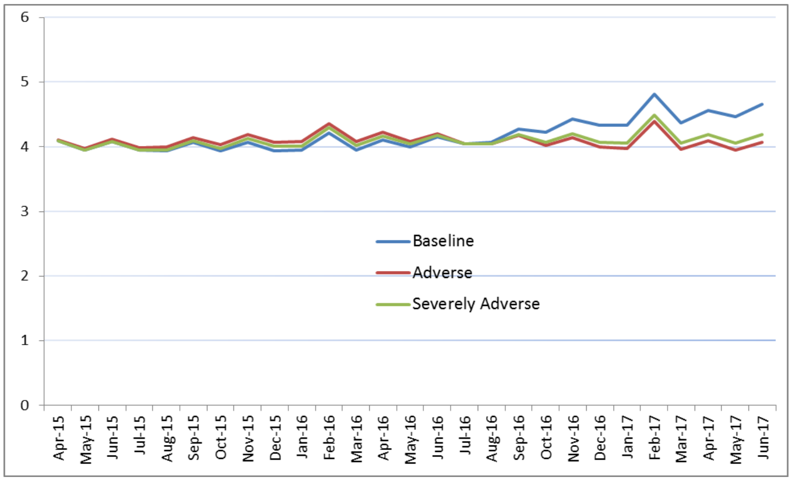
Historical data was not used for the qualitative framework for this segment.

8.12.3. Summary of approach

Both of the qualitative frameworkes for the Other Mortgage Loans' balance and rate are based on run-off schedules through QRM.

The other mortgage loans portfolio is expected to run off over time based on the amortization schedule, subject to prepayment behavior linked to the interest rate environment. The prepayments are determined by a vendor model from Andrew Davidson & Co. (AD&Co) that is embedded in QRM and already validated for estimating prepayments under a range of interest rate scenarios. For the other mortgage loans' rate projection, since the business anticipates no new mortgage origination in this segment, rate forecasts at any given time point can be directly calculated based on the rates of individual other mortgage loan that still remain in the portfolio. Given that the contractual terms of individual other mortgage loan are available in QRM, the rate for the Other Mortgage Loans will be forecast as an average rate of the remaining portfolio using the maturity dates and rates of the individual exposures.

Figure 387: Dry-Run results for the Other Mortgage Loans Rates (%)

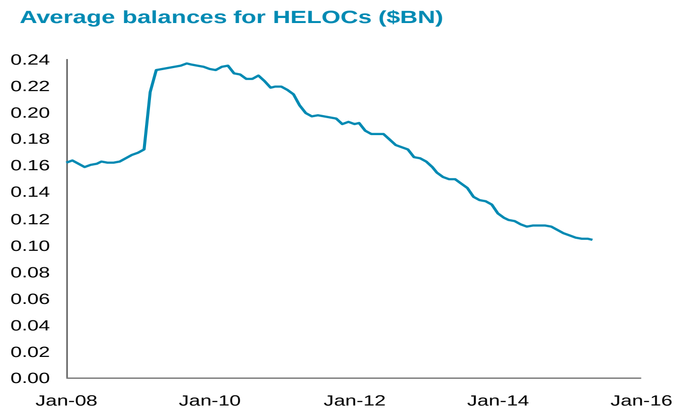


8.13. HELOC rates

8.13.1. Historical data

Home Equity Lines of Credit (HELOCs) are revolving loans and represent a relatively small segment of BNY Mellon's total loans, with a spot balance of $95 million as of December 2015, with approximately ~$93.5 million floating & ~$1.5 million fixed. The $95 million HELOC portfolio as of Dec 2015 consists of Legacy Mellon and Legacy BNY HELOC's as well as the Private Wealth HELOC portfolio. The legacy accounts are a much older portfolio and are in run-off. However historically we have seen smaller loans originations offered to Wealth Management clients on a request basis. Balances for HELOCs from January 2008 until March 2015 can be seen in Figure 1. The overall portfolio has been in runoff since 2010, however according to the Line of Business there may be occasional HELOCs issued to Wealth Management clients on a request basis in the future. While management does not expect the Private Wealth HELOC portfolio to grow, given the request-based nature of the portfolio they cannot be certain as to how many HELOCs will be issued. Further, as the figure below shows, this segment represents a relatively small set of balances (about $95 million).

Figure 388: Historical data for HELOCs Balances ($BN)



8.13.2. General data issues

Historical data was not used for the qualitative framework for this segment.

8.13.3. Summary of approach

The decision to adopt qualitative frameworkes for the HELOCs' balance and rate was discussed in several meetings with the Working Group. The HELOCs was also discussed with the business to determine potential macroeconomic drivers. As the historical data shows, the Legacy Mellon and Legacy BNY HELOC portfolios are in run off mode. However for Private Wealth HELOC portfolio we have seen smaller loans originations offered to Wealth Management clients on a request basis. A qualitative framework was therefore determined to be more appropriate for these revolving loans as opposed to a macroeconomic statistical model. Further, as Figure 1 above shows, this segment represents a small set of balances (~$95MM).

For HELOC rates, the qualitative framework is based on the assumptions from the line of business. The forecast will add a spread (provided by line of business assumptions for each forecasted scenario) to the 1-month LIBOR rate across the forecasting period. The line of business forecasts for the spreads to be used based on the CCAR 2016 scenarios are:

- Baseline: 2.5% (consistent with spread in the currently held HELOCs)
- Adverse: 2.7%
- Severely Adverse: 2.5%
- BHC: 1.4%

8.14. Iron Hound (IH) loan rates

8.14.1. Historical data

Because Iron Hound (IH) loans are a very new business segment, limited historical data is available. The historical rates were therefore not relevant for the qualitative framework.

General data issues

The reason for the qualitative framework is the lack of historical data that is available for BNY Mellon's Iron Hound portfolio. Because Iron Hound loans are a new business that was initiated in 2014 and the first loans weren't on-boarded until December 2014, only 4 months of data was available at the time of model development. As a consequence, it was not possible to develop statistical models for Iron Hound balances and rates.

Historical data was not used for the qualitative framework for this segment.

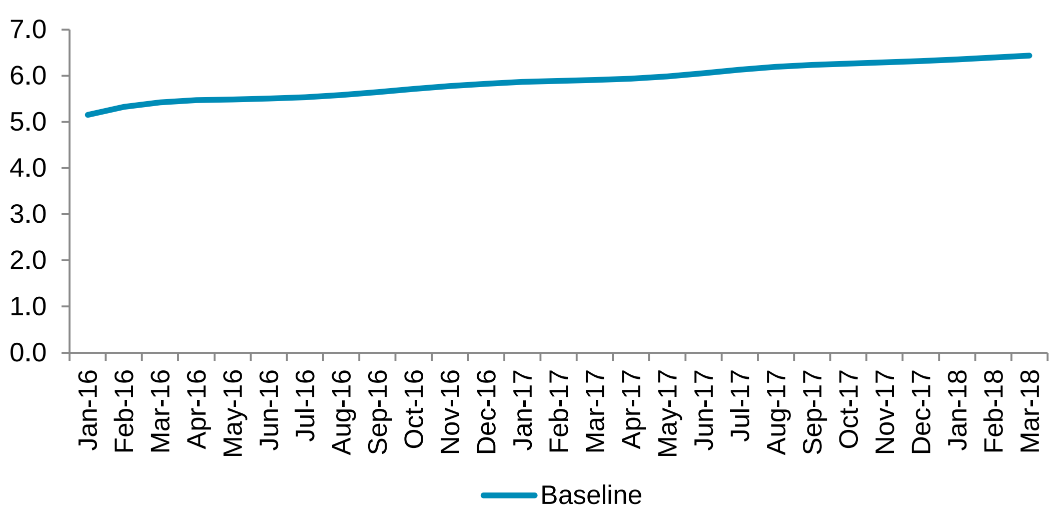
8.14.2. Summary of approach

Given that Iron Hound represents a new business segment for BNY Mellon, the forecast follows a qualitative method based on business expectation and intuition.

For Iron Hound CRE rates on new volumes, the qualitative framework is based on the 10-year LIBOR swap rate plus a spread in order to be in line with market pricing practices. Baseline scenario spread (280 bp) is aligned with the Company's Operating Plan. Stress scenarios pricing assumptions are not required since portfolio is held static.

Associated hedges are modelled independently in QRM and not in scope for this qualitative framework.

Figure 389: Iron Hound Forecast CRE Rates on New Volumes (%)



8.14.3. Approach limitations

As with all new businesses, the forecast is based on the best currently available assumptions. Business plans and strategy for this segment may be updated. As the Iron Hound business continues its growth phase, the assumptions will be closely monitored and revised if necessary to match new business plans and strategy.

8.15. Reverse mortgage loan rates

8.15.1. Historical data

Because the reverse mortgages business is a new business for BNY Mellon that was initiated in May 2015, the historical rates were not relevant for the qualitative framework.

The reverse mortgage loan segment is a growth segment. A reverse mortgage is a type of home loan for older homeowners that allow access to the home equity that has built up in homes. BNY Mellon entered the reverse mortgage business in 2015, in which the bank purchases, securitizes, and services reverse mortgages. The business also advises brokers, financial advisors, and asset managers on how to integrate reverse mortgages into retirement plans. These balances have grown to about $17.4 million on average by December 2015.

The business is currently focused on FHA-insured products, primarily floating Home Equity Conversion Mortgages (HECMs) in which borrowers leverage home equity for income.

8.15.2. General data issues

Historical data was not used for the qualitative framework for this segment.

8.15.3. Summary of approach

The Reverse Mortgage rates approach will be executed differently depending on the scenario. In the Baseline scenario, the model will act as prescribed by the Company Operating Plan (further detail below). In all stress scenarios, there would be no additional issuances. Both the baseline execution and the halt of activity in stress scenarios, stem from management discretion.

<u>Baseline – execution per Operating Plan</u>

The Reverse Mortgage business is a securitization pipeline and in 'business-as-usual' (baseline) scenarios is largely dependent on management decisions (balance sheet/funding availability). For Reverse Mortgage rates on new volumes, the qualitative framework is based on the 12-month LIBOR plus a spread in order to be in line with market pricing practices. Baseline scenario spread (270bp) is aligned with Company's Operating Plan.

<u>Stress scenarios – business would cease</u>

Inherent to being driven by management decision, the business can completely start or stop activity on its discretion. For reverse mortgages, the impact would be as follows: In stress scenarios there would be a seizure of securitization markets--the bank would cease issuance of reverse mortgages; loan balances as of the forecasting date (December 31, 2015) are assumed to be illiquid. The seizure would persist throughout the scenario--BNY Mellon holds the illiquid loan balances on balance sheet over the entire nine quarter forecast horizon, as a result, the spot balance as of December 31, 2015 is held constant. Therefore, stress scenarios rates for reverse mortgages are not required since portfolio is held static and the contractual rates of the mortgages on the book as of December 31, 2015, will be used.

8.15.4. Approach limitations

As with all new businesses, the forecast is based on the best currently available assumptions, business plans and strategiese for this segment may be updated. As the Reverse Mortgages business continues its growth phase, the assumptions will be closely monitored and revised if necessary to match new business plans and strategy.

8.16. Model limitations

The loan rates models have several limitations that potentially constrain their predictive power. First, the choice of methodology as described in Section 8.1 means that the forecasted quantities are blended rates across entire product segments. As noted earlier, for some product segments, there may be a wide range of rates being used, due to differences in loan type (e.g. fixed vs. floating rate) and rate/spread environment at the time of origination. The models produce stronger blended rate forecasts for product segments that are more homogeneous, for example those where the loan durations are short (e.g. margin loans, broker dealer loans). An exception is the Overdrafts segment; despite the overnight nature of overdrafts, pricing varies significantly by client, which produces significant volatility in observed historical blended rates.

An alternative to forecasting blended rates is to forecast balances and rates for new loan originations, and forecasting the existing loan book separately based on their actual contractual rates. This approach was not used given data limitations on historical new loan originations and their rates. However, for certain individual product segments, the data to support this approach does exist, e.g. for Wealth Management mortgages. This approach can therefore be used to construct alternative challenger models for these segments, or as further enhancement to the existing models.

Another limitation is that the historical data used as development data for the regression models starts at the beginning of 2008, which means that it does not span a full rate cycle and is missing a historical period of rising interest rates. The models therefore implicitly treat rising and falling interest rate environments in the same way, rather using a more complex methodology to determine behavior separately under rising and falling interest rate environments as is done for deposit rates. However, while sensitivity of deposit rates was deemed by the Working Group to depend on rising versus falling interest rate environments, this effect was hypothesized to be weaker or nonexistent for loan rates. Further taking lack of reliable data from earlier historical periods into consideration, the determined approach for modeling loan rates was to use a single regression on the available historical data.

9. Investment portfolio

9.1. Investment Portfolio overview

As a custodian bank, BNY Mellon's balance sheet is liability driven; for many of its core businesses, including Asset Servicing and Corporate Trust, the bank generates deposits in connection with the services it provides to its clients. Consequently, the level of assets on the bank's balance sheet is principally a function of the amount of deposit liabilities that BNY Mellon generates. As part of its overall balance sheet strategy, BNY Mellon monetizes these deposits through several asset-side activities, including its loan portfolio as well as its Investment Portfolio.

Management of BNY Mellon's Investment Portfolio is mainly constrained by liability-side funding: deposit expansion or contraction impacts the extent to which the Investment Portfolio can be grown or shrunk to a large degree. As part of BNY Mellon's balance sheet management approach, the bank invests its deposits in assets that conform to the characteristics of its liabilities. In addition, key risk considerations constraining management investment decisions include:

- **Other Comprehensive Income (OCI)**: the majority of BNY Mellon's Investment Portfolio is composed of Available for Sale (AFS) securities. As a result, changes in the fair value of the bank's holdings (a net of credit-related deterioration) are recorded in the firm's OCI measure. Under Basel III regulation, negative OCI is deducted from Common Equity Tier 1[43]. Changes in cash flows of securities, in the interest rate environment, and in credit spreads can all adversely impact the fair value of BNY Mellon's AFS holdings in the Investment Portfolio; this in turn directly impacts the bank's CET1 ratio
- **Liquidity:** along with internal liquidity limits, BNY Mellon is subject to the Basel III Liquidity Coverage Ratio (LCR) rule. Under this, the firm needs to have enough high quality liquid assets to cover the outflow assumptions of the LCR rule. BNY Mellon manages the composition of its Investment Portfolio to ensure the firm meets LCR requirements at all times. This can be accomplished by ensuring that any LCR-negative action (e.g. increase in transient deposits) is balanced by an LCR-positive action (e.g. increase in the bank's central bank deposits) such that the net LCR impact is neutral or positive
- **Interest Rate Risk:** BYN Mellon closely manages the duration and repricing gap of its liabilities and assets and ensures that interest rate sensitivity (both NII and EVE sensitivity) is within regulatory and internal limits. BNY Mellon manages the repricing and duration characteristics of its Investment Portfolio to comply with these requirements

In addition to these key risk considerations, there are two credit risk considerations that impact the management of the Investment Portfolio: its contribution to Risk-Weighted Assets and to Other Than Temporary Income (OTTI). Nevertheless, given its direct impact on the CET1 ratio, OCI is the most critical of the management considerations listed above and accordingly weighs most heavily in investment decisions.

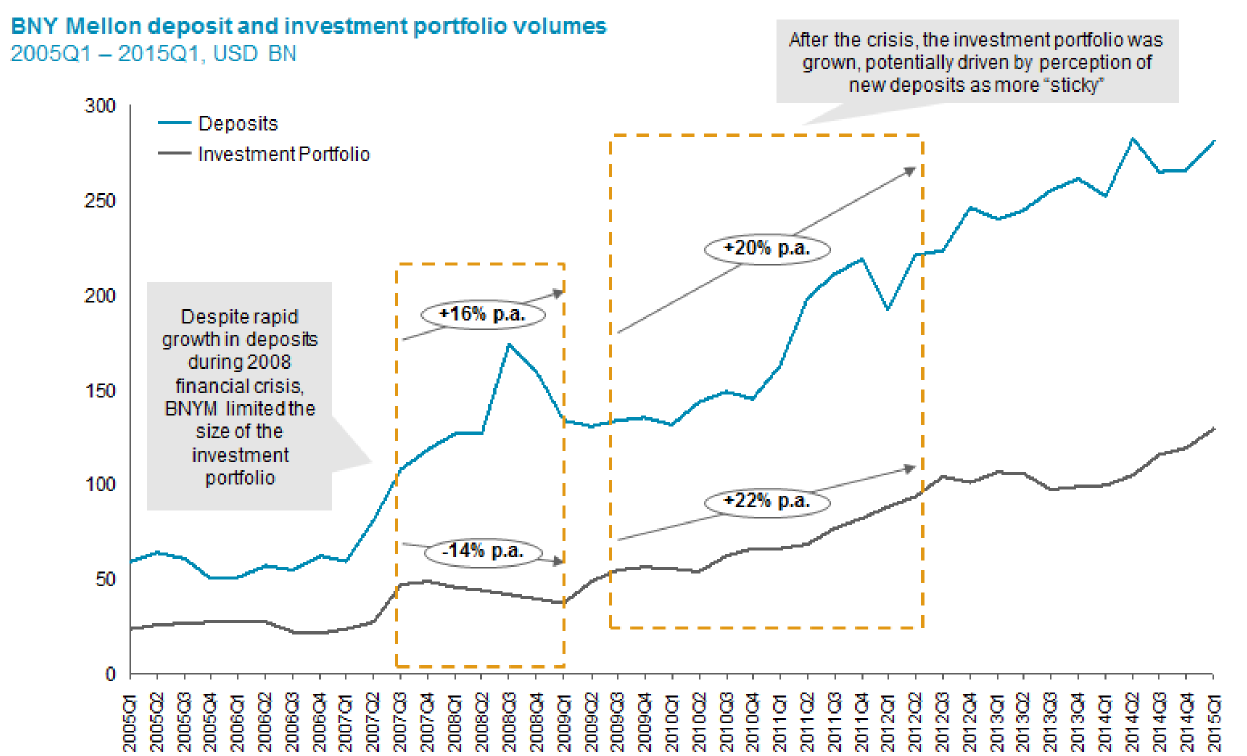
[43] Deduction of OCI from Common Equity Tier 1 is subject to a phase-in calendar.

BNY Mellon considers compliance with both regulatory and internal limits when managing the Investment Portfolio, as well as assessment of the portfolio against sensitivity tests (applying rate and spread shocks to the portfolio and testing the stressed portfolio against regulatory and internal limits). Every year, as part of the budgeting process, the bank develops a purchase plan for the Investment Portfolio. This purchase plan is developed in consideration of the expected baseline macroeconomic conditions, interest rates, expected timing and dollar value of maturing exposures within the portfolio, the market outlook, and the bank's overall strategy.

9.1.1. Portfolio size

BNY Mellon's Investment Portfolio increased 18% per annum from 2005 to May 2015, largely in line with the inflow of deposits, which increased 17% per annum over the same period. In some cases, notably the financial crisis of 2008, the portfolio was actively managed down by placing incoming deposits at the central bank rather than the Investment Portfolio due to expectations that these deposits would leave under more stable macroeconomic conditions. From May 2015 to December 2015 the portfolio, across all currencies and asset types, also shrank from $127.3bn to $111.7bn, as it was managed down to help compliance with regulatory ratios (in May, 2015, the Investment Portfolio accounted for approximately 32% of all BNY Mellon assets). See Figure 5 for historical deposit and Investment Portfolio volumes from 2005 to the first quarter of 2015.

Figure 390: Deposit and Investment Portfolio volumes

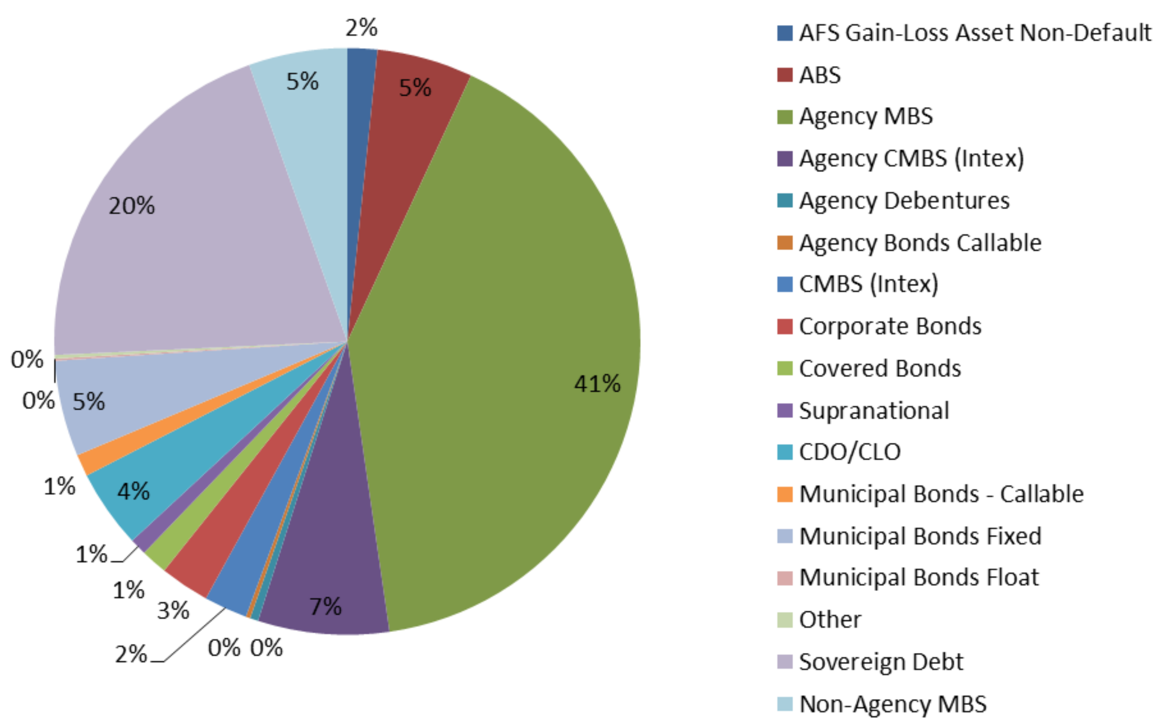


9.1.2. Portfolio composition

BNY Mellon's Investment Portfolio is mainly composed of high-quality liquid assets denominated in USD, EUR and GBP and primarily contains Treasuries, sovereign debt and Agency MBS. The portfolio also has investments in CMBS, ABS, municipal bonds, non-agency MBS, international non-agency MBS, and corporate bonds. For investment management purposes, the portfolio is often reviewed and analyzed in segments by investment manager, currency, security type, and Held to Maturity (HTM) versus Available for Sale (AFS) assets. Individual investment decisions are made based on a number of complex and idiosyncratic considerations, including deposit volume and currency, LCR position, and forward-looking views on interest rates, among others.

Of the $111.7 BN dollar portfolio in December 2015, roughly 83%, or $92.7 BN, were US dollar assets, with Available for Sale securities in all currencies accounting for about 62% of the total portfolio, and the USD AFS component accounting for about 59% of total USD assets. Figure 6 shows the distribution of assets within the USD AFS component of the portfolio (total size of $54.9 BN).

Figure 391: Distribution of USD Available for Sale (AFS) securities among asset classes



9.1.3. Business-as-usual size and composition determinants

Under business-as-usual activity, the Investment Portfolio size is rolled forward making adjustments according to internal purchase and reinvestment plans as determined by management. Investment decisions are highly idiosyncratic and reflect a number of considerations and constraints beyond the macroeconomic environment.

9.2. Determination of forecast approach

The modeling team assessed whether a statistical approach could be employed to forecast the Investment Portfolio following the criteria presented in Section 3.1. Although historical time series data for the portfolio is available, the Working Group determined that the segment did not meet the criteria of having an economic relationship – that is, even if a statistical relationship between historical balances and macroeconomic variables were found, it could not be expected to persist into the future. The reason is that the portfolio strongly depends on internal managerial decisions. Portfolio size is determined by the Corporate Treasury department based on a number of factors including the department's view of whether deposits are expected to remain at the bank, its view on interest rates and attractiveness of investment opportunities, the bank's loan origination capabilities, and other considerations. These designed investment strategies are then executed by internal and external portfolio managers. Due to its highly management-driven size and composition, as well as the fact that it is often used to balance on-balance sheet positions, a qualitative framework was considered to be more appropriate for the Investment Portfolio.

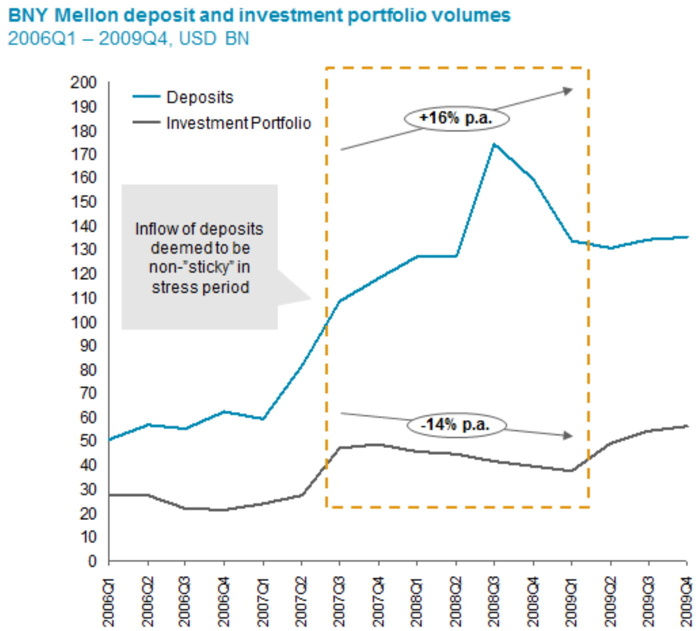
The decision to adopt a qualitative framework was discussed in several meetings with the Working Group, the Steering Committee, BNY Mellon's Corporate Treasury team and Market Risk groups. The consensus among meetings was that, due to its highly idiosyncratic nature, statistical models would not accurately forecast investment decisions.

The idiosyncratic considerations that drive investment decisions include:

- Changing regulatory guidelines on risk-based capital, available capital, leverage, and liquidity rules
- Interest rate environments and according adjustments to portfolio composition
- Strategic decisions based on the risk-return profile of various investment options

Figure 392 shows a historical example of an idiosyncratic investment decision based on management's perception of deposit activity during a stress period.

Figure 392: Deposit and Investment Portfolio volumes during the financial crisis



BNY Mellon experienced a rapid inflow of deposits during the financial crisis, representing 16% per annum growth from 2007Q3 to 2009Q1. Incoming deposits were viewed to be excess and were expected to leave after the macroeconomic stress period; as a result, management decided to reduce the size of the Investment Portfolio. No data is available to measure the shift in management's perception of the characteristics of the deposits, nor is data available of the characteristics of the deposits during that time period as they would be assessed under BNY Mellon's deposit characterization approach in place today. The portfolio decreased 14% per annum over the same period, with the ratio of portfolio size to deposit balances declining to approximately 23% in 2008Q3 despite pre-crisis levels above 40%. The fact that the ratio between the Investment Portfolio size and deposit balances changed significantly during this period is illustrative of the idiosyncratic management decision-making that drives portfolio size and composition.

9.3. Forecasting methodology

9.3.1. Development of approach

When developing a qualitative forecast approach for the Investment Portfolio, the modeling team considered the business-as-usual constraints impacting the management of the Investment Portfolio. The team assessed how funding (deposit dynamics) and risk considerations (impact on OCI, liquidity, rate) would apply under stress scenarios and what their impact would be on portfolio size and composition.

As the size of the total balance sheet shifts under stress, funding remains a central driver of portfolio management. Among risk considerations, the direct impact of portfolio's market value changes on Leverage Ratio via OCI was identified as a primary driver. Deposit dynamics, specifically deposit volumes, and portfolio's impact on OCI are therefore the main factors to consider for determining target portfolio size and composition and making investment decisions in a stress scenario.

With these primary constraints identified, the modeling team developed a framework for projecting changes to the Investment Portfolio in stress scenarios as deviations from the baseline plan. This involved analyzing the behavior and effects of deposit dynamics and OCI on asset purchases and sales under the stress scenarios. In order to determine when in a stress period action would be taken to adjust the Investment Portfolio size and composition, we assessed how deposit dynamics, including the volume and characteristics of incoming or outgoing deposits, and relevant OCI at risk metrics, which serve as warning indicators for a weak capital position, affect investment decisions. For deposits, the relevant limits which prompt adjustment to the Investment Portfolio are based on central bank balances and funds that can be mobilized from Reverse Repos, Placements and the Securities Financing Portfolio, as these would be balances used to fund liquidity in a deposit runoff scenario before any sales of securities from the Investment Portfolio would be considered; for OCI, the limits are based on capital ratios.

The ingoing assumption for the Investment Portfolio forecast is that, unless pre-set thresholds are exceeded or defined management limits related to the portfolio are breached, the portfolio size and composition will be determined by the management-defined purchase plan. Exceeding pre-set limits or breaching thresholds, however, would lead to adjustments to the purchase plan, for example halting reinvestment of maturing securities or under extreme circumstances, even the sale of securities. This conceptual approach follows BNY Mellon internal policies that are already in place and also policies that are being implemented for business-as-usual operation containing limits for both central bank balances and OCI at risk metrics.

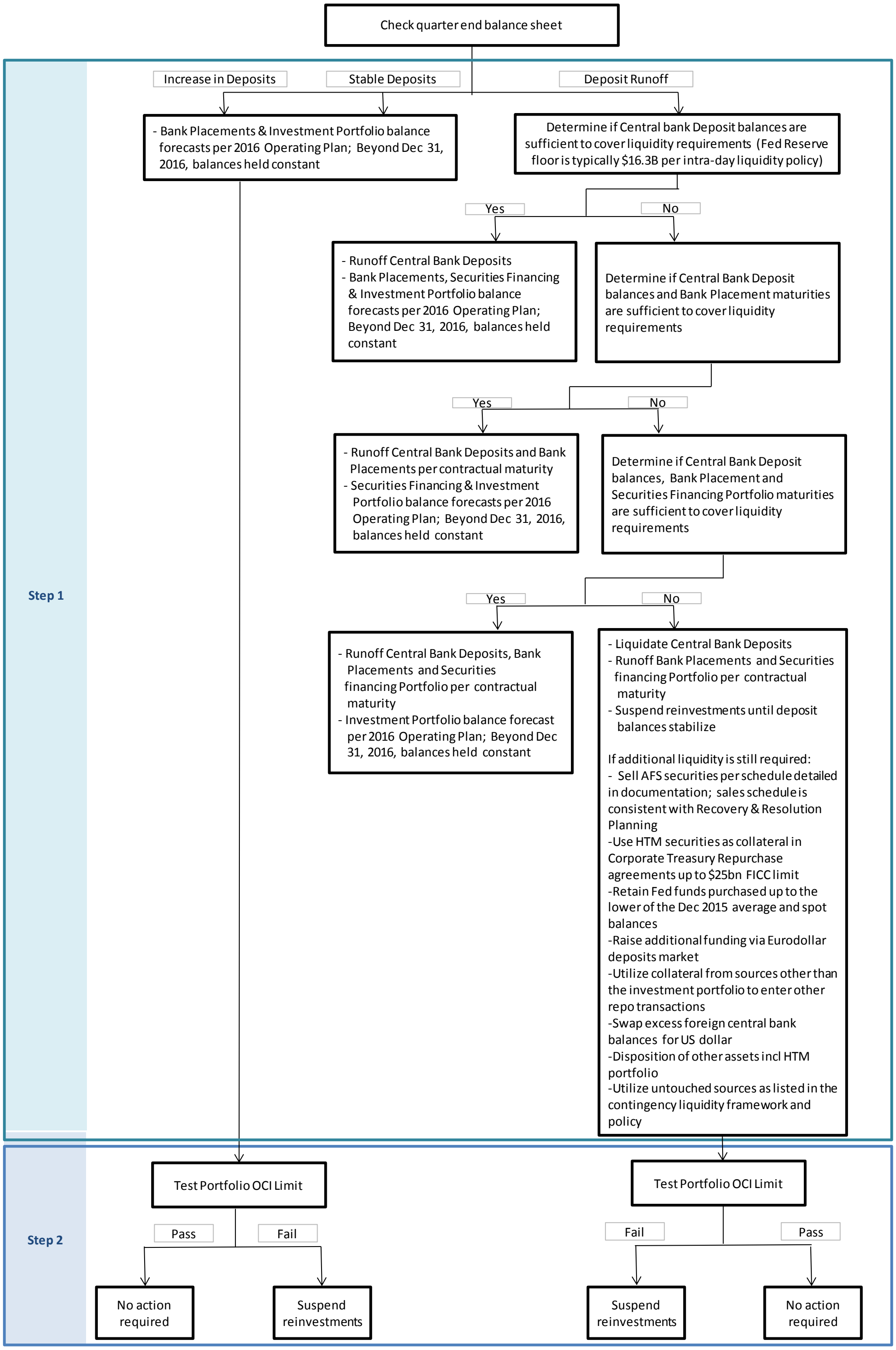
9.3.2. Overall forecast approach

The Investment Portfolio will be forecast using a two-step evaluation process consisting first of assessing deposit dynamics and second of assessing OCI at risk metrics. In both steps, limits will be checked for breaches which will help inform the action to be taken:

- **Summary of Step 1**: The forecast will follow the management plan for 2016, after which balances will be held constant. However if under a stress scenario, sufficient deposit runoff has taken place by quarter end such that a central bank balances have been run off down to a predetermined limit, and other available funds have been used, BNY Mellon will sell securities according to a pre-determined sales plan, described in further detail below.
- **Summary of Step 2**: OCI at risk metrics will be assessed. Pre-specified rate and spread shocks will be applied to the portfolio once deposit dynamics have been assessed. The resulting leverage and CET1 ratios will then be checked against their limits. Under certain stress scenarios, more than one shock may result in a limit breach. If possible, action should be taken such that all limit breaches across shock scenarios are rectified.

The high-level process for forecasting Investment Portfolio size is mapped below based on these two steps. A more detailed description of each step is provided below.

Figure 393: Process applied to forecast Investment Portfolio



9.3.2.1. Step 1 Detailed Overview: Assess deposit volume

In different macroeconomic stress environments, changing rates and spreads may lead to either deposit inflow or runoff. Logic has been developed to determine how exactly this deposit activity affects the size and composition of the Investment Portfolio.

<u>Deposit Inflow</u>

In the course of normal business activity, if deposits have increased, BNY Mellon management will determine if the incoming balances were deposited during a period of macroeconomic stress. In past such scenarios (which could be the result of a “flight to safety” or decreased rates, for example), management has assumed that the inflow of deposits will be withdrawn from the bank after the stress has ended and has not increased the size of the balance sheet; if management decides that the macro-economy is not under stress, management has assumed that deposit inflow is a part of normal business growth and can be used to fund the Investment Portfolio purchase plan. As such a determination would not be possible in the CCAR context without foresight of the scenario, in the case of increasing deposit balances the modeling team assumes that the bank will follow its operating plan with respect to the size and composition of the Investment Portfolio. Such an assumption is transparent, repeatable, and conservative in that it does not assume that the bank would monetize its deposits via higher-yielding investments and as such will result in lower net interest income than if the Investment Portfolio were to grow in size (magnitude of the difference in NII depends on the spread between the average yield on the Investment Portfolio and the rate paid on Central Bank deposits).

<u>Deposit runoff</u>

Deposit runoff can occur for a variety of reasons. An outflow of deposits associated with a higher interest rate environment reflects an outflow of funds that were deposited at BNY Mellon for lack of more attractive alternative investment options as opposed to operational reasons. Deterioration of BNY Mellon’s credit quality or reputation could also result in an outflow of excess deposits; in this scenario, outflows might also reduce operational deposits if BNY Mellon loses clients.

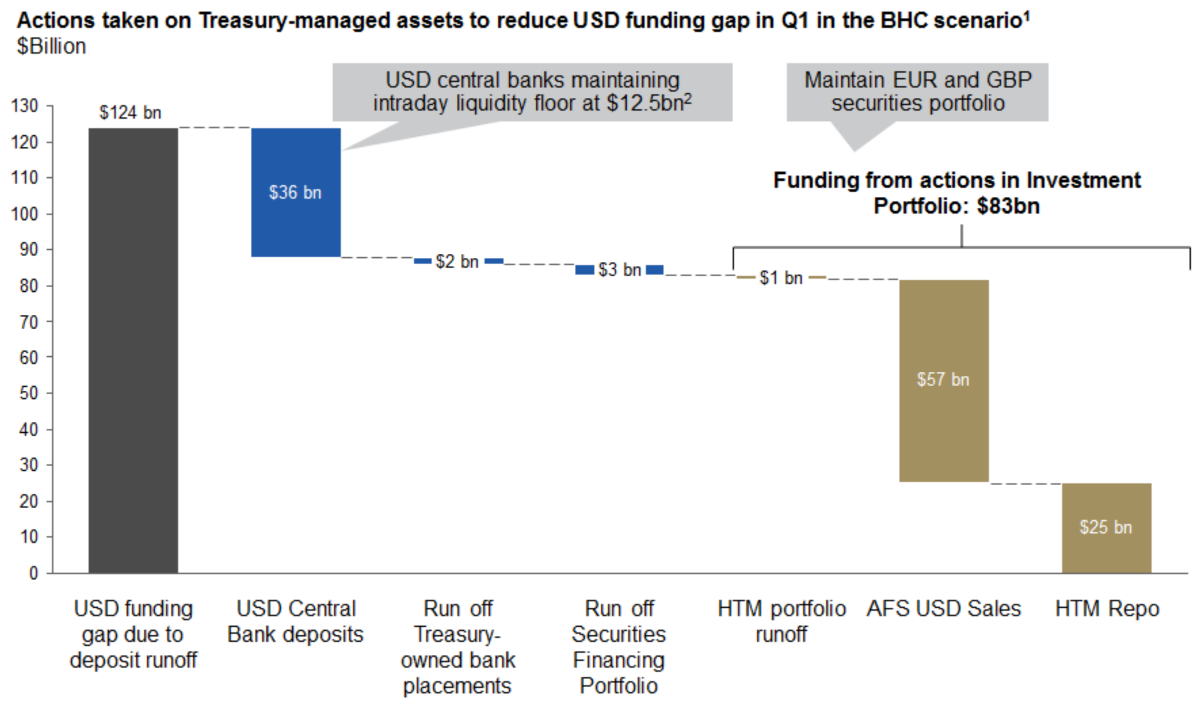
If deposits have decreased, corresponding action on the asset side of the balance sheet will follow a pre-determined order. To the extent that decreases in deposits can be managed by reducing central bank balances, this approach assumes that the bank will follow its operating plan with respect to the size of the investment portfolio (unless OCI limits are breached). If the entire run-off cannot be managed by reducing central bank balances, the following pre-determined response order will be followed until deposit run-off is accounted for:

1. Central bank balances will be utilized and run down to a limit determined by BNY Mellon’s Intra-Day Liquidity Policy. In the BHC scenario which applies BNY Mellon’s Liquidity Stress Test assumptions in the first quarter, the limit for Central Bank balances at the Federal Reserve, which is typically $16.3bn, drops to an average balance of ~$12.5BN in the first quarter, net of requirements for Overdrafts and FMU & Cash Collateral Requirements (as determined by the Liquidity Stress Test assumptions for the Intra-Day Liquidity Policy).
2. Bank placements are run off as terms allow.
3. The Securities Financing Portfolio is run off as the contractual terms allow.
4. Reinvestment of maturing securities in the investment portfolio are halted

If additional liquidity is still required:

5. AFS securities are sold according to the predefined sales plan discussed below
6. HTM securities are used as collateral in Corporate Treasury Repurchase agreements up to $25 Bn FICC limit
7. Fed Funds Purchased are raised up to limit equal to lowest of either spot or average balance in final month of historical data
8. Additional funding in Corporate Treasury Deposits via Eurodollar market is raised, limited by lowest of either spot or average balance in final month of historical data
9. Collateral from sources other than the investment portfolio to enter other repo transactions is utilized
10. Excess foreign central bank balances are swapped for US dollar
11. Disposition of other assets including the HTM portfolio
12. Funding per contingency liquidity framework and policy is sought

Figure 394: Investment Portfolio Balance Sheet Forecast Results



1. Actions on treasury managed assets are based on average balance difference between December 2015 and March 2016
2. Net of overdrafts and LST FMU collateral

BNY Mellon created a securities sales plan to follow in cases when sales out of the Investment Portfolio are needed for additional liquidity to fund deposit runoff. Potential sales plans were assessed across a number of dimensions including operational feasibility, asset liquidity, and favorable pricing. The modeling team recommended that the considered sales plans do not assume any scenario foresight and are based on existing internal documentation and policies. BNY Mellon Corporate Treasury team proposed a plan that performs well across each of these dimensions and which will be employed for CCAR purposes.

The sales plan determines that BNY Mellon will sell exclusively from the AFS portfolio. The plan involves considering selling assets to comply with liquidity requirements in the following order:

The sales plan determines that BNY Mellon will initially sell exclusively from the AFS portfolio. The plan involves considering selling assets to comply with liquidity requirements in the following order:

USD Balance Sheet

1. Unhedged longer dated Treasuries
2. Unwind hedges and sell the hedged longer dated treasuries
3. Remaining Treasuries and Govt. guaranteed debt
4. Agency debentures
5. GNMA securities
    a. Passthroughs
    b. CMO
    c. Hybrids
6. Conventionals (FHLMC, FNMA) 30Y MBS
7. Conventionals (FHLMC, FNMA) 15Y MBS
8. Conventionals (FHLMC, FNMA) CMO
9. Agency Hybrid/ARM
10. Agency CMBS
11. Supranationals and Level 2A Corporates
12. Municipal Bonds
13. Non HQLA securities

EUR Balance Sheet (driven by EUR deposit run-off)

1. Core country sovereigns : Longer to shorter dated
2. Peripheral country sovereigns: Longer to shorter dated
3. Supranationals and Level 2A corporate bonds
4. Non HQLA securities

GBP Balance Sheet (driven by GBP deposit run-off)

1. Unhedged longer dated Gilts
2. Unwind hedges and sell the hedged longer dated gilts
3. Remaining gilts and govt. guaranteed debt
4. Supranationals and Level 2A Corporate Bonds
5. Non HQLA securities

According to the sales plan, all Treasuries should be sold before any Agency MBS are sold, just as all Agency MBS should be sold before less liquid assets are sold. Furthermore, Treasury enters repurchase agreements on the HTM HQLA securities constrained by a cap on total Corporate Treasury repos of $25bn.

The securities sales plan is fully consistent with the Bank's Resolution plan, where the HQLA portfolio (Level 1 and Level 2A assets) is completely liquidated on day 30 of the runway period. .

9.3.2.2 Step 2 Detailed Overview: Assess OCI at risk metrics

OCI could also impact overall portfolio size as a high portfolio mark may lead to halting reinvestment of maturing securities. Step 2 evaluates whether designated capital ratios breach their Market Risk limits once a shock has been applied.

Pre-specified rate and spread shocks will be applied to the portfolio once deposit dynamics have been assessed. Two primary stress adjusted OCI at risk metrics – the Basel III leverage ratio and the Common Equity Tier 1 ratio (CET1) – will then be tested under each shock scenario. For CCAR purposes, the macro-economy will already be under stress, but additional rate and spread shocks will nevertheless be applied at each quarter (implying an additional stress within a stress period). This is consistent with the business-as-usual case as BNY Mellon applies such shocks on a monthly basis for risk management purposes and would not cease to do so during times of economic distress.

OCI will be negatively impacted when increases in interest rates or spreads drive down security prices, directly hitting capital. If internal limits for either of the capital ratios being monitored – the leverage ratio and CET1 – are breached, action affecting Investment Portfolio size may be taken:

- Basel III Leverage ratio: 4.25% firm limit (to be formalized)
- Common Equity Tier 1: 7% firm limit (to be formalized)

Determining which shocks to apply to the portfolio was discussed with BNY Mellon's Market Risk team. There are several shocks that the BNY Mellon Market Risk team routinely applies to the Investment Portfolio. When measuring OCI at risk metrics, the most severe of these shocks will be applied to the AFS portion of the portfolio: a shape scenario with both interest rates and credit spreads shocked (3/5/10 parallel) and a rates shock scenario which shocks interest rates up 200bps. (For detail on the 3/5/10 parallel scenario, see tables 1 and 2 below). The routine application of shocks ensures that BNY Mellon will have adequate capital to handle severe market shocks. Shocked ratio values will be compared against internal limits with the following impacts:

- If the applied shocks do not result in a metric breach, BNY Mellon will continue purchases as planned
- If the applied shocks do result in a metric breach, BNY Mellon will stop reinvestments and re-purchases in the amount necessary to rectify limit breaches

As seen in the illustrative diagram in the figure below, point 1 represents a quarter at which the shocked leverage ratio hits the internal firm limit of 4.25%. At this point, BNY Mellon would stop reinvestment of maturing securities.

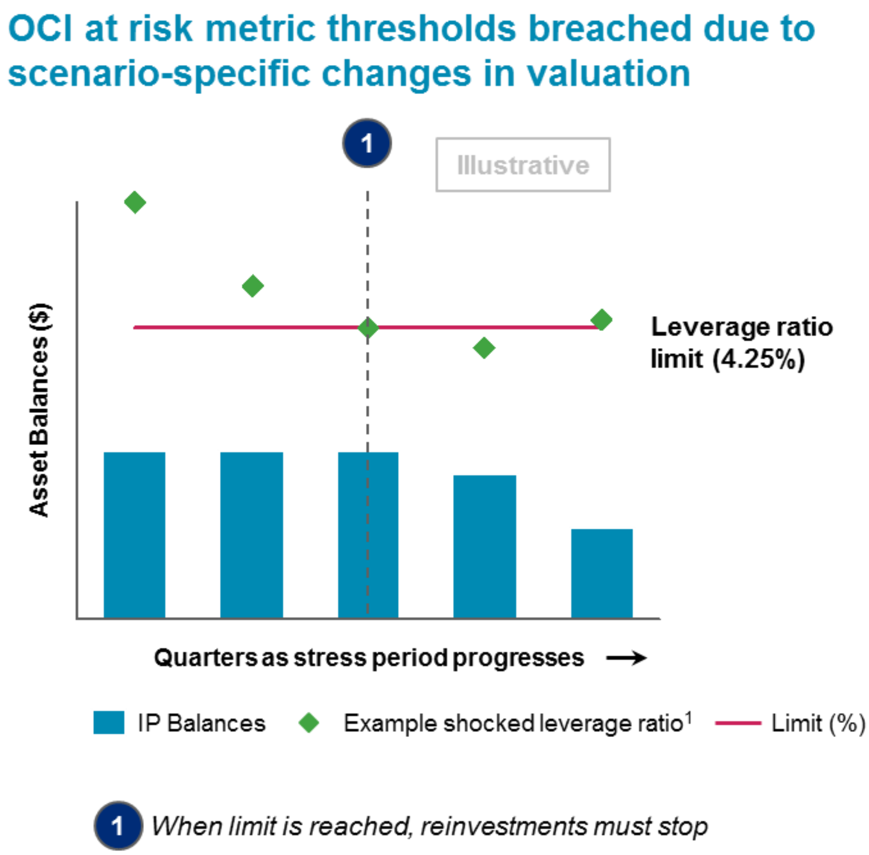
Table 1: 3/5/10 Parallel Scenario Credit Spreads Shocks

	Shape / Spread Only
	All
Sector	OAS Shock (bps)
Agency MBS	73
Non Agency MBS	89
International Structured Products	89
ABS	89
CMBS	89
Treasuries	0
Agency Bonds	89
Municipal Securities	131
Sovereign Debt	149
Supranational	149
Corporates	89
CDO/CLO/CBO	89
Cash Securities	0
Derivatives	0

Table 2: 3/5/10 Parallel Scenario Interest Rate Shocks

IR Scenario	Tenor	0.25 3M	1 12M	2 2Y	3 3Y	5 5Y	Interp 7 7Y	10 10Y	Interp 15 15Y	Interp 20 20Y	Interp 25 25Y	30 30Y
Shape Scenarios	*(in bps, for a 20-day window)*											
3/5/10 Parallel		(13)	24	79	105	86	86	86	83	79	75	71

Figure 395: OCI at risk metrics impact Investment Portfolio size



At the subsequent quarters, there is a decrease in the Investment Portfolio size as funds from maturing securities are used for liquidity purposes, rather than for reinvestment.

9.3.3. Testing of approach

During the development of this forecast approach for BNY Mellon's Investment Portfolio, the modeling team evaluated the framework for comprehensiveness across possible stress scenarios and for feasibility of implementation. To facilitate ease of introducing the forecast approach into business-as-usual activities, already existing internal limits or limits under consideration for implementation were used where possible. For example, the shocks that are applied under stress scenarios to test for OCI at risk metric breaches are shocks that are routinely applied to the portfolio. The limits that are set for central bank balances will potentially be calculated based on reserve requirements and the internal Intraday Liquidity Asset Buffer.

Based on rates from CCAR 2015 scenarios, the modeling team has tested the robustness and comprehensiveness of the Investment Portfolio forecast approach. The forecast deposit runoff after nine quarters of $35 BN in the Supervisory Adverse scenario, characterized by rising rates, was evaluated for its impact on the Investment Portfolio. Under the framework, liquidity would be sourced from central bank balances, which totaled USD $71 BN in April of 2015. The runoff would reduce central bank balances to $36 BN, leaving a total of $35 BN. Sales from the Investment Portfolio would only be considered if the established floor is in excess of $35 BN.

9.4. Investment Portfolio rates forecasting

Rates for the Investment Portfolio are being forecast separately in the BNY Mellon OCI project.

10. "Other balance sheet" balances

10.1. Overview

Section 3.1.3 discusses the segmentation used for "Other balance sheet" segments, which includes balance sheet items outside of deposits, loans, and the investment portfolio. The tables below show the segmentation, along with the type of forecasting method used to forecast balances for each segment.

Table 360: "Other balance sheet" segments – Assets

#	Other assets	Description	Apr'15 Balance ($ BN)	Balance forecasting method
1	Central bank deposits: Fed deposits	Central bank deposits at the US Federal Reserve	71	Qualitative
2	Central bank deposits: Foreign Central Bank deposits	Central bank deposits at foreign central banks	29	Qualitative
3	Placements: Nostro	Short-term unsecured deposits at foreign non-central bank accounts in foreign currency	5.1	Simple model
4	Placements: Pershing	Short-term unsecured deposits held by Pershing at non-central banks	5.7	Simple model
5	Placements: Treasury	Short-term unsecured deposits held by branches and subsidiaries of BNY Mellon at non-central banks, excluding Pershing and Nostro placements	9.5	Qualitative
6	Fed funds sold and reverse repos (Non-Pershing)	Fed funds sold and reverse repos of BNY Mellon excluding Pershing	0.5	Qualitative
7	Securities Borrowing & Reverse repos (Pershing)	Securities borrowing and reverse repos conducted by Pershing	11	Model
8	Securities financing: ABCP, SF loans, Reverse repo	Term loans collateralized by investment securities; includes loans, reverse repos, and asset-backed commercial paper	24	Model
9	Trading assets (Global Markets)	Debt, equity, and derivative instruments not designated as hedging instruments and held for short-term trading by Global Markets business	6.6	Model
10	Trading assets (Capital Markets)	Debt, equity, and derivative instruments not	3.0	Model

		designated as hedging instruments and held for short-term trading by Capital Markets business		
11	Non-interest earning assets (excl. Goodwill, Intangibles)	Assets that do not accrue interest, excluding goodwill and intangibles	33	Qualitative
12	Non-interest earning assets: Goodwill	Goodwill resulting from acquisitions	18	Qualitative
13	Non-interest earning assets: Intangibles	Intangible assets with a finite useful life	4.0	Qualitative

*Investment Portfolio not included here, as it is treated separately in its own section due to its size

Table 361: "Other balance sheet" segments – Liabilities

#	Other liabilities	Description	Apr'15 Balance ($ BN)	Balance forecasting method
1	Trading liabilities (Global Markets)	Trading liabilities generated by the Global Markets business	6.6	Simple model
2	Trading liabilities (Capital Markets)	Trading liabilities generated by the Capital Markets business	0.6	Simple model
3	Short-term borrowings: Broker dealer customer payables	Funds awaiting re-investment and short sale proceeds payable on demand to Pershing clients	23	Model
4	Short-term borrowings: Fed funds, Repos (Treasury)	Fed funds and repos held by BNY Mellon excluding Pershing	8.6	Qualitative
5	Short-term borrowings: Capital market repos	Repos used to fund capital markets HQLA activity	1.2	Qualitative
6	Short-term borrowings: Repos (Pershing)	Repos made by Pershing	6.4	Model
7	Short-term borrowings: Commercial Paper	Commercial paper issued by BNY Mellon	4.8	Qualitative
8	Short-term borrowings: Other borrowed funds	Short-term borrowings other than Fed funds, repos, customer payables, and commercial paper; primarily consisting of Eurodollar deposits	1.1	Qualitative
9	Long term debt	Long term debt issued by BNY Mellon	21	Qualitative
10	Non-interest bearing liabilities	Liabilities that do not accrue interest	14	Qualitative

Some segments in "Other balance sheet" balances used a modeling approach. In many cases, macroeconomic variables do not have high explanatory power; in these cases, the models can be used to produce a starting point for forecasts. This includes cases where the historical data for the segment balances is dominated by a growth trend.

Several of balances and rates forecasts under the "Other Asset" and "Other Liability" segments of the balance sheet required a qualitative framework. Such qualitative frameworkes will require business input and management review to ensure balance and rate forecasts are consistent with expectation and intuition under different scenarios.

The qualitative frameworkes can be categorized as shown in the table below.

Table 362: Description of qualitative frameworkes

#	Category	Description	Other segments covered
1	**Management driven**	Changes in balances heavily influenced by management decision Qualitative framework may rely on statistical model to produce starting point for forecasts, or use data-driven assumptions	Investment Portfolio (covered separately) Treasury placements (treated as part of Investment Portfolio) Non-interest earning assets (excl. Goodwill, Intangibles) Non-Interest bearing liabilities Long-term debt Fed funds sold and rev repos: Reverse repos (Non-Pershing)
2	**Direct quantitative relationship with other segments**	Balances can be calculated using other segments' balances, either mathematically or with a simplified model	Central bank deposits (US) Central bank deposits (Foreign) Pershing placements Trading liabilities (Global Markets) Trading liabilities (Capital Markets) Capital market repos
3	**Accounting**	Forecasts are determined by accounting treatment	Goodwill Intangibles
4	**Runoff**	No new origination planned Balances to decrease according to contractual terms	Commercial paper Other mortgage loans

10.2. Central bank deposits: Fed deposits

10.2.1. Business overview

Central bank deposits are excess liquidity held as overnight balances at the US Federal Reserve and other central banks, depending on currency. As of Q1 2015, BNY Mellon holds $70 BN at the Federal Reserve.

BNY Mellon maintains central bank balances at the Federal Reserve, European Central Bank ("ECB"), Bank of England ("BOE"), and the Bank of Japan (BOJ). ALM-IRR forecasts the change in central bank balances based on forecasted balance sheet balance changes by currency (i.e. deposit run-off).

10.2.2. Historical data

Historical data is not used to produce forecasts for this segment.

10.2.3. Summary of approach

In each scenario, central bank balances are the balancing line to deposits on the liability side of the balance sheet and the loans plus the Investment Portfolio on the asset side of the balance sheet. The impact on central bank balances by scenario will be determined separately for each currency, that is, USD, Euros, GBP, and Yen. Specifically, after all the segments of the balance sheet have been forecasted, the excess funds are deposited into the Central Bank balances (for each currency separately).

While central bank balances might be grown in the case of deposit volume increase, balance reduction could take place if deposits run off. An outflow of deposits could be associated with a higher interest rate environment and result in an outflow of funds that were deposited at BNY Mellon for lack of more attractive alternative investment options as opposed to operational reasons. Or, a deterioration of BNY Mellon's credit quality or reputation could also result in an outflow of excess deposits; in this scenario, outflows might also reduce operational deposits if BNY Mellon loses clients.

For the balances held at the Federal Reserve, a lower bound is maintained in all scenarios per BNY Mellon's Intra-Day Liquidity Policy. In the BHC scenario, which applies BNY Mellon's Liquidity Stress Test assumptions in the first quarter, the limit for Central Bank balances at the Federal Reserve, which is typically $16.3bn, drops to an average balance of ~$12.5BN in the first quarter, net of requirements for Overdrafts and FMU & Cash Collateral Requirements (as determined by the Liquidity Stress Test assumptions for the Intra-Day Liquidity Policy).

Should a deposit outflow occur in the BHC scenario that would result in Federal Reserve balances that are smaller than $12.5 billion, funding sources other than the Federal Reserve balances would be mobilized to cover the shortfall and the Federal Reserve balances would be held flat at $12.5 billion.

10.3. Central bank deposits: Foreign Central Bank deposits

10.3.1. Business overview

This segment consists of overnight deposits held at foreign central banks. There are reserves held at the European Central Bank ("ECB"), Bank of England ("BOE"), and the Bank of Japan (BOJ). As of Q1 2015, BNY Mellon holds $29 BN at the various foreign central banks.

10.3.2. Historical data

Historical data is not used to produce forecasts for this segment.

10.3.3. Summary of approach

In each scenario, central bank balances are the balancing line to deposits on the liability side of the balance sheet and the loans plus the Investment Portfolio on the asset side of the balance sheet. The impact on central bank balances by scenario will be determined separately for each currency, that is, USD, Euros, GBP, and Yen. Specifically, after all the segments of the balance sheet have been forecasted, the excess funds are deposited into the Central Bank balances (for each currency separately).

While foreign central bank balances might be grown in the case of deposit volume increase, balance reduction could take place if deposits run off. An outflow of deposits associated with a higher interest rate environment reflects an outflow of funds that were deposited at BNY Mellon for lack of more attractive alternative investment options as opposed to operational reasons. Deterioration of BNY Mellon's credit quality or reputation could also result in an outflow of excess deposits; in this scenario, outflows might also reduce operational deposits if BNY Mellon loses clients.

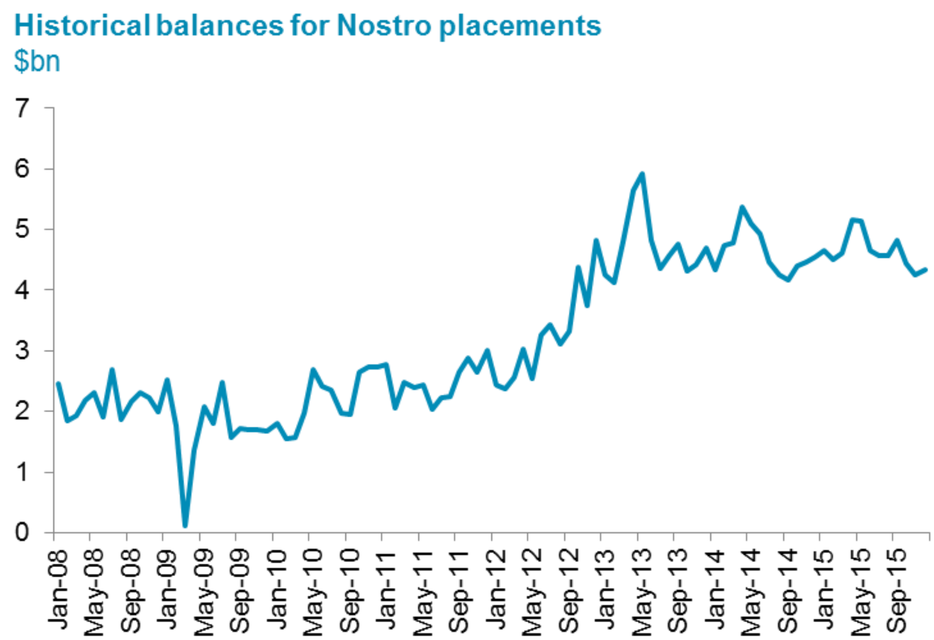
As a reduction in deposit balances takes place, the runoff will be funded using foreign central bank balances until a defined floor is hit. This floor is set based on the central bank in question's reserve requirements plus intraday liquidity requirements for the relevant currency (GBP, EUR, or JPY). Once the floor is hit, foreign central bank balances will remain constant and, if additional liquidity is required, it will be sourced through the Investment Portfolio.

10.4. Nostro Placements

10.4.1. Business overview

Nostro Placements are cash held in nostro accounts at foreign banks. These balances are based mostly in countries where BNY Mellon does not have access to the country's central bank. The balances are mostly cash held on behalf of Asset Servicing clients that result from servicing securities that are denominated in foreign currencies. Therefore, business intuition suggests that the amount of client deposits held in foreign currencies that are denominated in currencies other than USD, EUR and GBP is closely linked to the Nostro Placement balance.

10.4.2. Historical data



10.4.3. General data issues

The historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Nostro Placements. As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

10.4.4. Summary of approach

Nostro placement balances are tied to the Asset Servicing business as Nostro placements are absorbing customer deposits in currencies in which BNY Mellon does not have access to Central Bank balances. As such, business intuition strongly suggests that the Nostro balances would follow the behavior of the Asset Servicing deposit balances.

10.4.4.1. Approach

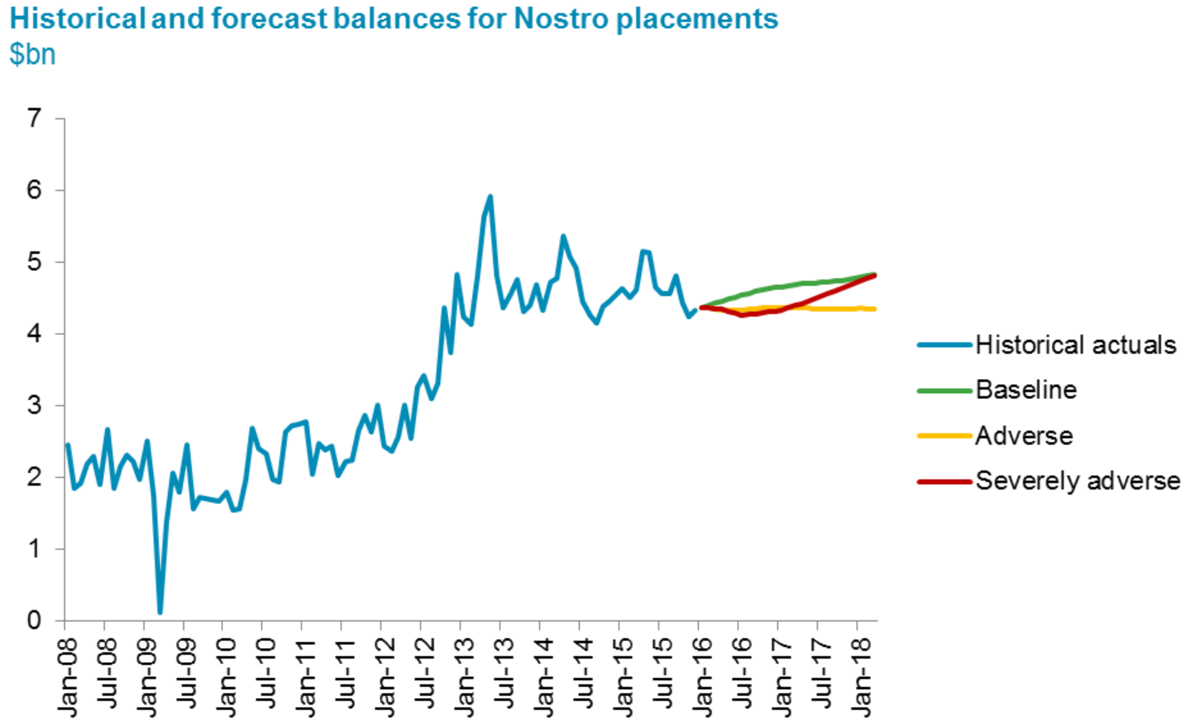
The simple model for Nostro Placements links the Nostro Placement balances to the AS IB deposits balances are linked via a scaling factor that accounts for the relative size of the Nostro placement balances in relation to the AS IB portfolio, as the Asset Servicing business holds the majority of Nostro balances, and as such, business intuition suggests that Nostro balances behavior should closely resemble that of the Asset Servicing deposit balances.

To determine the scaling factor, the modeling team took the average of the latest three months for both sets of balances, from October 2015 to December 2015. The average AS IB balance during this time period was $40.86 billion, while Nostro balances averaged $4.35 billion. Thus the scaling factor will be 10.64% based on the following calculation:

$$Scaling\ factor = \frac{Average\ Nostro\ balances\ Oct - Dec\ 2015}{Average\ AS\ IB\ balances\ Oct - Dec\ 2015}$$

To forecast Nostro balances each month of the forecast, the simple model will multiply the AS IB balance forecasted by the AS IB statistical model for that month by the scaling factor determined above. As a result, Nostro balances will remain 10.46% of the AS IB balances over the forecasting period. Thus Nostro balances move in the same direction as AS IB balances, but remain roughly one tenth the amount. In this way, the two will move in-step as anticipated by business intuition.

Figure 396: Historical and forecast balances for Nostro placements



10.4.4.2. Previous Statistical approach

The modeling team first attempted to develop a statistical model for this segment, in order to capture the movement with economic environment. The drivers included MSCI, Overnight repo rate, and 10 Year T-Note Volatility. The model was statistically good, but with quite model weaknesses in development data. The model weakness was that the developing period only covers a time consisting mainly of low interest rates. And thus the fitted model overly reacts to the short-term interest rate increase scenario. The conclusion that the Nostro balances statistical model was overly sensitive to interest rates is supported by a comparison to the Asset Servicing models. As previously stated, the Asset Servicing business holds the majority of Nostro balances, and as such, business intuition suggests that Nostro balances behavior should closely resemble that of the Asset Servicing deposit balances. However, the Nostro model predicted more extreme behavior than the Asset Servicing models did under stress scenarios, necessitating a qualitative framework. For instance, a three percentage point increase in a US short-term interest rate results in a decrease of $2.4 billion, or about 50 percent of the March 2015 balances. For the same percentage point increase, the Asset Servicing Interest Bearing deposits model predicts a decrease of $5.5 billion, or about 13 percent of the March 2015 balances. This suggests that the Nostro balances have a disproportionately high sensitivity to interest rates compared to the Asset Servicing deposits. Given this, and the intuitive linkage to the Asset Servicing business, a simple model was determined to be more appropriate for this segment.

10.4.5. Approach limitations

The Nostros placement approach has the same limitations as the AS IB balance model.

10.5. Pershing Placements

10.5.1. Business overview

Pershing Placements are primarily 15c3-3 lock-up balances and calculated by a FINRA prescribed formula as below based on current period balances. It is therefore inappropriate to use a statistical model to infer placements based on regression to macroeconomic factors.

<u>FORMULA FOR DETERMINATION OF CUSTOMER AND PAB ACCOUNT RESERVE REQUIREMENTS OF BROKERS AND DEALERS UNDER § 240.15c3-3</u>

Excess of total credits (sum of items 1-9) over total debits (sum of items 10-14) required to be on deposit in the "Reserve Bank Account" (§ 240.15c3-3(e)). If the computation is made monthly as permitted by this section, the deposit must be not less than 105% of the excess of total credits over total debits.

Credits from liabilities
1. Free credit balances and other credit balances in customers' security accounts.
2. Monies borrowed collateralized by securities carried for the accounts of customers
3. Monies payable against customers' securities loaned.
4*. Customers' securities failed to receive.
5*. Credit balances in firm accounts which are attributable to principal sales to customers.
6*. Market value of stock dividends, stock splits and similar distributions receivable outstanding over 30 calendar days.
7*. Market value of short security count differences over 30 calendar days old.
8*. Market value of short securities and credits (not to be offset by longs or by debits) in all suspense accounts over 30 calendar days.
9*. Market value of securities which are in transfer in excess of 40 calendar days and have not been confirmed to be in transfer by the transfer agent or the issuer during the 40 days.

Debts from (Assets)
10. Debit balances in customers' cash and margin accounts excluding unsecured accounts and accounts doubtful of collection.
11. Securities borrowed to effectuate short sales by customers and securities borrowed to make delivery on customers' securities failed to deliver.
12*. Failed to deliver of customers' securities not older than 30 calendar days.
13*. Margin required and on deposit with the Options Clearing Corporation for all option contracts written or purchased in customer accounts.
14*. Margin required and on deposit with a clearing agency registered with the Commission under section 17A of the Act (15 U.S.C. 78q-1) or a derivatives clearing organization registered with the Commodity Futures Trading Commission under section 5b of the Commodity Exchange Act (7 U.S.C. 7a-1) related to the following types of positions written, purchased or sold in

customer accounts: (1) security futures products and (2) futures contracts (and options thereon) carried in a securities account pursuant to an SRO portfolio margining rule.

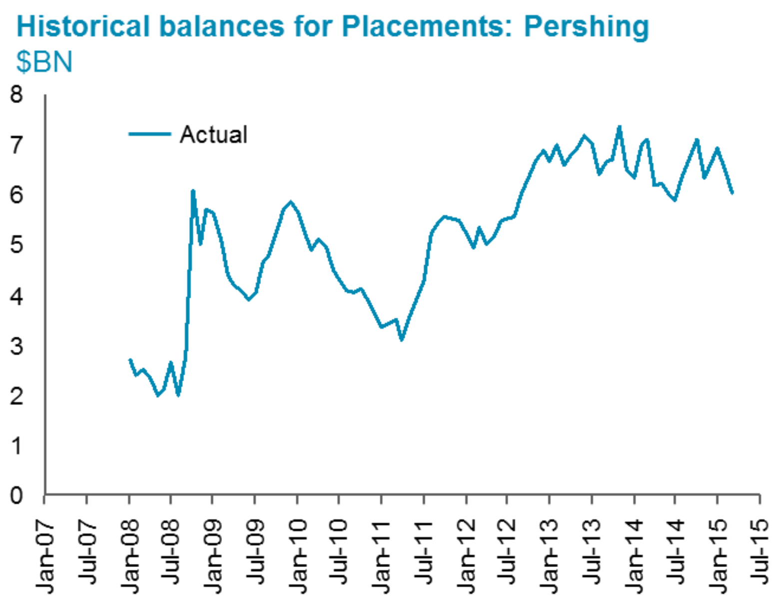
* Balances required to calculate the required minimum balance in lockup are currently out of scope in the current balance sheet model used by BNY Mellon for CCAR.

Ideally one would use the underlying balances to calculate the placement per the statutory formula. However, the segments of the Pershing balance sheet modeled for PPNR includes only interest bearing assets (loans and reverse repos/securities borrowing) , DDAs and interest bearing liabilities (payables, short term borrowing, repos/security lending). As such the minimum balance can't be calculated without the remaining non-interest bearing terms.

These non-interest bearing lines are brought in at the consolidated level (not subsidiary) into BNY Mellon's balance sheet model, they are based on GL balances and therefore cannot be used to inform the calculation of the placement required by FINRA on behalf of Pershing.

10.5.2. Historical data

Figure 397: Average balances for Placements: Pershing ($ BN)



The historical balances of Placements: Pershing have remained relatively stable over the last several years. As of December 2015, Placements (Pershing) portfolio has a size of $6.58 BN.

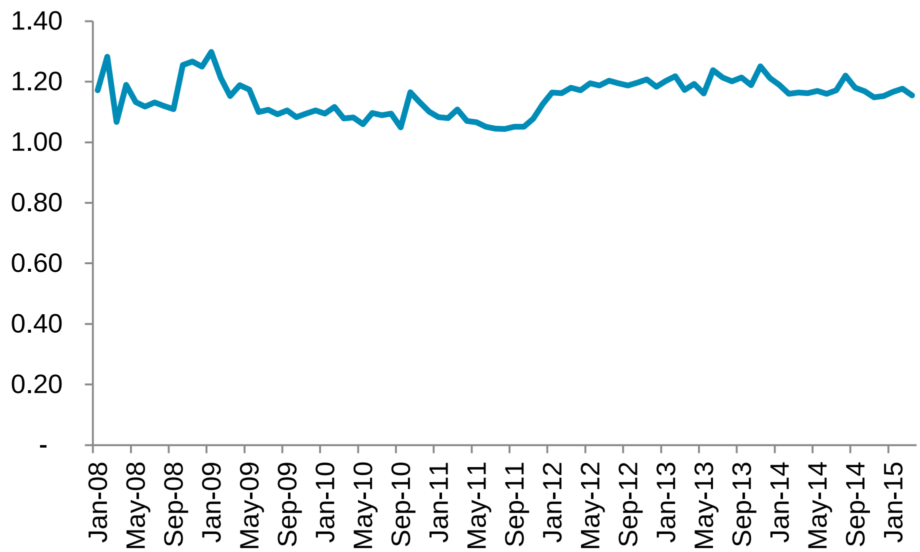
10.5.3. General data issues

No data issues were observed in the historical time series for BNY Mellon Placements (Pershing).

10.5.4. Summary of approach

Although historically placements have shown an absolute growth trend, on a relative basis, there is a relatively stable relationship between the sum of placements, margin loans and stock borrowing with the funding generated by Broker Dealer Payables with an average of 115% (Asset/Liability) and stock lending, and a Standard Deviation 15%, as shown below. The ratio is expected to be approximately 1, however intercompany funding has impacted the historical ratio.

Figure 398: Ratio of Selected Assets to Liabilities



Therefore the simple model assumes instead that the ratio is 1. This mimics the methodology used by the Line of Business when forecasting their expected placements on a pro forma basis.

Placements= (*Broker Dealer and Customer Payables*) + Stock Lending – *Margin Loans* - (*Reverse Repos and Stock Borrowings)*

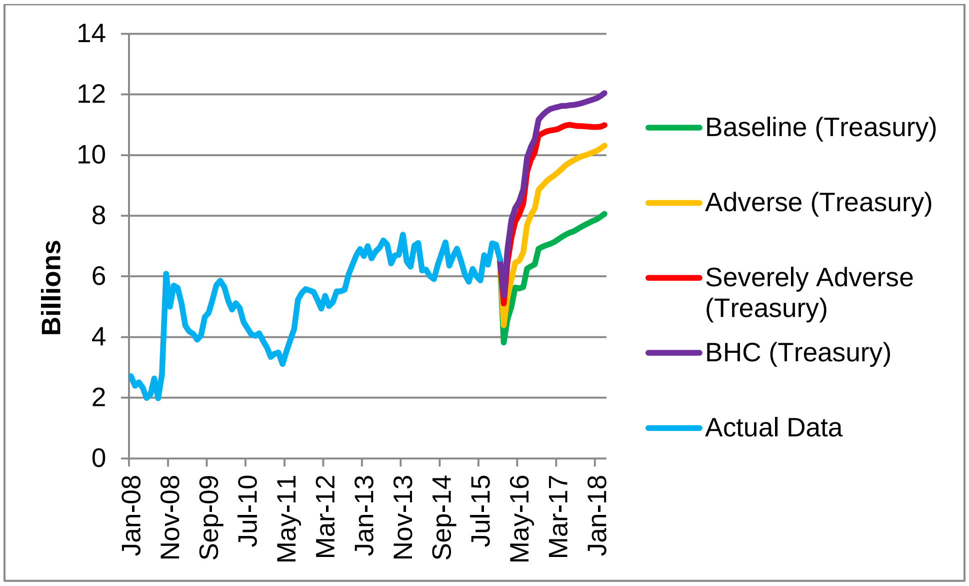
Stock Lending is projected along with Pershing Repurchase agreements in Model 2502 as M33. To forecast only stock lending, the fraction of stock lending over stock lending + repurchase agreements as of December 2015 was used. 29.2%=1.669 /5.716 ($Bns, monthly average per MAQ)

Therefore the equation is programmed as:

Placements= (*Broker Dealer and Customer Payables*) + .292*(Repo and Securities Lending) – (*Margin Loans)* - (*Reverse Repos and Stock Borrowings)*

Broker Dealer Payables, Repo and Securities Lending, Margin loans and Reverse Repo and Stock Borrowings balances are forecasted using their respective models within #2502.

Figure 503: Historical and forecast balances for Pershing placements



10.6. Treasury Placements

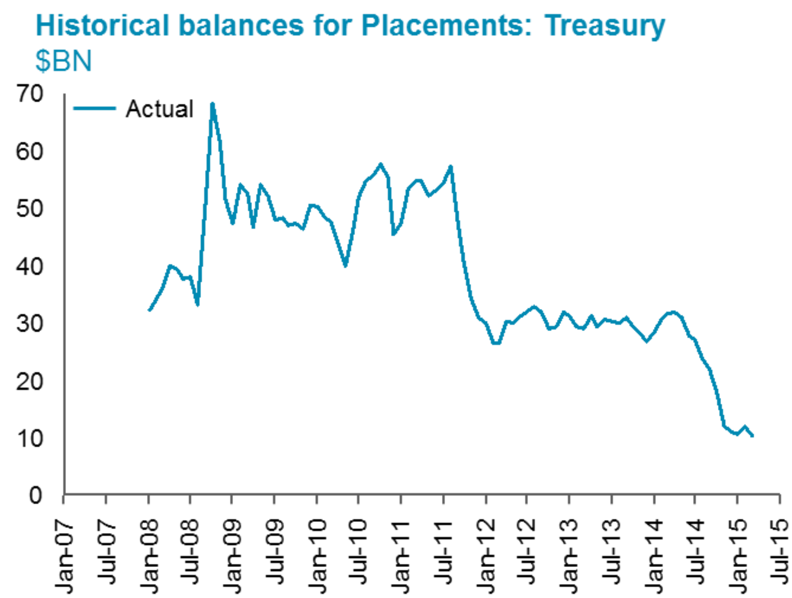
10.6.1. Business overview

Treasury Placements are managed by BNY Mellon Corporate Treasury to extract value from BNY Mellon's stable deposit base while managing interest rate and liquidity risks.

The Treasury Placement portfolio is composed of short-term (12 months or less) unsecured deposits with non-central banks. Treasury Placements comprise of bank placements made by branches and subsidiaries of BNY Mellon.

10.6.2. Historical data

Figure 399: Average balances for Placements: Treasury ($ BN)



Between 2012 and 2014, historical balances were approximately $30 BN. However, due to the new US Liquidity Coverage Ratio requirements concerning high-quality liquid assets, Corporate Treasury is reducing this asset class to $5 to $7 BN in balances. The cash generated from reducing interbank balances is being invested in securities that meet the definition of High Quality Liquid Assets under the new LCR rules. Senior Management and the Board of Directors had approved this change during the summer of 2014.

10.6.3. General data issues

No data issues were observed in the historical time series for BNY Mellon Treasury Placements.

10.6.4. Summary of approach

The Treasury Placements segment will be treated if they were another asset category within the Investment Portfolio. The balances in this segment serve as a source of additional liquidity if needed under stress.

For a detailed summary of the Investment Portfolio approach, please refer to Section 9 on the Investment Portfolio. The forecasting approach uses the operating plan to forecast future balances. The operating plan currently foresees the run-off of all placements made by the Institutional Bank and the London Desks, while the placements made by the Hong Kong, the Other Treasury and the Non-Treasury Desks will be continuously reinvested as they mature.

10.7. Fed Funds Sold and Reverse Repos (Non-Pershing)

10.7.1. Business overview

This segment discusses the non-Pershing components of Fed Funds Sold and Reverse Repos.

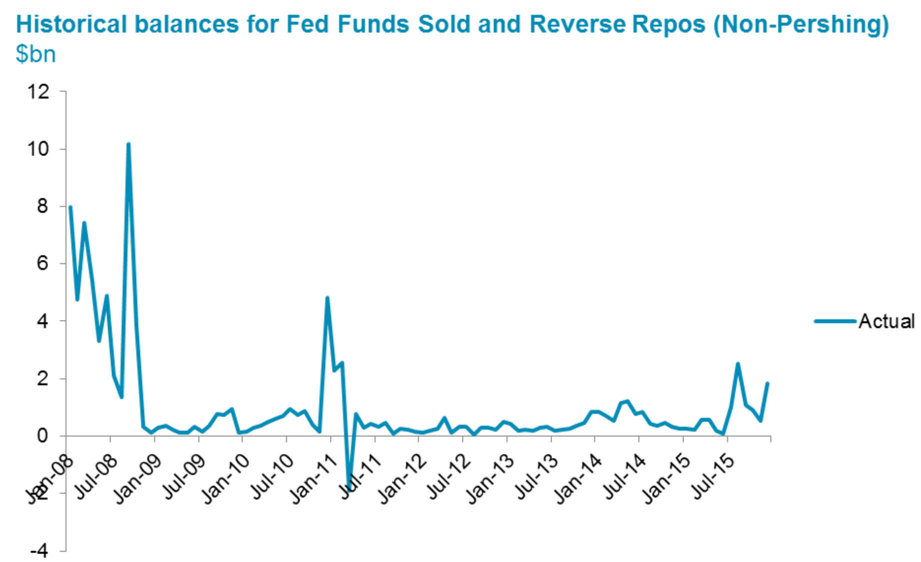
Feds Funds Sold consists of unsecured advances of excess balances in reserve accounts held at Federal Reserve banks. When the BNY Mellon advances federal funds to a third party, it is selling its excess reserves. These interest-bearing transactions typically have an original maturity of one business day.

A Reverse Repurchase Agreement ("Reverse Repo") is a transaction in which BNY Mellon agrees to purchase specific securities from a seller but also agrees to sell the securities back to the seller at a later date and at a premium above the original purchase price. This transaction represents a situation in which BNY Mellon is providing a short-term form of secured financing for other institutions in return for collateral that may be overnight or term. Reverse repurchase agreements are transactions fully collateralized with high-quality liquid securities. Reverse repo transactions carry minimal credit risk and thus its balances are grouped with Fed Funds Sold and the two considered as a single segment.

As of December 2015, the total balances in this segment were $1.8 BN.

10.7.2. Historical data

Figure 400: Average historical balances of Fed Funds Sold and Reverse Repos (Non-Pershing)



While historical data for this segment exist, these data (average balances for Fed Funds Sold and Reverse Repos (Non-Pershing)) show a low balances by the end of 2008, a pattern that continues to the present in 2015. This reflects the fact that Treasury does not have an active strategy to sell funds to other banks or engage in reverse repo transactions. While there is an outlier positive spike and outlier negative spike were observed during December 2010 and March 2011, respectively, these do not reflect changes in bank strategy. As there is no active strategy to sell funds to other banks or engage in reverse repo transactions, there was no ex-ante expectation of a macro-sensitive relationship for these balances, and a qualitative method was chosen to forecast the balances in this segment.

10.7.3. General data issues

The irregularity in data points do not impact the qualitative framework used to forecast this segment.

10.7.4. Summary of approach

Since Treasury does not have an active strategy to sell funds to other banks or engage in reverse repo transactions, a qualitative framework is used to forecast the segment's total balances, in which the spot balance of the most recent month will be held constant. The most recent balance seemed the most relevant data point available as Treasury has utilized these instruments previously but no longer apply an active strategy. As of December 2015, the last balance was $1.8bn.

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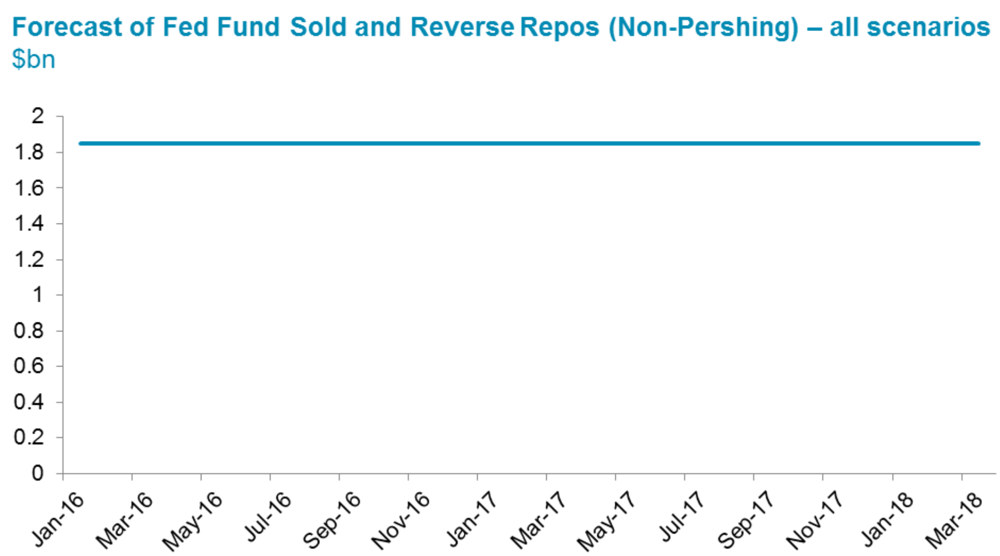
Figure 401: Actual and forecast for Fed Funds Sold and Reverse Repos



10.7.5. Approach limitations

The selected qualitative framework would not capture any future fluctuations in the level of balances. However, given the limited size of the portfolio over the past several years, impacts from a swing in balances beyond recent averages would likely not have material impact on the overall balance sheet.

10.8. Securities Borrowing and Reverse Repos (Pershing)

10.8.1. Business overview

A Reverse Repurchase Agreement ("Reverse Repo") is a transaction in which Pershing agrees to purchase specific securities from a seller but also agrees to sell the securities back to the seller at a later date and at a premium above the original purchase price. This transaction represents a situation in which Pershing is providing a short-term form of secured financing for counterparties in return for collateral and may be overnight or term. Regardless of the tenor, these transactions are secured, and are thus considered to be low risk.

Pershing enters repurchase agreements primarily with retail and institutional customers including Proprietary Accounts of Brokers (PAB) customers. These transactions are primarily used to provide coverage of clients' short-sale transactions.

This segment also includes securities borrowing balances. In securities borrowing transactions, similar to reverse repos, Pershing gives up cash to borrow stocks over short time periods.

10.8.2. Summary

A statistically sound model that is consistent with business intuition was found for Reverse repos. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity**: the model is estimated on month-over-month differences in Reverse repos, which are found to be stationary
- **Statistical significance**: the coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests**: the model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 363: Coefficient estimates for selected model for Reverse repos

Reverse repos (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized Coefficient**
Market Volatility	First difference – MoM	Index	24.43	0.39
MSCI WORLD Index	Percent change – MoM	Index	21.95	0.25
Total Bond Issuance (ex MBS ex gov)	First difference – QoQ	$ BN	3.69	0.35
Intercept	None (level)	$ MM	101.46	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity) –** VIX, which measures implied volatility of S&P 500 index options
- **Equity markets –** MSCI World Index, a benchmark for global stock funds based on securities from 23 countries
- **Debt issuances –** Total bond issuance

The intuition of these variables is as follows:

- The S&P volatility variable has a positive coefficient; when equity markets are more volatile, more trading activity may take place, including short sales, increasing the demand for reverse repos to cover client short positions
- The MSCI World Index has a positive coefficient, with the rationale that Pershing reverse repo agreements will increase as equity investments become more attractive, driving greater volume of investment activity, including short sales
- Total bond Issuance has a positive coefficient, with the rationale that as activity in fixed income markets increases, more client trading activity may take place, increasing the need for reverse repos to cover increased short-selling activity

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 402: Candidate models for Reverse repos (Pershing)

	Candidate models				
Drivers Considered	**1**	**2**	**3**	**4**	**5**
Relative credit worthiness of BNYM				BNYM - Peer Group Debt Yield Spread (Diff QoQ)	
Equity markets			MSCI WORLD Index (% MoM)		KBW Bank Index (% MoM)
Market volatility/ uncertainty	Market Vol (Diff MoM)	Market Vol (Diff MoM)	Market Vol (Diff MoM)	Ovrnt LIBOR-1wk OIS spread (Diff MoM, 1M Lag)	Market Vol (Diff MoM)
Debt issuances	ABS Issuance (% QoQ)	US Bond Issuance (ex MBS ex gov) (Diff QoQ)	US Bond Issuance (ex MBS ex gov) (Diff QoQ)	US Bond Issuance (ex MBS ex gov) (Diff QoQ)	US Bond Issuance (ex MBS ex gov) (Diff QoQ)
Short-term rates	Ovrnt LIBOR (Diff QoQ)	1M-3M Treasury Spread (Level, 1M Lag)			
Variation in balances explained through estimated first differences	**85%**	**88%**	**88%**	**87%**	**85%**
R-squared (differences)	**23%**	**19%**	**17%**	**16%**	**16%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

10.8.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

10.8.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The time series for the Reverse repos segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the tables below.

Table 364: Unit root tests and stationarity tests including a trend variable on balances

Reverse repos – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	2	-1.1	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.8	0.68	Fail to reject unit root
KPSS	5	0.27	<0.01	Reject stationarity

Table 365: Unit root tests and stationarity tests including a constant on first differences

Reverse repos – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-9.4	<0.01	Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	11	0.25	0.19	Fail to reject stationarity

Stationarity tests for Pershing Reverse Repos balances yielded the following results: The ADF and PP tests failed to reject the presence of a unit root while the KPSS test rejected stationarity. These results suggest the segment's balances are non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Pershing Reverse Repo balances are modeled on their first differences.

10.8.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Reverse repos.

10.8.4. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 403: Summary of drivers for Reverse repos

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Economic weakness may lead to increased volume of short sales, which drives reverse repo volumes	• Real GDP growth, US unemployment rate
Financial economy	**Equity markets**	• Strong market performance entices more investments and trading activity from clients, including short sales activity	• DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Debt issuances	• As activity in fixed income markets increase, more client trading activity may take place, increasing the need for reverse repos to cover short-selling activity	• Corporate debt outstanding, total bond issuance
	Relative credit worthiness of BNYM	• If BNY Mellon experiences a severe downgrade in creditworthiness, counterparties may be unwilling to enter into repo transactions at normal volumes, preferring to limit their exposure	• Spread between BNYM CDS and industry average CDS (North American, EU, UK bank indices), spread of BNYM debt rate to industry peer rate
	Market volatility/ uncertainty	• Higher market volatility results in more short-selling activity, increasing demand for securities to cover short sales	• VIX, rates volatility, US LIBOR-OIS spread, equity indices, FDIC insurance on DDA dummy variable, Fed stress indices
Rates	**Short-term rates**	• As short term rates increase, investment activity may decrease, including short sales activity that drives reverse repo volumes	• Overnight LIBOR, Fed Funds rate, Treasury yields, SONIA, EONIA, Money Market fund yield indices, repo rates

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

10.8.5. Influential pointModel sensitivity

10.8.5.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 366: Sensitivity to changes to independent variables for Reverse repos

Reverse repos – model sensitivity					
Independent variable	**Transformation**	**Unit**	**Standardized Coefficient**	**Std. dev of independent variable**	**Change in balances resulting from 1 std. dev change in the independent variable ($ BN)**
Market Volatility	First difference – MoM	Index	0.39	7.18	0.18
MSCI WORLD Index	Percent change – MoM	Index	0.25	5.02	0.11
Total bond Issuance (ex MBS ex gov)	First difference – QoQ	$ BN	0.35	46.2	0.16
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the Market Volatility variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Market Volatility variable results in a 0.39 standard deviation ($0.18 BN) increase in the predicted monthly change of the total commitment for the FI loan segment.

10.8.5.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 367: Statistical sensitivity tests for Reverse repos

Reverse repos (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of Coefficients	HAC P-value of shortened period Coefficient	Conclusion
Market Volatility	24.43	22.28	0.66	Statistically insignificant
MSCI WORLD Index	21.95	17.39	0.47	Statistically insignificant
Total Bond Issuance (ex MBS ex gov)	3.69	3.50	0.81	Statistically insignificant
Intercept	101.46	-	0.74	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.92	Statistically insignificant

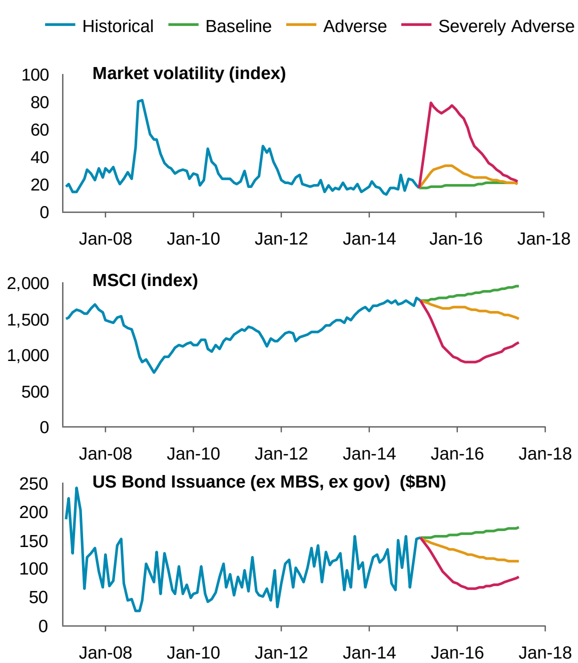
10.8.5.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

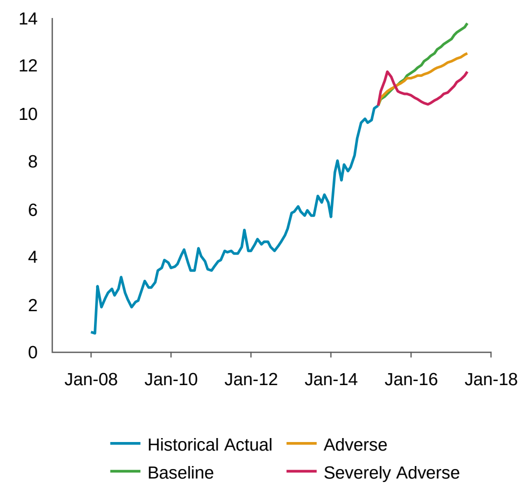
Figure 404: Final model forecast for Reverse repos

Historical and forecast independent variables



Historical and forecast balances for Securities Borrow and Reverse Repo (Pershing)
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	3.42 (33%)	2.18 (21%)	1.39 (13%)	-
Start to peak	3.42 (33%)	2.18 (21%)	1.44 (14%)	3.02 (377%)
Start to trough	N/A	N/A	N/A	-0.04 (-5%)



The Working Group considered the forecast behavior for the selected Reverse repos model as directionally reasonable. The business reviewed the forecasts and expressed that securities borrows and reverse repos are primarily driven by client short-selling activity; without modeling short-selling activity, it is difficult to model the business requirement for reverse repos.

- **Severe recession (Severely Adverse) scenario:** The model predicts an increase followed by a significant decline in Reverse repos, with an eventual gradual recovery in balances. In a review of the forecasts with the line of business, this was noted to be directionally consistent with expectations. The spike in balances at the start of the 9-quarter period is first being driven by the positive correlation on the market volatility variable. As equity markets go into crisis under the scenario, balances begin to come down, tracking the shape of the MSCI World Index and Total bond issuance forecasts
- **Interest rate shock (Adverse) scenario**: Business intuition is that Reverse repos decrease as rates rise due to a decreased desire for holding risky assets, and a corresponding decrease in the demand for funding through repos. This is seen in moderate growth in the forecast relative to the baseline scenario
- **Baseline scenario**: The model predicts that Reverse repos will grow over the 9-quarter period. It would be expected that more trading activity would take place relative to a stressed macro-economy, thus increasing the demand for repos for additional funding

10.8.6. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Reverse repos are statistically significant. The intercept is found to be statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 368: Statistical significance tests of model and variables for Reverse repos

Reverse repos (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	1%	10%	Statistically significant
Market Volatility	24.43	<1%	10%	Statistically significant
MSCI WORLD Index	21.95	<1%	10%	Statistically significant
Total bond Issuance (ex MBS ex gov)	3.69	<1%	10%	Statistically significant
Intercept	101.46	3%	10%	Statistically significant

10.8.7. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

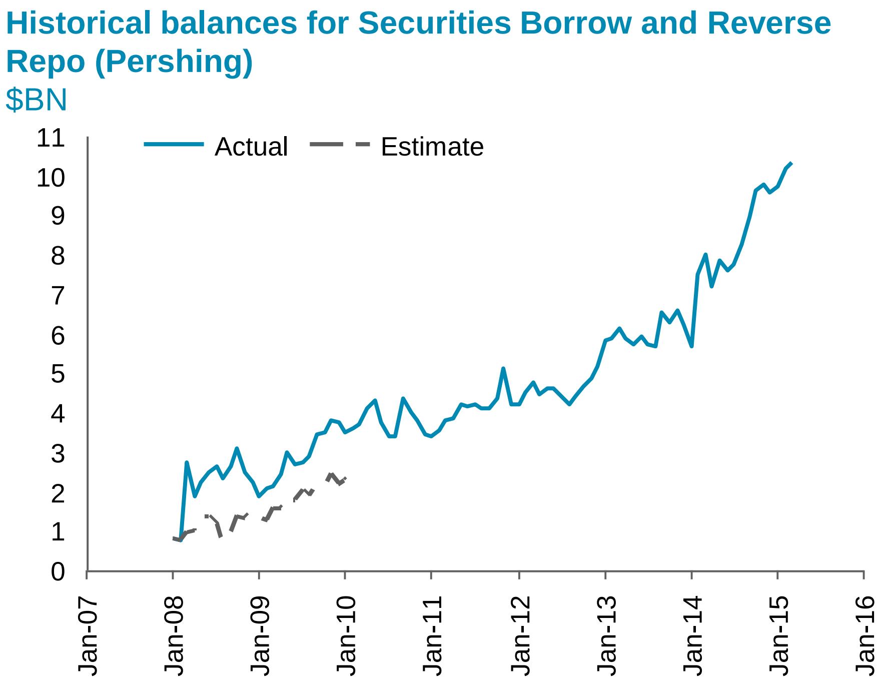
The diagnostic tests reviewed are exhibited below.

Table 369: Model Diagnostics for Reverse repos

Reverse repos (in USD MM) – Model diagnostics

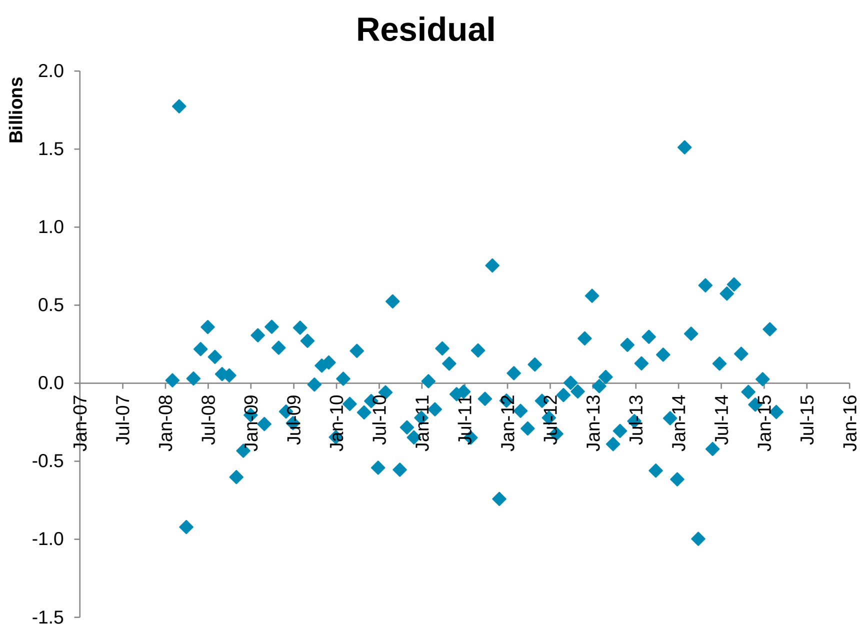
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of Fit	R-squared	17%	-	-
	Adjusted R-squared	14%	-	-
Heteroskedasticity	Breusch-Pagan test (P-value)	86%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum P-value up to 4 lags)	5%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.55	5	No multicollinearity
Linearity	RESET test	33%	10%	Linear specification appropriate

Figure 405: 9-quarter In-sample Prediction for Reverse repos



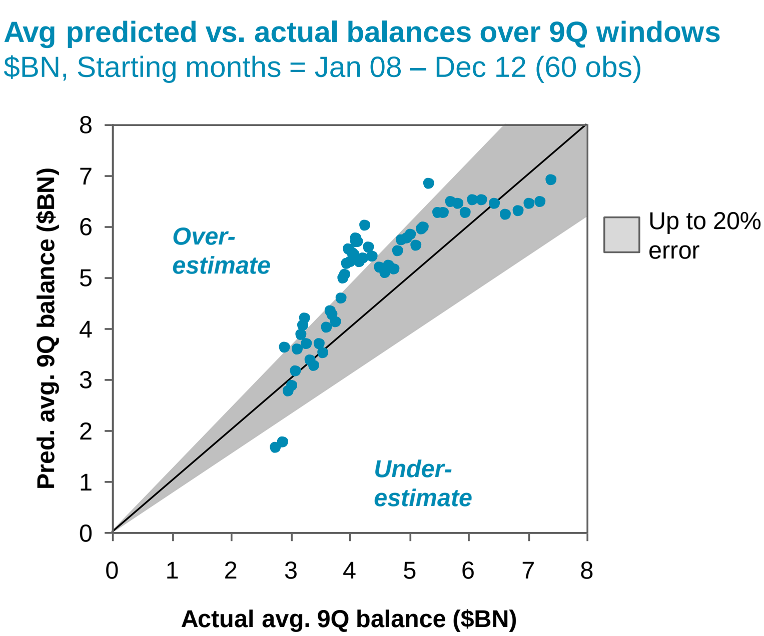
The in-sample back test of the model starting from January 2008 tracks the directional behavior of the balances, although does not capture the magnitude of changes arising from the high month-to-month volatility in the historical time series.

Figure 406: Residual Plot for Reverse repos ($ BN)



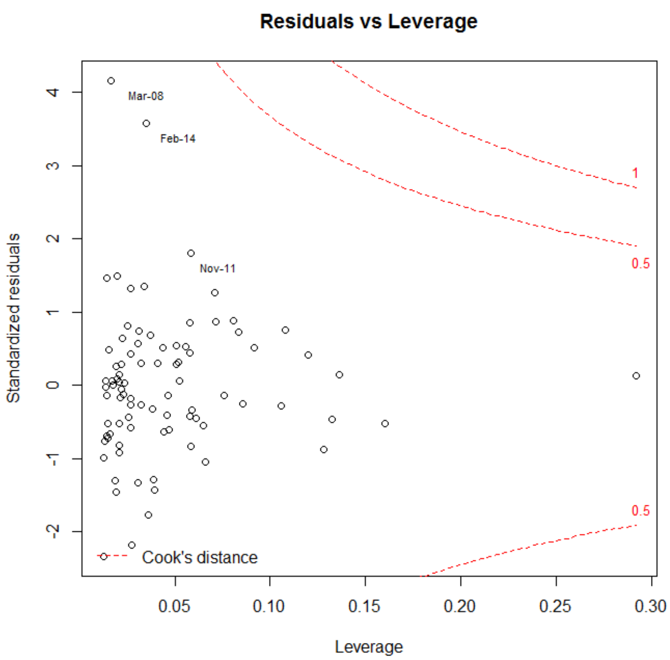
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 407: Estimation Scatterplot for Reverse repos



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for some of the 9-quarter forecast windows. The model does not capture the high month-over-month volatility in the historical overdraft balances, which leads to some overestimation or underestimation over 9-quarter forecast windows, depending on which month is taken as the starting month of the forecast.

Figure 408: Influential points for Securities borrowing and Reverse Repos (Pershing)



The segment does not contain any highly influential points

10.8.8. Model limitations

Any model based on macroeconomic factors would not be able to capture the high month-over-month volatility in the historical Pershing repo balances. Therefore, the model results should be interpreted as the general expected trend for the balances, without the volatility that arises from more idiosyncratic behavior.

The line of business expressed that the model for Reverse repos should tie to forecasts for client short-selling activity. Future enhancements to the model can be made to forecast short-selling activity and establish a quantitative link to forecasts for Reverse repos for Pershing.

10.9. Securities Financing

10.9.1. Business overview

BNY Mellon's Securities Financing is a new business that began in early 2011. As part of the Securities Financing program, BNY Mellon enters in Term Reverse Repos, originates Securities Financing Loans and purchases Asset Backed Commercial Paper. The Reverse Repo transactions are generally one year in tenor and reset quarterly and the Reverse Repo portfolio is a growth portfolio in USD and EUR. Teams based in New York City, New York and in London, UK manage the business.

10.9.2. General data issues

As a result of Securities Financing being a new business at BNY Mellon, starting in 2011, there is limited historical data available. In addition, the limited time series shows a strong growth trajectory, which lowers the sensitivity of balances to macroeconomic facts. Therefore, any model results could serve as a starting point while expert knowledge will be further applied in review of the results.

10.9.3. Summary of approach

Initially a strictly qualitative framework was proposed to the Working Group. However, after discussion with the Working Group, the recommended approach was the use of a statistical model as a starting point while expert knowledge will also be used in the balance sheet forecasting review. As such, a statistical model based on business intuition and uses macroeconomic factors was found for Securities Financing.

However, as the portfolio has grown consistently since launch, macroeconomic variables can only provide a partial explanation of the historical actuals and forecast of this portfolio; management scrutiny is needed.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for Securities Financing, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 370: Coefficient estimates for selected model for Securities Financing

Securities Financing (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
MSCI WORLD Index	Percent change – MoM	%	32.54	0.28
30Y Treasury	First difference – QoQ	%	-693.07	-0.52
Intercept	None (level)	$ MM	309.19	N/A

The model contains the following drivers and variables:

- **Equity Markets** – The MSCI World stock index
- **Long-term Rates –** The yield on 30-year US Treasuries

The following justifications were considered as part of these variables:

- The MSCI World stock index has a positive coefficient with the rationale that stronger performing equity markets means that clients have greater value of collateral to use for secured loans
- The 30-year treasury yield has a negative coefficient with the rationale that higher long-term rates encourages deployment of BNY Mellon funds in longer-term assets not part of the Securities Financing portfolio, which primarily consists of shorter-term investments

In a review and challenge meeting, the line of business stated that while the growth trend of this segment makes it difficult to model, the resulting model is a reasonable starting point while expert knowledge will also be used in the balance sheet forecasting review.

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

10.9.4. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

10.9.4.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Securities Financing is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 371: Unit root tests and stationarity tests including a trend variable on balances

Securities Financing – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-1.1	>0.10	Fail to reject unit root
Phillips-Perron	1	-0.3	0.99	Fail to reject unit root
KPSS	4	0.18	0.02	Reject stationarity

Table 372: Unit root tests and stationarity tests including a constant on first differences

Securities Financing – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-4.5	<0.01	Reject unit root
Phillips-Perron	1	-4.5	<0.01	Reject unit root
KPSS	3	0.3	0.14	Fail to reject stationarity

Stationarity tests for Securities Financing balances yield mixed results: The ADF and PP tests failed to reject a unit root but the KPSS test rejects stationarity. These results suggest the segment's balances may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Securities Financing balances are modeled on their first differences.

10.9.4.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

While there were no outliers found in the balance of the Securities Financing portfolio, the growth trend since inception calls into the question the viability of a statistical model; for this reason, the Working Group considers the results of this model as a starting point while expert knowledge will also be used in the balance sheet forecasting review.

10.9.5. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 409: Summary of drivers for Securities Financing

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• A better performing economy would increase both supply and demand for secured lending	US GDP growth, US unemployment rate
Financial economy	**Debt issuances**	• Higher bond issuance may serve as a substitute for secured loans	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets lead to increased capacity for clients to borrow as well as their demand to borrow from BNY Mellon	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Hedge fund index	• Stronger hedge fund performance leads to greater capacity and demand to borrow	HFRX index, Eurekahedge HF index, Eurekahedge FoF index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty may decrease BNY Mellon's appetite for secured lending, given that collateral may fluctuate in value	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk may lead to decreased appetite to offer secured lending	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increases in rates makes borrowing more expensive, which would likely have a stronger demand effect of decreasing demand than a supply effect of increasing supply, due to management limits on the size of the portfolio	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

10.9.6. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold

Individual statistical significance of coefficient estimates – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Securities Financing are statistically significant. The intercept is found to be statistically significant.

Table 373: Statistical significance tests of model and variables for Securities Financing

Securities Financing (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	0%	10%	Statistically significant
MSCI WORLD Index	32.54	4%	10%	Statistically significant
30Y Treasury	-693.07	<1%	10%	Statistically significant
Intercept	309.19	<1%	10%	Statistically significant

10.9.7. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which while in other models presented shows the in-sample back-test results over the 2008–2009 financial crisis for the model, in the case of Securities Financing shows the 9-quarter since inception in March 2011
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

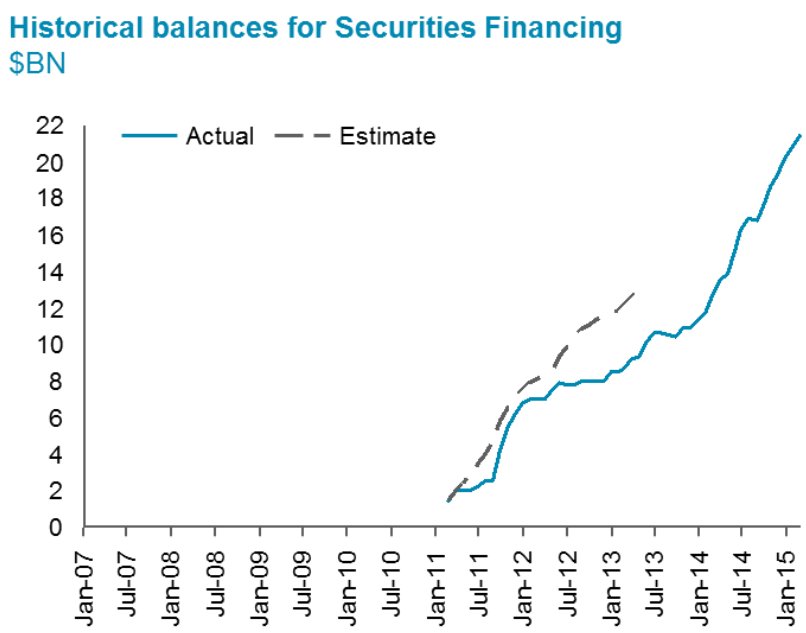
The diagnostic tests reviewed are exhibited below.

Table 374: Model Diagnostics for Securities Financing

FI loans – total commitment (in USD MM) – Model diagnostics

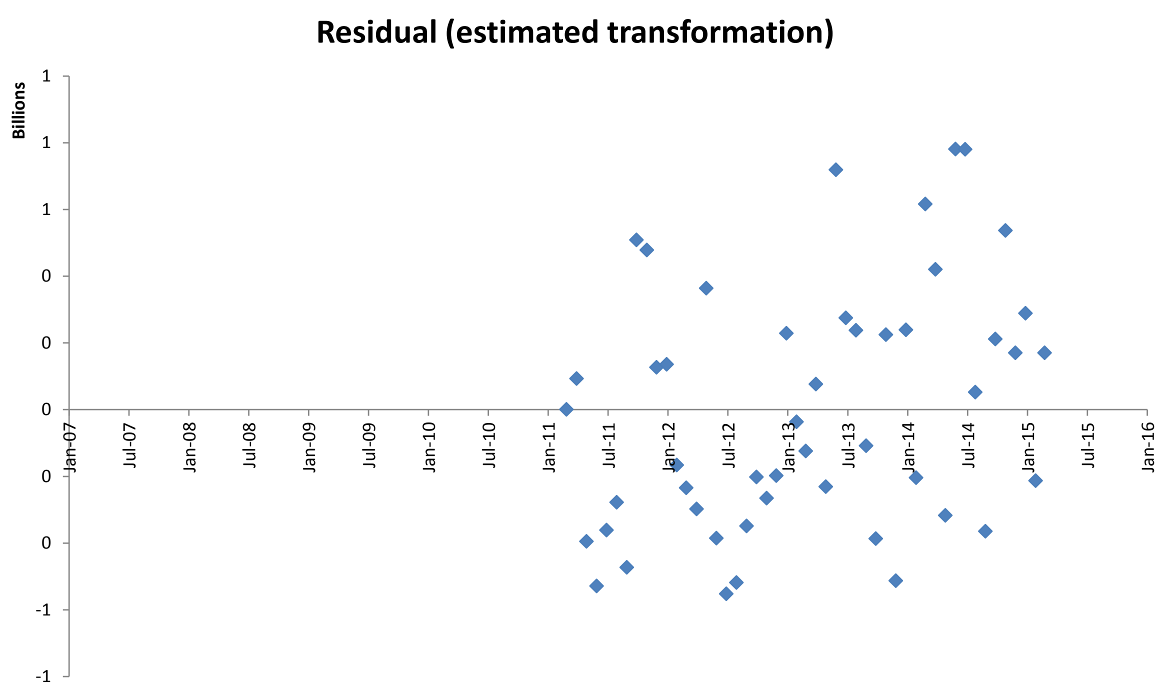
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	27%	-	-
	Adjusted R-squared	23%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	16%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	10.89%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.09	5	No multicollinearity
Linearity	RESET test	11%	10%	Linear specification appropriate

Figure 410: 9-quarter In-sample Prediction for Securities Financing



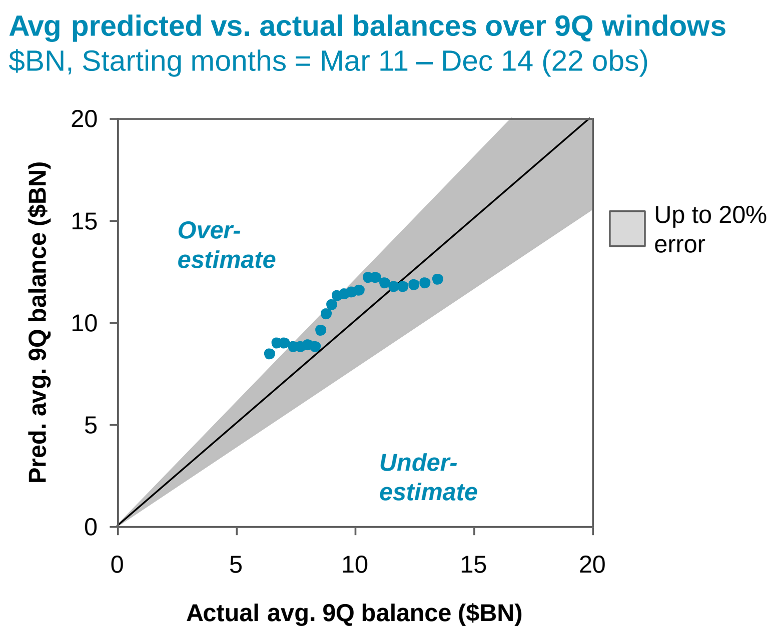
The in-sample back-test of the model starting from March 2011 begins to have significant tracking error by July 2012. Nonetheless, the expected directional behavior is captured.

Figure 411: Residual Plot for Securities Financing ($ BN)



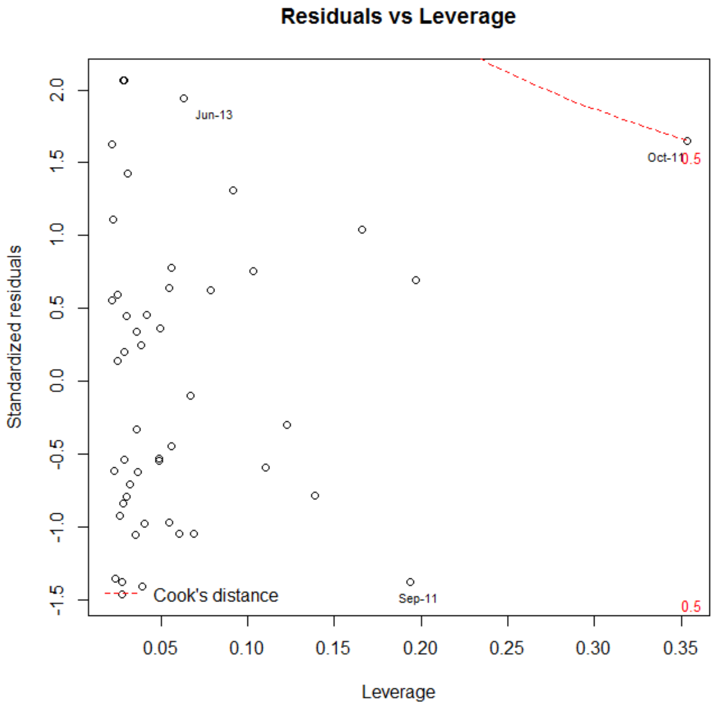
As expected, the residuals appear randomly distributed along the horizontal axis.

Figure 412: Estimation Scatterplot for Securities Financing



Estimated average 9-quarter levels generally track with the actual average 9-quarter levels for different 9-quarter forecast windows, with the majority of average values within or close to 20% of actual average values.

Figure 413: Influential points for Securities Financing



The segment does not contain any highly influential points.

10.9.8. Model sensitivity

10.9.8.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 375: Sensitivity to changes to independent variables for Securities Financing

Securities Financing – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev. change in the independent variable ($ BN)
MSCI WORLD Index	Percent change – MoM	%	0.28	5.02	0.12
30Y Treasury	First difference – QoQ	%	-0.52	0.37	-0.23
Intercept	None (level)	$ MM	N/A	N/A	N/A

10.9.8.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically significant collectively. This suggests the model does not maintain stability when removing observations from the development data.

Table 376: Statistical sensitivity tests for Securities Financing

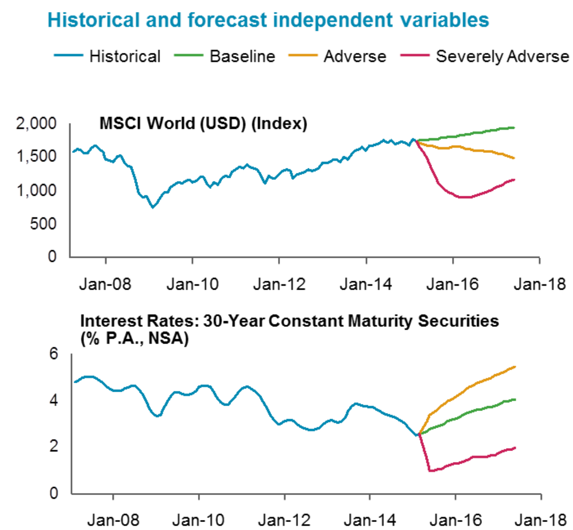
Securities Financing (in USD MM) – Statistical significance tests of model and variables				
Tested independent variable	**Original coefficient estimate**	**Sum of coefficients**	**P-value of shortened period coefficient**	**Conclusion**
MSCI WORLD Index	32.545	50.749	0.04	Statistically significant
30Y Treasury	-693.067	-822.042	0.74	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.01	Statistically significant

10.9.8.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

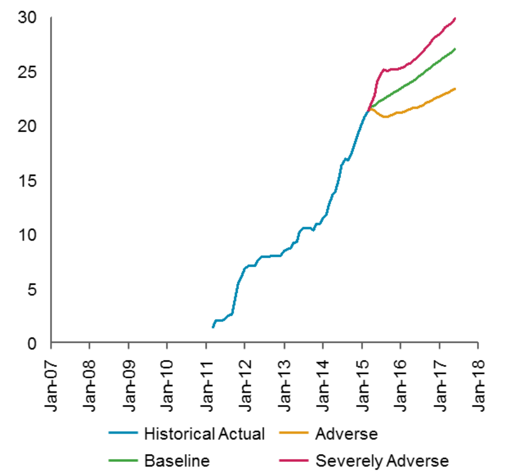
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 414: Final model forecast for Securities Financing



Historical and forecast balances for securities financing
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	5.65 (26%)	1.94 (9%)	8.42 (39%)	-
Start to peak	5.65 (26%)	1.94 (9%)	8.42 (39%)	N/A
Start to trough	N/A	-0.57 (-3%)	N/A	N/A



Based on discussions with the business, the Securities Financing portfolio has an authorized limit of $30 BN in balances by the end of 2016.

The forecasts of the model selected do not breach this limit. The Working Group agrees with the general direction and trend of the forecast, but due to the model weaknesses, the quantitative forecast will be used as a starting point while expert knowledge will also be used in the balance sheet forecasting review.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant rise in balances in the Securities Financing portfolio. This is primarily driven by the lower long-term interest rates. However, the magnitude and duration of this rise may exceed expectations. Therefore, the results of this model should be monitored closely when the final outputs for submission are generated.
- **Interest rate shock (Adverse) scenario**: The model predicts a drop followed by a steady rise of the balances in the Securities Financing portfolio, this is reasonable as less trading may occur during times of interest rate shock
- **Baseline scenario**: The model predicts a steady growth in the balances of the Securities Financing portfolio. The growth trend is in line with statements from discussions with both the Working Group and the business

10.9.9. Model limitations

As stated in Section 7.6.3, model limitations primarily exist around the limited number of observations in the historical data for the Securities Financing portfolio, combined with the strong intercept in the model arising from the steady growth trend of the balances. Meanwhile, expert knowledge will also be used in the balance sheet forecasting review.

10.10. Trading Assets (Global Markets)

10.10.1. Business overview

BNY Mellon's Trading Assets stem from its trading in derivatives, Global Markets, and Capital Markets, representing the groups that originated these balances. Each of these businesses has both interest bearing and non-interest bearing assets. After multiple discussions with the Working Group and business, for CCAR purposes, the segmentations for Trading Assets are constructed along the business groups.

Trading assets include debt and equity instruments and derivative assets, primarily interest rate and foreign exchange contracts, not designated as hedging instruments. Trading assets (Global Markets) represent those assets generated by the Global Markets group as classified by MAQ.

10.10.2. General data issues

While BNY Mellon has three businesses that have balances under Trading Assets (Global Markets, Capital Markets, and Derivatives), MAQ rollup of the Derivatives business contains negligible balances, with the aggregate balances of the Global Markets and Capital Markets rollup comprising 100% of total Trading Assets. The segmentation used aligns to MAQ, which is the system of record for management accounting purposes.

10.10.3. Summary of approach

While a statistical model that uses macroeconomic factors was found for Trading Assets (Global Markets), the variables used in the forecast were considered unintuitive based on discussion with the BNY Mellon Working Group and business. Macroeconomic variables had weak explanatory power for trading activities that drive the balances in this segment; therefore expert knowledge will also be used in the balance sheet forecasting review.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for Trading Assets (Global Markets), which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 377: Coefficient estimates for selected model for Trading Assets (Global Markets)

Trading Assets (Global Markets) (in USD MM) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
S&P volatility (30-day moving average)	First difference – MoM	Index	1,512.55	0.32
Total Bond Issuance (ex mortgage, treasuries)	Percent change – MoM, 1M Lag	%	-14.40	-0.37
5Y US Swap Rate	First difference – MoM	%	-1,795.63	-0.29
Intercept	None (level)	$ MM	90.85	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – 30-day moving average of close-of-day values of VIX, measuring S&P volatility
- **Debt issuances –** Togtal US Bond Issuance, excluding mortgages and Treasuries
- **Long-term rates –** 5-year US Swap Rate

In a review and challenge meeting, the line of business stated that there is low intuition in using any macroeconomic variables to forecast balances. The Working Group decided to employ a statistical model as a base for forecasts, with full expectation that significant management scrutiny of the results will be needed.

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

10.10.4. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

10.10.4.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Trading Assets (Global Markets) is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 378: Unit root tests and stationarity tests including a trend variable on balances

Trading Assets (Global Markets) – Unit root test with trend on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	9	-3.4	0.05	Reject unit root
Phillips-Perron	1	-4.1	0.01	Reject unit root
KPSS	4	0.18	0.03	Reject stationarity

Table 379: Unit root tests and stationarity tests including a constant on first differences

Trading Assets (Global Markets) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	0	-11	<0.01	Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	3	0.03	0.98	Fail to reject stationarity

Stationarity tests for Trading Assets (Global Markets) balances yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. These results suggest the segment's balances may be non-stationary. In contrast, the monthly first difference series rejected unit root for ADP and PP and the KPSS failed to reject stationary. These results strongly suggest that the first differences series is stationary.

Based on these results, the Trading Assets (Global Markets) balances are modeled on their first differences.

10.10.4.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

By the nature of its business, the balances in the Trading Assets (Global Markets) are volatile. However, the balances observed through the historical period of January 2008 to March 2015 did not show any issues beyond this expected volatility.

10.10.5. Hypotheses and independent variable identification

Based on discussions with the Working Group, the ALM team, Credit Risk, and the line of business, it was determined there was weak intuition in using macroeconomic factors to model this segment. Therefore, the modeling team allowed the full set of independent variables in candidate models, noting that the weak intuition on drivers would necessitate management review of results.

10.10.6. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Trading Assets (Global Markets) are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 380: Statistical significance tests of model and variables for Trading Assets (Global Markets)

Trading Assets (Global Markets) (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	26.85	<1%	10%	Statistically significant
S&P volatility (30-day moving average)	1,512.55	<1%	10%	Statistically significant
Total Bond Issuance (ex mortgage, treasuries)	-14.40	<1%	10%	Statistically significant
5Y US Swap	1,795.63	<1%	10%	Statistically significant
Intercept	90.85	48%	10%	Statistically not significant

10.10.7. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

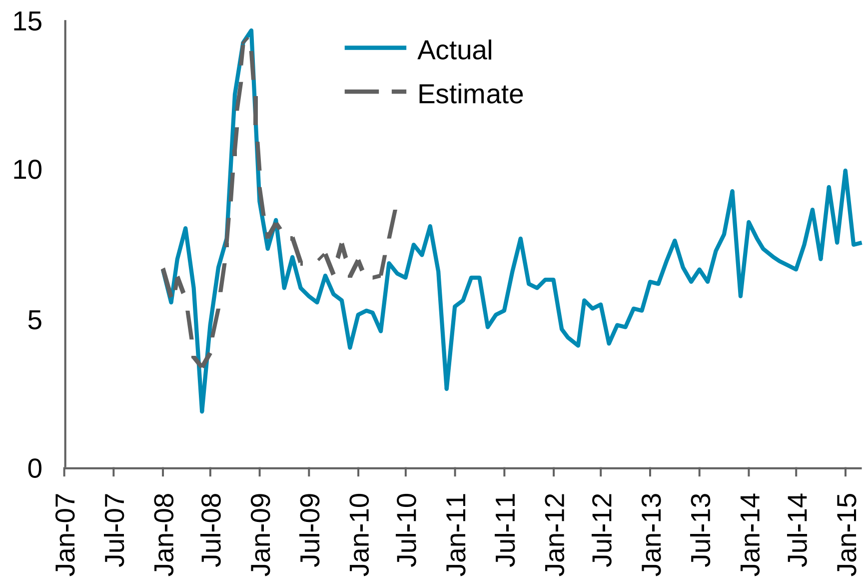
The diagnostic tests reviewed are exhibited below.

Table 381: Model Diagnostics for Trading Assets (Global Markets)

FI loans – total commitment (in USD MM) – Model diagnostics

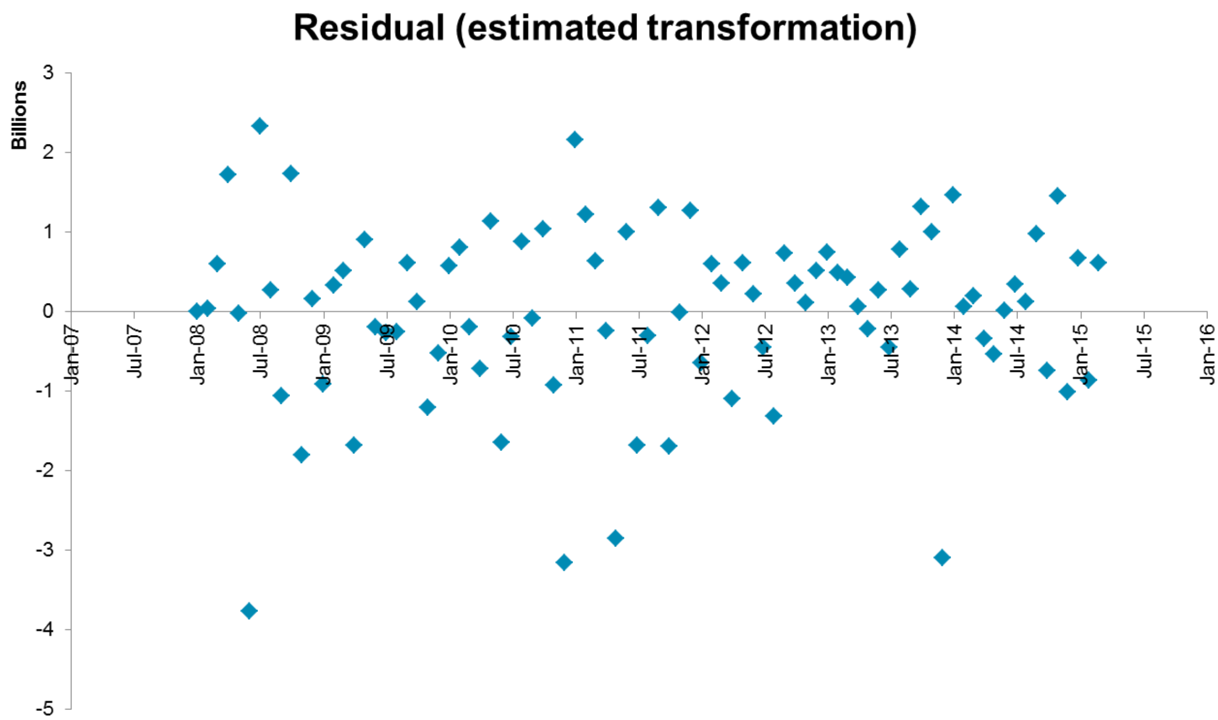
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	50%	-	-
	Adjusted R-squared	48%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	33%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.13	5	No multicollinearity
Linearity	RESET test	28%	10%	Linear specification appropriate

Figure 415: 9-quarter In-sample Prediction for Trading Assets (Global Markets)



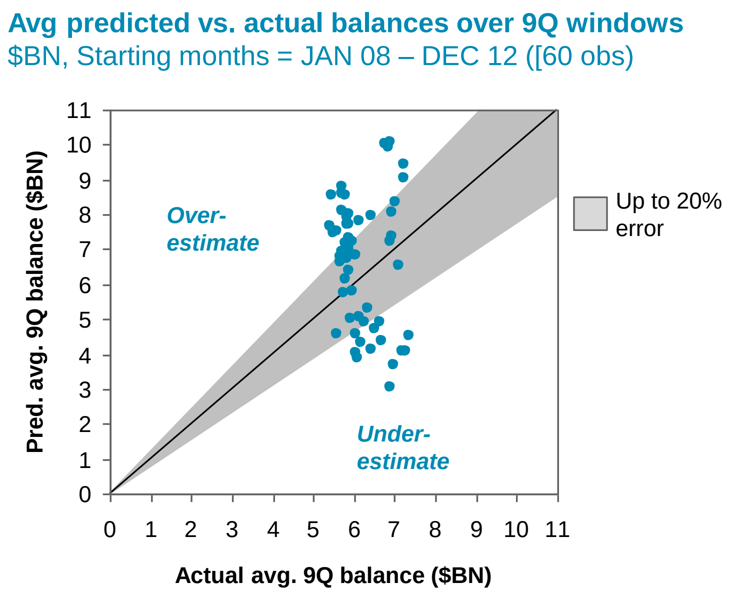
The in-sample back test of the model starting from January 2008 tracks fairly closely with the actual levels, capturing the correct directional behavior. The model fails to pick up a small portion of the decrease in balances in 2009, which leads to overestimation towards the end of the forecast window.

Figure 416: Residual Plot for Trading Assets (Global Markets) ($ BN)



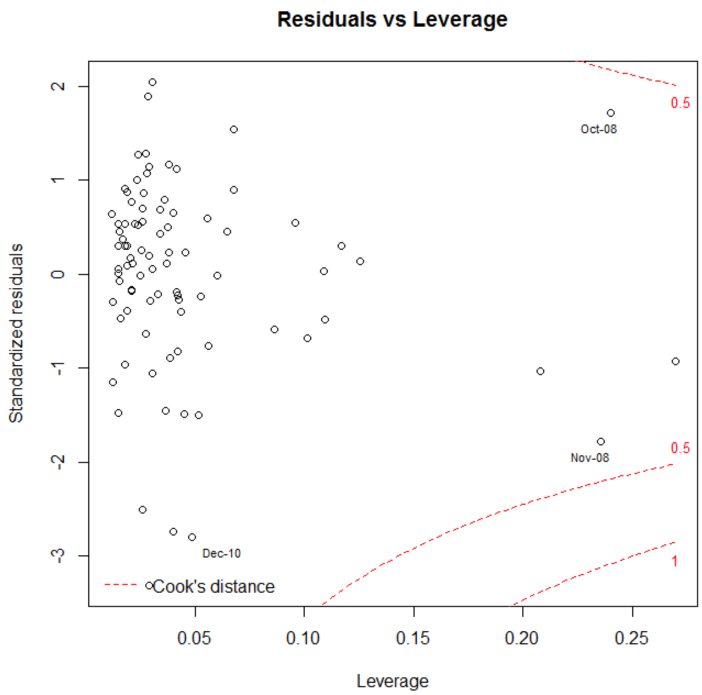
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 417: Estimation Scatterplot for Trading Assets (Global Markets)



Estimated average 9-quarter levels generally track with the actual average 9-quarter levels for different 9-quarter forecast windows, with the majority of average values within or close to 20% of actual average values. Outliers are due to forecast windows using starting months at local extrema, which lead to consistent overestimation or underestimation since the model is unable to pick up all of the volatility in the historical balances.

Figure 418: Influential points for Trading Assets (Global Markets)



The segment does not contain any highly influential points.

10.10.8. Model sensitivity

10.10.8.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 382: Sensitivity to changes to independent variables for Trading Assets (Global Markets)

Trading Assets (Global Markets) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
S&P volatility (30-day moving average)	First difference – MoM	Index	0.32	0.32	0.51

Trading Assets (Global Markets) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in deposit balances resulting from 1 std. dev change in the independent variable ($ BN)
Total Bond Issuance (ex mortgage, treasuries)	Percent change – MoM, 1M Lag	$ MM	-0.37	41.02	-0.59
5Y US Swap	First difference – MoM	%	-0.29	0.27	-0.47
Intercept	None (level)	%	N/A	N/A	N/A

10.10.8.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 383: Statistical sensitivity tests for Trading Assets (Global Markets)

Trading Assets (Global Markets) (in USD MM) – Statistical significance tests of model and variables

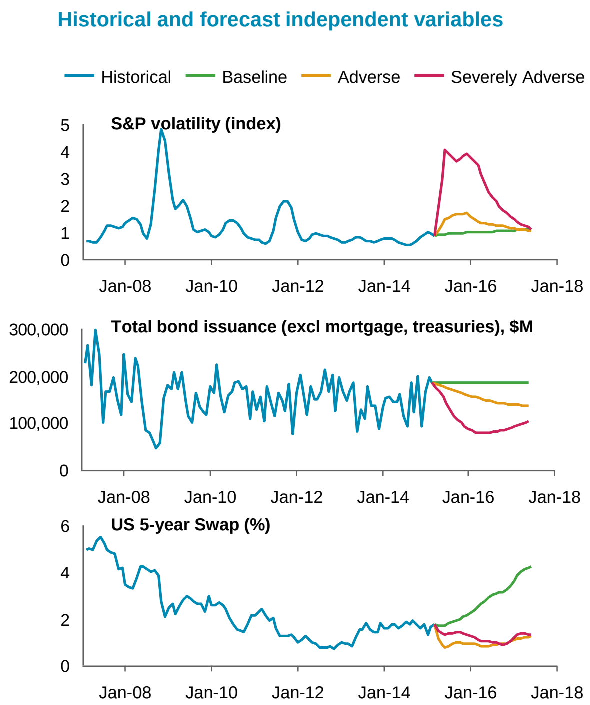
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
S&P volatility (30-day moving average)	1512.547	1629.735	0.58	Statistically insignificant
Total Bond Issuance (ex mortgage, treasuries)	-14.397	-12.466	0.53	Statistically insignificant
5Y US Swap	-1795.634	-1492.033	0.26	Statistically insignificant
Intercept	90.848		0.11	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.23	Statistically insignificant

10.10.8.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

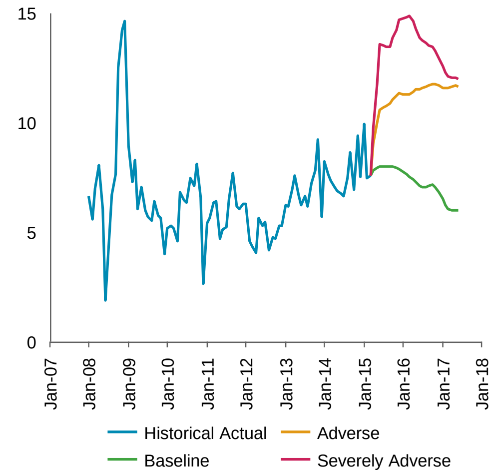
The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 419: Final model forecast for Trading Assets (Global Markets)



Historical and forecast balances for Trading assets (FX group)
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	-1.6 (-21%)	4.1 (54%)	4.44 (59%)	-
Start to peak	0.46 (6%)	4.19 (55%)	7.33 (97%)	8 (121%)
Start to trough	-1.6 (-21%)	N/A	N/A	-4.74 (-71%)



The Working Group did not have strong intuition for the forecast behavior of the variables behind the selected Trading Assets (Global Markets) model. Expert knowledge will also be used in the balance sheet forecasting review.

- **Severe recession (Severely Adverse) scenario:** The model predicts a significant rise in Trading Assets followed by a drop downwards. This is partially driven by the increase in S&P 500 volatility; consistent with the large spike observed during the 2008–2009 financial crisis.The magnitude and duration of the increase in balances in the severely adverse forecast are a result of the S&P volatility index. The S&P volatility index's assumption under severe adverse is in a bi-peak pattern. This is intuitional based on our driver selection process and discussion with working group and subject matter experts. Still, the results of this model should be monitored closely when the final outputs for submission are generated
- **Interest rate shock (Adverse) scenario**: The model predicts a rise in the Trading Assets (Global Markets) balances as a result of the negative coefficient on the US 5-year swap rate. The magnitude and even direction of this jump may be unintuitive, and therefore may require particular attention during management review and challenge
- **Baseline scenario**: The model predicts a decline in Trading Assets (Global Markets) under the baseline scenario. Management scrutiny is highly recommended to ensure the forecast aligns with expectations

10.10.9. Model limitations

The main model limitation is around the weak intuitiveness of the macroeconomic variables to explain balances in Trading Assets (Global Markets). The Working Group believed that using macroeconomic variables in a statistical model for this segment results in weak explanatory power, and will use the modeled results as a starting point while expert knowledge will also be used in the balance sheet forecasting review.

10.11. Trading Assets (Capital Markets)

10.11.1. Business overview

BNY Mellon's Trading Assets stem from its trading in derivatives, Global Markets, and Capital Markets, representing the groups that originated these balances. Each of these businesses has both interest bearing and non-interest bearing assets.

After multiple discussions with the Working Group and business, for CCAR purposes, the segmentations for Trading Assets are constructed along the business groups.

Trading assets include debt and equity instruments and derivative assets, primarily interest rate and foreign exchange contracts, not designated as hedging instruments. Trading assets (Capital Markets) represent those assets generated by the Capital Markets group as classified by MAQ.

10.11.2. General data issues

While BNY Mellon has three businesses that have balances under Trading Assets (Global Markets, Capital Markets, and Derivatives), MAQ rollup of the Derivatives business contains negligible balances, with the aggregate balances of the Global Markets and Capital Markets rollup comprising 100% of total Trading Assets. The segmentation used aligns to MAQ, which is the system of record for management accounting purposes.

10.11.3. Summary of approach

A statistical model that uses macroeconomic factors was found for Trading Assets (Capital Markets). However, the variables used in the forecast were considered unintuitive based on discussion with the BNY Mellon Working Group and business. Macroeconomic variables provide weak explanation for trading activities that drive this segment; management scrutiny and are needed in on-going monitoring.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for Trading Assets (Capital Markets), which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 384: Coefficient estimates for selected model for Trading Assets (Capital Markets)

Trading Assets (Capital Markets) (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
S&P Vol (30D MAVG)	First difference – MoM	Index	296.29	0.29
10 Year US T-Note Volatility Index	Percent change – QoQ	%	-3.50	-0.24
Total Bond Issuance (ex MBS, gov)	First difference – QoQ	$ MM	0.002	0.24
Intercept	None (level)	$ MM	27.69	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – 30-day moving average of close-of-day values of VIX, measuring S&P volatility
- **Market volatility/uncertainty (rates) –** 10-year US T-Note Volatility Index
- **Debt issuances –** Total US Bond Issuance, excluding MBS and government bonds

In a review and challenge meeting, the line of business stated that there is low intuition in using any macroeconomic variables to forecast balances. However, the Working Group decided to employ a statistical model as a base for forecasts, with full expectation that significant management scrutiny will be needed in on-going monitoring.

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

10.11.4. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

10.11.4.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The Trading Assets (Capital Markets) is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 385: Unit root tests and stationarity tests including a trend variable on balances

Trading Assets (Capital Markets) – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-1.5	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.1	0.93	Fail to reject unit root
KPSS	5	0.15	0.04	Reject stationarity

Table 386: Unit root tests and stationarity tests including a constant on first differences

Trading Assets (Capital Markets) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-7.5	<0.01	Reject unit root
Phillips-Perron	1	-7.6	<0.01	Reject unit root
KPSS	2	0.19	0.29	Fail to reject stationarity

Stationarity tests for Trading Assets (Capital Markets) balances states that the ADF and PP tests failed to reject a unit root and the KPSS test rejects stationarity. These results suggest the segment's balances may be non-stationary. In contrast, the monthly first difference series passed all tests. These results strongly suggest that the first differences series is stationary. As such, the choice was made to model using first difference.

10.11.4.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

By the nature of its business, the balances in the Trading Assets (Capital Markets) are volatile. However, the balances observed through the historical period of January 2008 to March 2015 did not show any issues beyond this expected volatility.

10.11.5. Hypotheses and independent variable indentification

Based on discussions with the Working Group, the ALM team, Credit Risk, and the line of business, it was determined there was weak intuition in using macroeconomic factors to model this segment. Therefore, the modeling team allowed the full set of independent variables in candidate models, noting that the weak intuition on drivers would necessitate management review of results.

10.11.6. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Trading Assets (Capital Markets) are statistically significant. The intercept is found to be statistically insignificant.

Table 387: Statistical significance tests of model and variables for Trading Assets (Capital Markets)

Trading Assets (Capital Markets) (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	3.93	1%	10%	Statistically significant
S&P Vol (30D MAVG)	296.29	2%	10%	Statistically significant
10 Year US T-Note Volatility Index	-3.50	4%	10%	Statistically significant
Total Bond Issuance (ex MBS, gov)	0.002	3%	10%	Statistically significant
Intercept	27.69	45%	10%	Statistically not significant

10.11.7. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable

- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

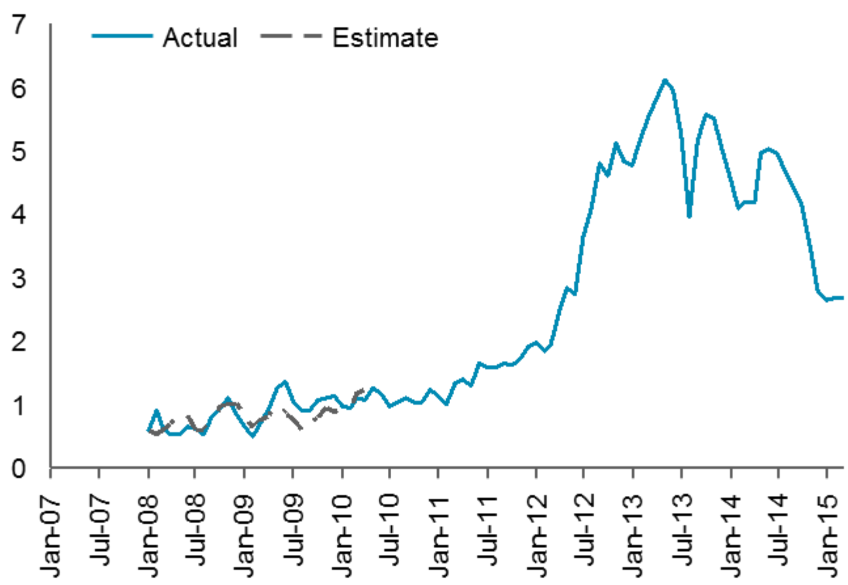
The diagnostic tests reviewed are exhibited below.

Table 388: Model Diagnostics for Trading Assets (Capital Markets)

FI loans – total commitment (in USD MM) – Model diagnostics

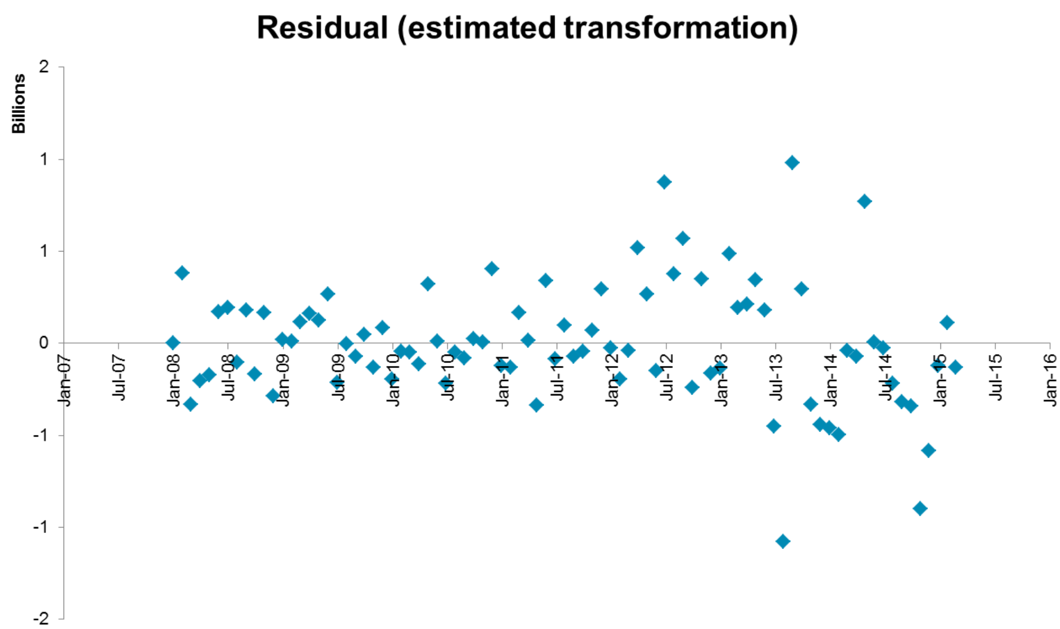
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	13%	-	-
	Adjusted R-squared	9%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	71%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	21.82%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.28	5	No multicollinearity
Linearity	RESET test	34%	10%	Linear specification appropriate

Figure 420: 9-quarter In-sample Prediction for Trading Assets (Capital Markets)



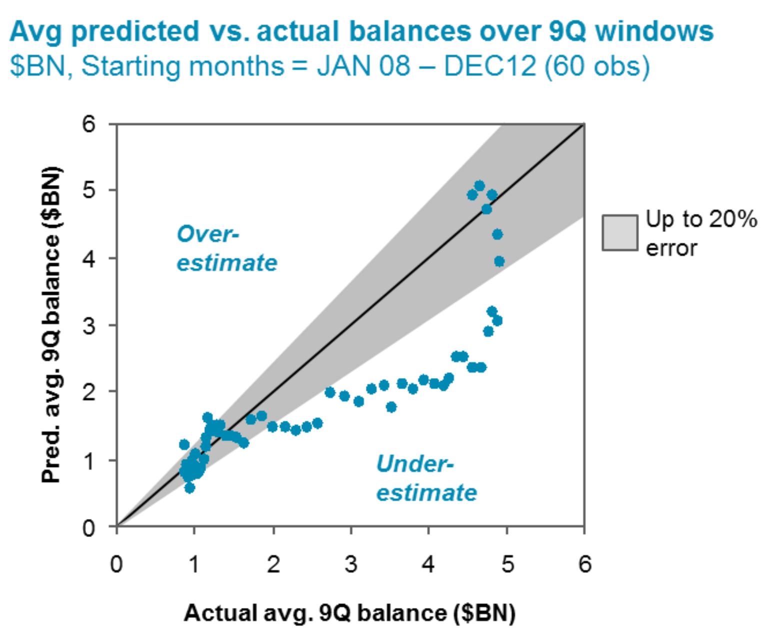
The in-sample back test of the model starting from January 2008 tracks very closely with the actual levels.

Figure 421: Residual Plot for Trading Assets (Capital Markets) ($ BN)



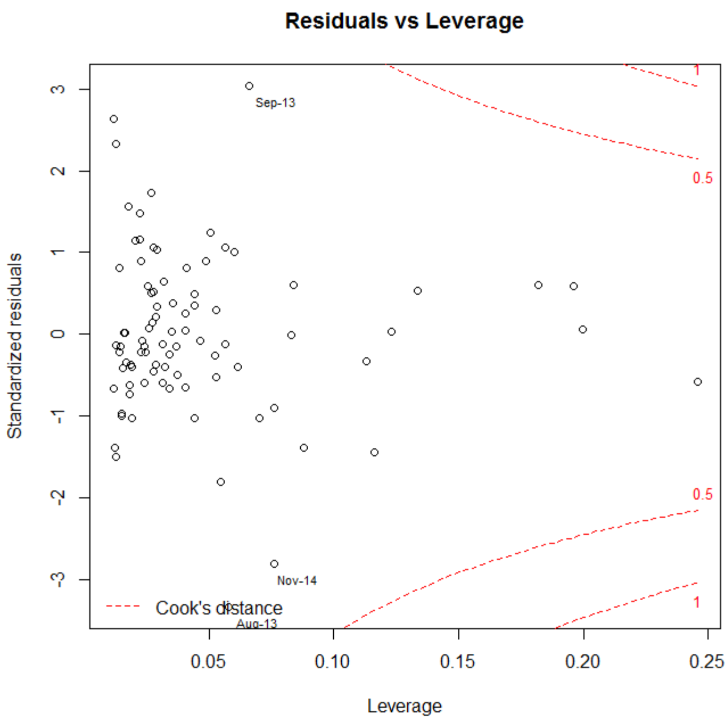
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 422: Estimation Scatterplot for Trading Assets (Capital Markets)



Estimated average 9-quarter levels generally track with the actual average 9-quarter levels for different 9-quarter forecast windows, with the majority of average values within or close to 20% of actual average values. Outliers are due to forecast windows using starting months at local extrema, which lead to consistent overestimation or underestimation since the model is unable to pick up all of the volatility in the historical balances.

Figure 423: Trading Assets (Capital Markets)



The segment does not contain any highly influential points.

10.11.8. Model sensitivity

10.11.8.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 389: Sensitivity to changes to independent variables for Trading Assets (Capital Markets)

Trading Assets (Capital Markets) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
S&P Vol (30D MAVG)	First difference – MoM	Index	0.29	0.32	0.10
10 Year US T-Note	Percent change – QoQ	%	-0.24	24.65	-0.08

Volatility Index					
Total Bond Issuance (ex MBS, gov)	First difference – QoQ	$ MM	0.24	46193.40	0.08
Intercept	None (level)	%	N/A	N/A	N/A

10.11.8.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically significant collectively. This suggests the model may not maintain stability when removing observations from the development data. In addition, the coefficient of the S&P volatility and total bond issuance variables are significant individually.

Table 390: Statistical sensitivity tests for Trading Assets (Capital Markets)

Trading Assets (Capital Markets) (in USD MM) – Statistical significance tests of model and variables

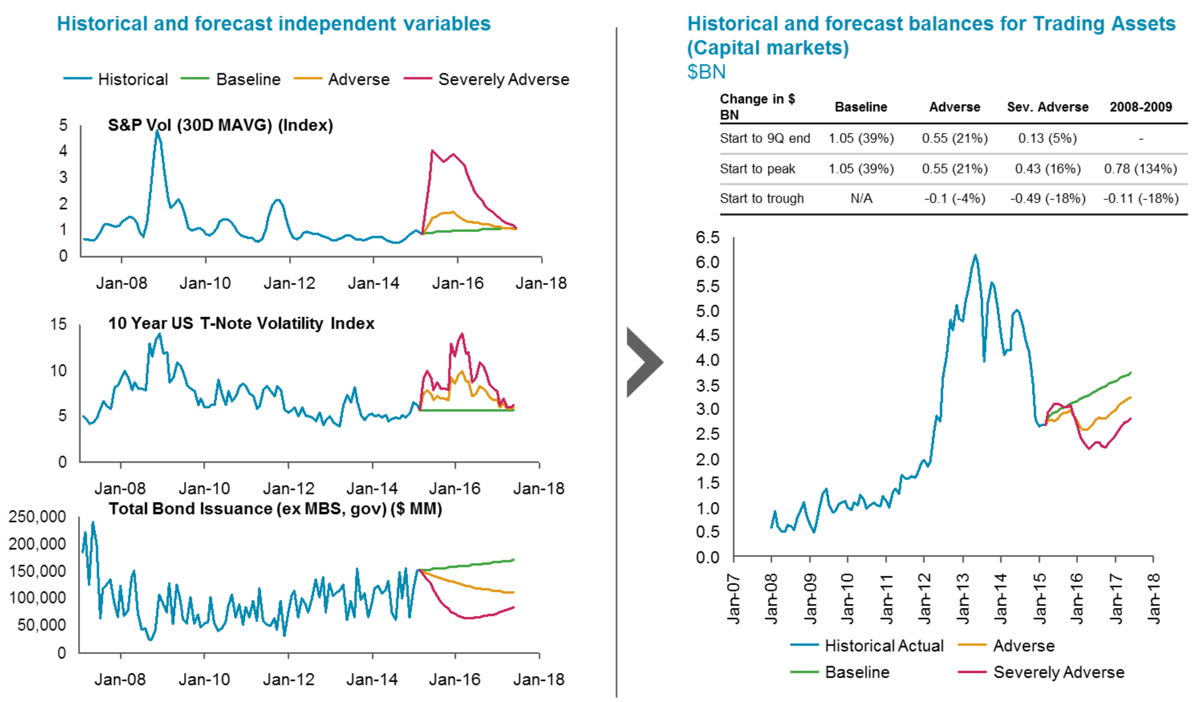
Tested independent variable	Original coefficient estimate	Sum of coefficients	P-value of shortened period coefficient	Conclusion
S&P Vol (30D MAVG)	-	236.152	0.03	Statistically significant
10 Year US T-Note Volatility Index	296.290	-1.913	0.50	Statistically insignificant
Total Bond Issuance (ex MBS, gov)	-3.503	0.001	0.06	Statistically significant
Intercept	0.002		0.04	Statistically significant
Chow-test on all shortened period coefficients	-	-	0.00	Statistically significant

10.11.8.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 424: Final model forecast for Trading Assets (Capital Markets)



The Working Group did not have strong intuition for the forecast behavior of the variables behind the selected Trading Assets (Capital Markets) model. Management review will be needed.

- **Severe recession (Severely Adverse) scenario:** The model predicts an increase followed by a sharp drop in Trading Assets (Capital Markets). Given the limited intuition from the business and Working Group, expert knowledge will also be used in the balance sheet forecasting review.
- **Interest rate shock (Adverse) scenario**: Similar to the severe recession scenario, the model predicts a short rise followed by a drop and then an increase in the balance of Trading Assets (Capital Markets). Similar to the severe recession scenario, management scrutiny would be required
- **Baseline scenario**: The model predicts a steady rise in the balances of Trading Assets (Capital Markets) as the independent variables selected tend to trend slowly upwards. These results should be reviewed and challenged by management to ensure alignment with expectations and intuition

10.11.9. Model limitations

The main model limitation is around the weak intuitiveness of the macroeconomic variables to explain balances in Trading Assets (Global Markets). The Working Group believed that using macroeconomic variables in a statistical model for this segment results in weak explanatory power, and will use the modeled results as a starting point while expert knowledge will also be used in the balance sheet forecasting review.

10.12. Non-interest earning assets (excluding Goodwill and Intangibles)

10.12.1. Business overview

Non-interest earning assets (excluding Goodwill and Intangibles) consist of assets that do not produce interest income for BNY Mellon. This segment specifically excludes Goodwill and Intangibles, because the two segments can be treated with accounting rules.

Components of this segment include:

- Accrued Interest Receivable
- Accounts Receivable
- Bank-owned Life Insurance
- Cash and Due
- Coin and Currency
- Income Tax Receivable
- Premises and Equipment
- Pre-paid Expenses
- Reserve for Loan Loss
- VIE Assets

As a whole, the components in this segment do not have a strong correlation to macroeconomic factors, and therefore the Working Group deemed that a qualitative framework would be appropriate for this segment.

10.12.2. Historical data

Figure 425: Spot balances for Non-interest earning asset (excluding Goodwill, Intangibles) ($BN)

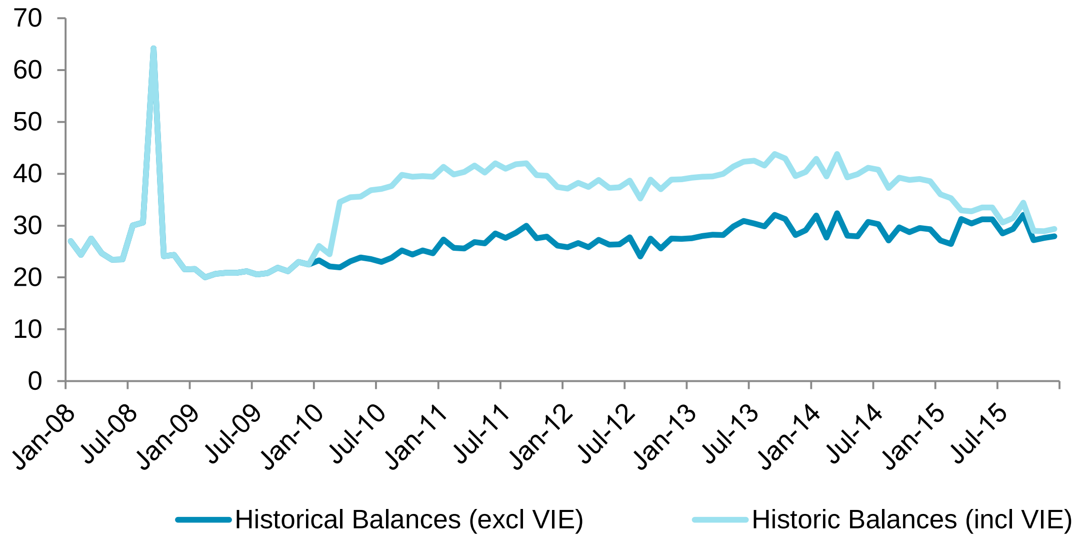
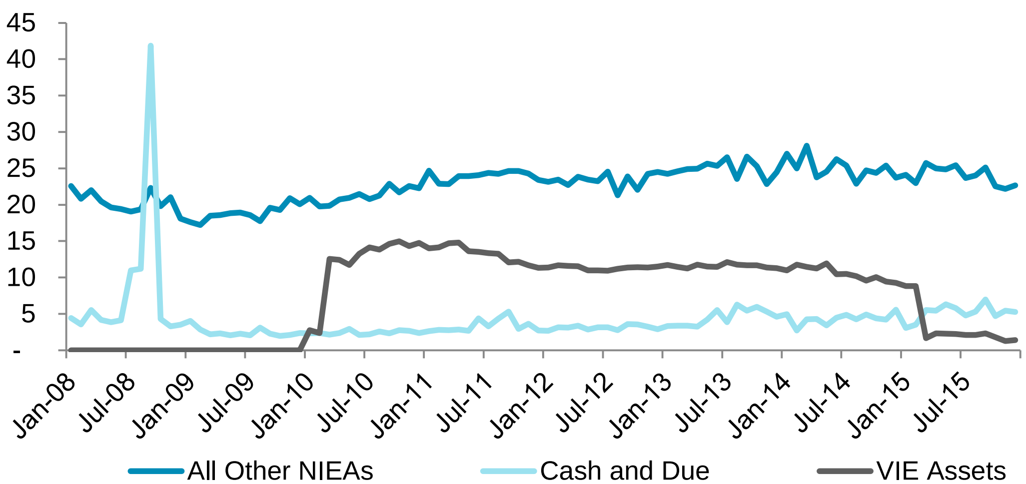


Figure 426: Non-Interest Earning Assets Line Item Monthly Balances, excl Goodwill, Intangibles ($BN)



As shown in figure 1, outside of the accounting adjustments and one time spike in the Cash and Due line item, the segment's balances are relatively stable over time. The accounting adjustments noted are due to changes in the accounting treatment for VIE Assets: in 2010 and 2015, VIE assets were consolidated and deconsolidated (respectively) from the balance sheet.

The spike in the NIEA segment that occurred in the third quarter of 2008 represents a momentary spike in the NIEA Cash and Due line item: although the spot balance of the spike in September 2008 was $41.9 billion, the average Cash and Due balance in that month was only $12.3 billion, indicating a momentary spike which quickly returned to lower levels. Given how much higher the spot balance is than the average, it is likely that balances only remained at $41.9bn for a few days. This spike was likely due to the highly liquid, cash-based nature of this segment, rather than to macroeconomic drivers.

10.12.3. Data issues

As a result of accounting regulation changes (discussed in further detail below), large adjustments were made in March 2015 and June 2015 to bring quarterly averages in line with restated amounts. To prevent these adjustments from impacting the forecasts for this segment, the forecasting approach first considered VIE Asset balances separately from the rest of the sub-segments in this segment.

In February 2015, the FASB issued ASU 2015-02 "Amendments to the Consolidation Analysis", an amendment to ASC 810, Consolidation. This ASU eliminated the indefinite deferral of ASU 2010–2010 "Amendments for Certain Investment Funds" for asset management funds with characteristics of an investment company and also eliminated the presumption that a general partner should consolidate a limited partnership. Entities that comply with or operate in accordance with the requirements that are similar to those of Rule 2a-7 of the Investment Company Act of 1940 for registered money market funds are excluded from the scope of the ASU. This ASU also changed the consolidation analysis, particularly when a reporting entity has fee arrangements that meet certain requirements and for related party relationships.

The ASU is effective January 1, 2016, with early adoption permitted during an interim period in fiscal year 2015. In the second quarter of 2015, BNY Mellon elected to early adopt the new accounting guidance retrospectively to January 1, 2015. As a result results were restated in the first quarter 2015 financial statements.

Adoption of the ASU resulted in a net decrease in consolidated total assets on BNY Mellon's balance sheet at January 1, 2015 of $7.7 BN, a decrease of approximately 2%. When evaluating an entity for possible consolidation, BNY Mellon must determine whether or not it has a variable interest in the entity. Variable interests are investments or other interests that absorb portions of an entity's expected losses or receive portions of the entity's expected returns. BNY Mellon's variable interests may include its decision maker or service provider fees, its direct and indirect investments and investments made by related parties, including related parties under common control. If it is determined that BNY Mellon does not have a variable interest in the entity, no further analysis is required and BNY Mellon does not consolidate the entity.

BNY Mellon's VIEs generally include certain retail, institutional and alternative investment funds, including CLOs offered to its retail and institutional customers in which it acts as the fund's investment manager. The funds are established to provide BNY Mellon clients access to investment vehicles with specific investment objectives and strategies that address the client's investment needs. BNY Mellon earns investment management fees on these funds as well as performance fees in certain funds. BNY Mellon may also provide start-up capital for new funds. The VIEs are primarily financed by the customer's investments in the funds' equity or debt.

As shown in figure 1, outside of the accounting adjustments and one time spike in the Cash and Due line item, the segment's balances are relatively stable over time. The accounting adjustments noted are due to changes in the accounting treatment for VIE Assets: in 2010 and 2015, VIE assets were consolidated and deconsolidated (respectively) from the balance sheet.

The spike in the NIEA segment that occurred in the third quarter of 2008 represents a momentary spike in the NIEA Cash and Due line item: although the spot balance of the spike in September 2008 was $41.9 billion, the average Cash and Due balance in that month was only $12.3 billion, indicating a momentary spike which quickly returned to lower levels. Given how much higher the spot balance is than the average, it is likely that balances only remained at $41.9bn for a few days. This spike was likely due to the highly liquid, cash-based nature of this segment, rather than to macroeconomic drivers.

As a whole, the components in this segment do not have a strong correlation to macroeconomic factors, and therefore the Working Group deemed that a qualitative framework would be appropriate for this segment.

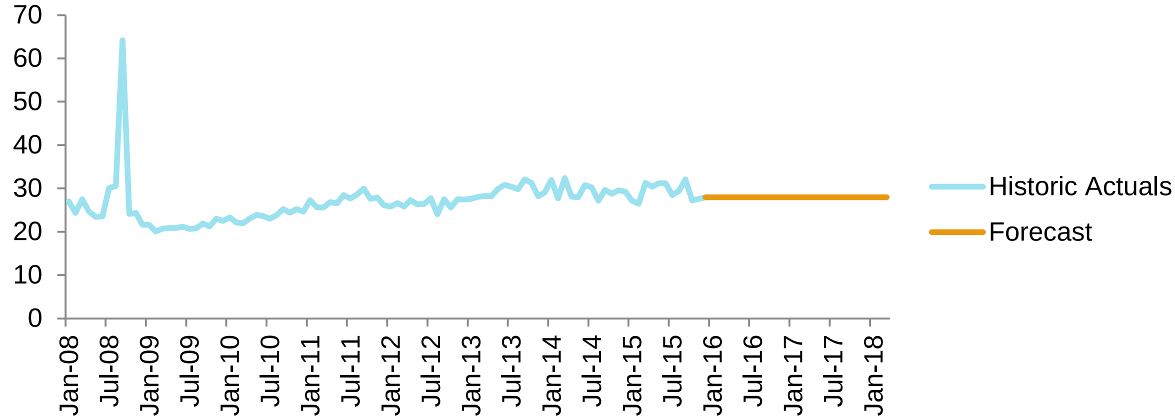
10.12.4. Summary of approach

Based on discussion with the Working Group, it was originally hypothesized that NIEA (excluding Goodwill and Intangibles) can be grown at the historical growth rate while holding VIE Assets flat.

However, the data received pointed strongly to a static trend in the remaining balances of the segment, excluding VIE Assets. Application of a historical growth rate would be sensitive to the historical time period selected to calculate the growth rate. The forecast will instead hold the entire segment constant to the December 2015 spot balance, excluding the remaining VIE assets that remain on the balance sheet in December 2015, as they are in run-off and expected to decrease to zero in the future.

The results hold the forecast at the December 2015 spot balance for the NIEA segment, excluding the remaining NIEA VIE assets still on the balance sheet. Because VIE Assets were deconsolidated from the balance sheet in 2015 and do not impact the forecast, the graph below shows historic actuals without VIE assets included. The December 2015 spot balance (excluding VIE) was $27.9 billion:

Figure 427: Non-Interest Earning Assets: Historic and Forecasted Balances ($BN)



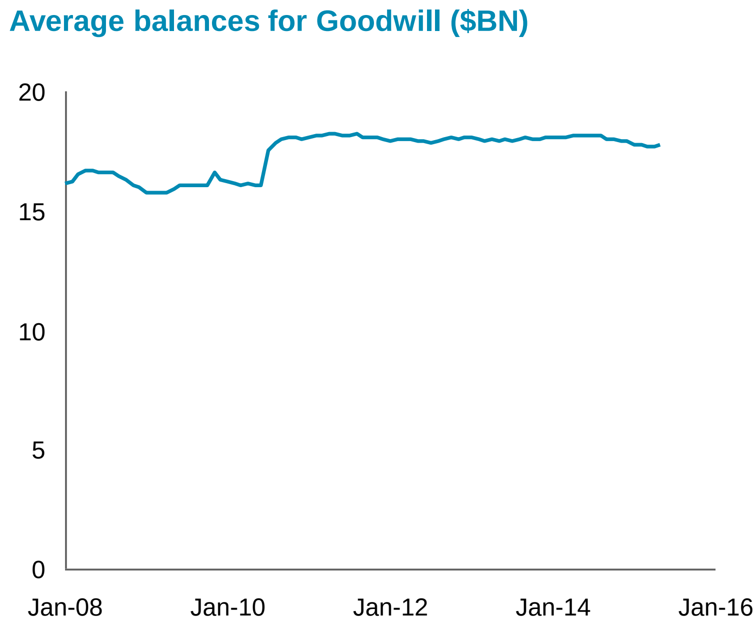
10.13. Non-interest earning assets: Goodwill

10.13.1. Business overview

Goodwill covers payments made by BNY Mellon for acquisitions exceeding the fair market value of the acquired companies' assets and liabilities. As of April 2015 Goodwill accounted for $18 BN on BNY Mellon's balance sheet, with the Goodwill related to the merger with Mellon Financial at approximately $16 BN of this total. As such, Goodwill balances are driven primarily by episodic acquisitions, which are not directly related to macroeconomic conditions. Therefore a statistical model would be inappropriate.

10.13.2. Historical data

Figure 428: Average balances for Goodwill ($ BN)



Historic data for Goodwill has held flat overtime, except in cases where acquisitions were made by BNY Mellon.

10.13.3. General data issues

No data issues were discovered in the historical actuals reviewed.

10.13.4. Summary of approach

To align with accounting regulations, this segment utilizes a qualitative framework that is consistent with US GAAP.

Goodwill with indefinite lives is not amortized, but is assessed annually for impairment or more often if events and circumstances indicate it is more likely than not they may be impaired. Under US GAAP (FAS 142) issued in June 2001, Goodwill can no longer be amortized and may only be impaired. The BNY Mellon Working Group assumes that no impairment will take place under baseline or stress scenarios. Therefore, the balance forecast will be held constant to the most recent historical month.

This embeds an assumption that no impairment will take place under baseline or stress, which was viewed as appropriate given that the decision to impair Goodwill is based in part on management judgment and business-specific performance that cannot be codified into a set of fixed rules for CCAR execution

10.13.5. Model limitations

Accounting regulations require the treatment of Goodwill as mentioned above. However, the decision of whether impairment is necessary or not is based on underlying business models that assess the value of the goodwill in question. In the case of scenario forecasting, however, an assumption must be made as a detailed review of business model and performance for a specific acquisition is likely not possible.

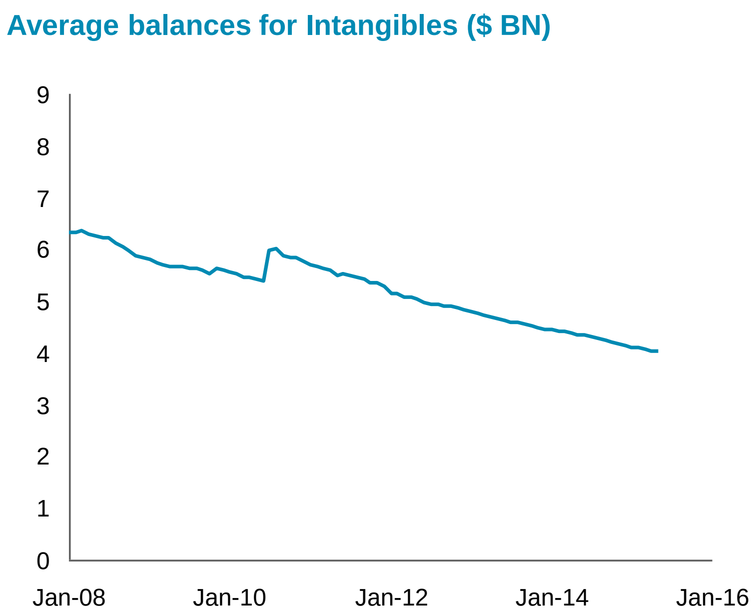
10.14. Non-interest earning assets: Intangibles

10.14.1. Business segment

Intangible assets are non-physical assets with definite lives that are either acquired or developed internally by BNY Mellon companies. As of April 2015, intangibles accounted for $4.1 BN on the balance sheet.

10.14.2. Historical data

Figure 429: Average balances for Intangibles ($ BN)



Historic data for Intangibles has steadily decreased over time due to amortization, except in cases where new intangible assets with definite lives are created or bought by BNY Mellon.

10.14.3. General data issues

No data issues were discovered in the historical actuals reviewed.

10.14.4. Summary of approach

To align with accounting regulations, this segment utilizes a qualitative framework that is consistent with the requirements under US GAAP. BNY Mellon's identified intangible assets are amortized in a schedule consistent with the assets' identifiable cash flows if they have estimable lives, or using a straight-line method over their remaining estimated benefit periods if the pattern of cash flows is not estimable. Intangibles are forecasted using a straight-line following the internal bank schedule of amortization, including a recent acquisition. The schedule of amortization through 2018 is presented below, and aligns with the bank's financial reporting and internal accounting as represented in the bank's 10-K filing.

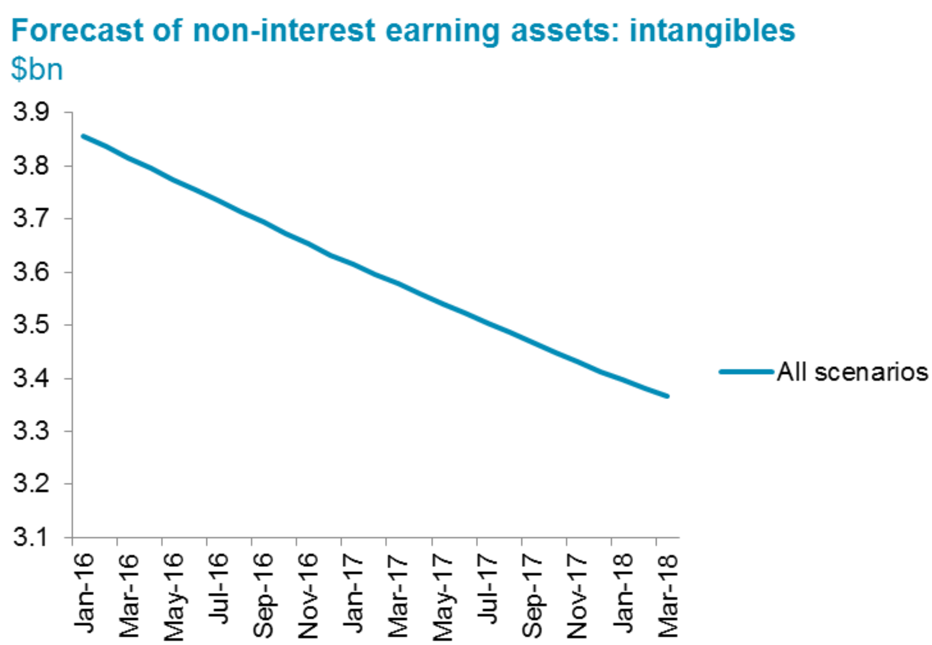
Figure 430: Intangible amortization schedule

Intangible amortization schedule
$mm

2016	245
2017	220
2018	186

Following this amortization schedule results in the following forecast:

Figure 431: Forecast of non-interest earning assets: intangibles



10.14.5. Approach limitations

Accounting regulations require the treatment of Intangibles as mentioned above. BNY Mellon management ensures that the proper accounting classifications and assumptions are followed in order to meet accounting guidelines. The qualitative framework does not take any impairment into account outside of expected amortization.

10.15. Trading Liabilities (Global Markets)

10.15.1. Business overview

In addition to Trading Assets discussed earlier, BNY Mellon has Trading Liabilities stemming from the derivatives, Global Markets, and Capital Markets businesses. Trading Liabilities include debt instruments, equity instruments, and derivative liabilities (primarily interest rate and foreign exchange contracts), not designated as hedging instruments.

In line with the segmentations for Trading Assets, the Trading Liabilities segmentation were constructed along the business group lines.

Trading Liabilities (Global Markets) represents those liabilities generated by the BNY Mellon Global Markets business.

10.15.2. General data issues

The historical data for Trading Liabilities come from an organizational structure in MAQ that attributes whether the balance belongs to the Global Markets or the Capital Markets group.

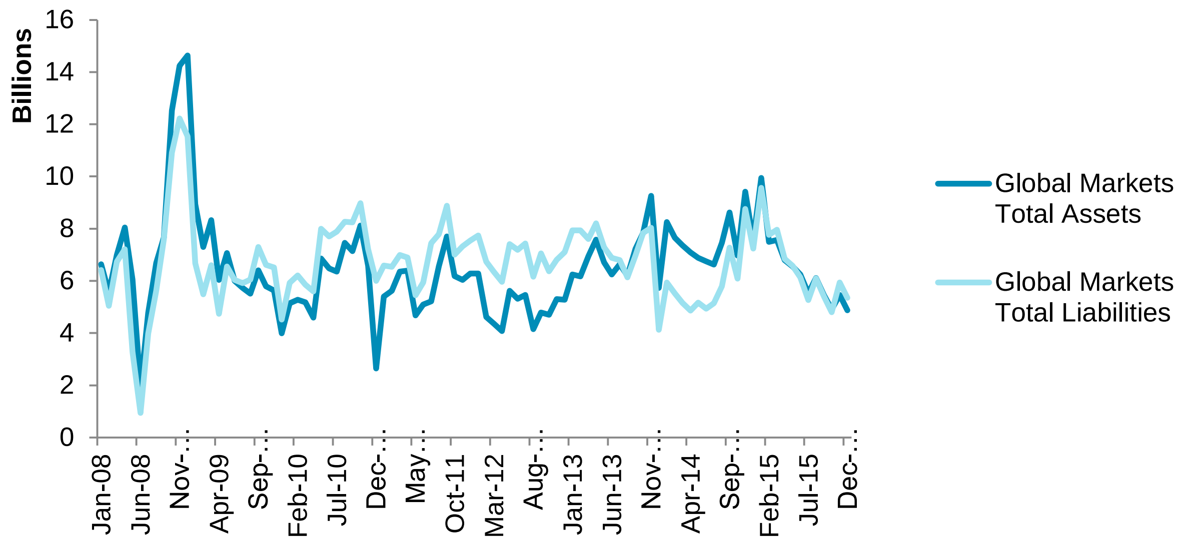
While BNY Mellon has three groups that generate balances under Trading Liabilities Global Markets, Capital Markets, and Derivatives, the aggregated balance of the Derivatives group in MAQ is negligible, with the aggregate balances of Global Markets and Capital Markets comprising 100% of the total Trading Liabilities balance.

10.15.3. Summary of approach

While the BNY Mellon business experts and Working Group considers Trading Assets and Trading Liabilities demonstrate strong correlation to one another. Trading assets and liabilities for Global Markets are dominated by the accounting present values of notional amounts due and owing on Global Markets swaps, respectively. Aside from the present value from embedded interest rate differences and the impact of netting allowances, these balances will tend to moving together.

Thus, the Trading Assets historical and forecast balances will be used to forecast the balances of Trading Liabilities. For reasons of consistency and parsimony, a decision was made to tie the Trading Liabilities to the Trading Assets for this Global Markets.

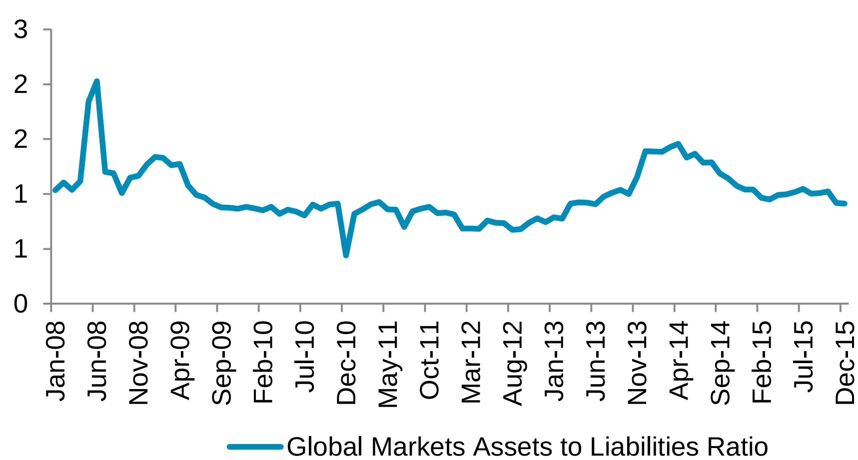
Figure 432: Historic Global Markets Assets and Liabilities



The decision to forecast Trading Liabilities based on Trading Assets, with Trading Assets forecast based on a statistical model, was based on the Working Group's assessment of the relative strength of models developed on each time series.

To forecast Trading Liabilities based on Trading Assets, the average monthly ratio of Trading Assets to Liabilities is first calculated. The average ratio of Trading Assets (Global Markets) to Trading Liabilities (Global Markets) from January 2008 to December 2015 is shown in the chart below. The table next to it reports descriptive statistics of this ratio, namely its average, minimum and maximum.

Figure 433: Historic Global Markets Assets to Liabilities Ratio



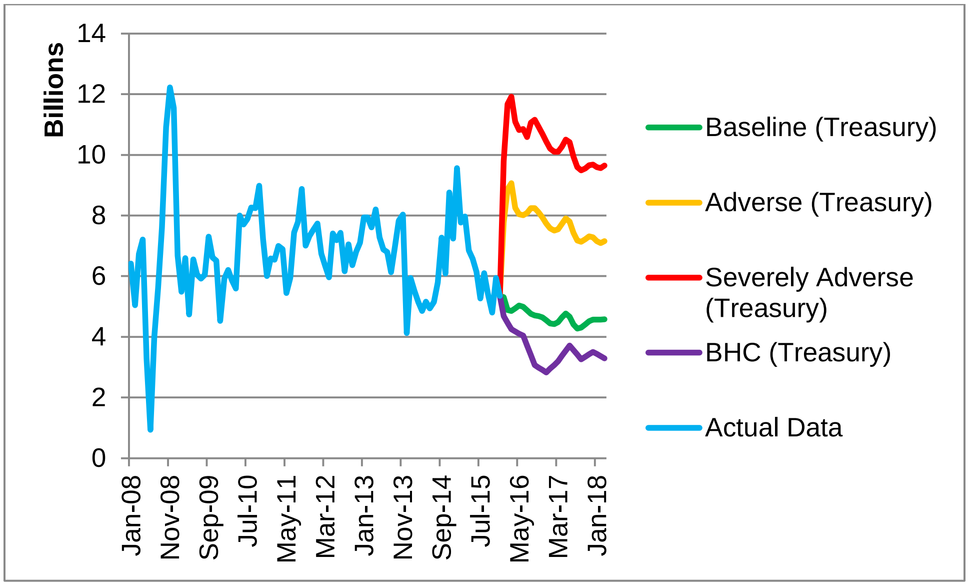
Avg	**1.00**
Min	**0.44**

Max	**2.026926**

This average ratio is then applied to the Trading Assets forecast based on a statistical model, in order to determine the monthly Trading Liabilities forecast:

Trading Liabilities Forecast = Trading Assets forecast / average historic ratio

Figure 504: Historical and forecast balances for Trading Liability (Global Markets) based on Simple Model



10.15.4. Model limitations

Given this approach, the quality of the Trading Liabilities (Global Markets) model will share the same limitations as the Trading Assets (Global Markets) model.

10.16. Trading Liabilities (Capital Markets)

10.16.1. Business overview

BNY Mellon has Trading Liabilities stemming from the Global Markets and Capital Markets businesses. The Trading Liabilities (Capital Markets) described in this document represents those liabilities generated by the BNY Mellon Capital Markets business.

10.16.2. General data issues

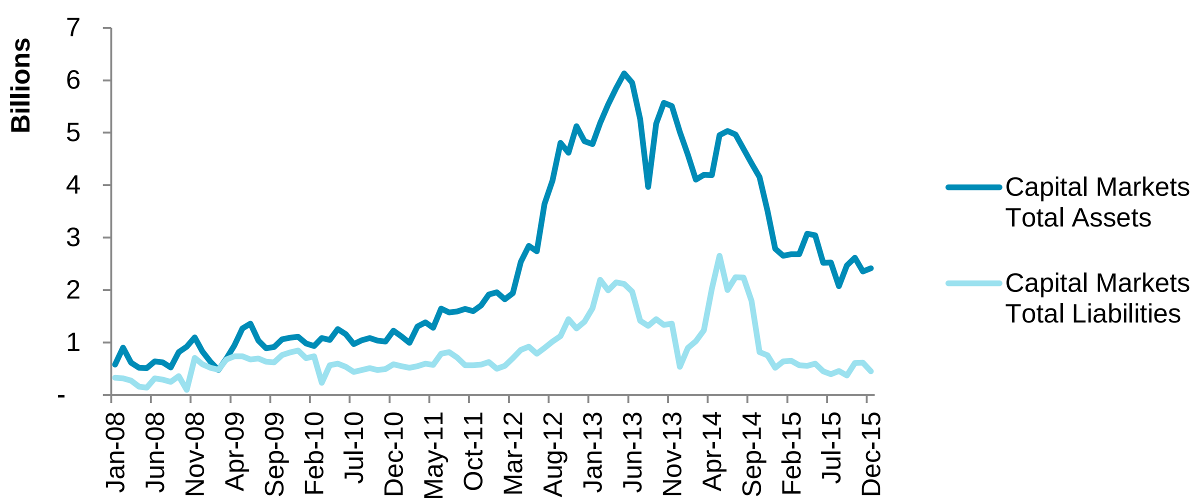
The historical data for Trading Liabilities come from an organizational structure in MAQ that attributes whether the balance belongs to the Global Markets or the Capital Markets group.

While BNY Mellon has three groups that generate balances under Trading Liabilities Global Markets, Capital Markets, and Derivatives, the aggregated balance of the Derivatives group in MAQ is negligible, with the aggregate balances of Global and Capital Markets comprising 100% of the total Trading Liabilities balance.

10.16.3. Summary of appraoch

While the BNY Mellon business experts and Working Group considers Trading Liabilities generated by the Capital Markets group have a strong correlation to the Trading Asset balances generated by the same business group. For reasons of consistency and parsimony, a decision was made to not build an independent model with macroeconomic variable drivers for Trading Liabilities. Instead, this segment's forecast is tied directly to the forecast of the corresponding Trading Assets. The decision to forecast Trading Liabilities based on Trading Assets was based on the Working Group's assessment of the relative strength of models developed on each time series.

Figure 434: Historics for Capital Markets Assets and Liabilities

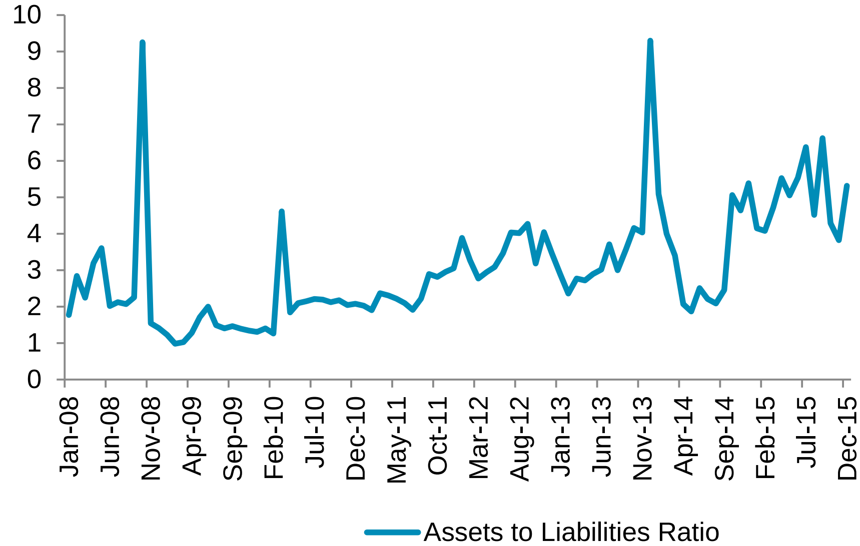


The decision to forecast Trading Liabilities based on Trading Assets, with Trading Assets forecast based on a statistical model, was based on the Working Group's assessment of the relative strength of models developed on each time series.

To forecast Trading Liabilities based on Trading Assets, the average monthly ratio of Trading Assets to Liabilities is first calculated. The average ratio of Trading Assets (Capital Markets) to Trading Liabilities (Capital Markets) from January 2008 to December 2015 is shown in the graph below. The table next to it reports descriptive statistics of this ratio, namely its average, minimum and maximum.

Avg.	**3.059076**
Min	**0.986479**
Max	**9.295907**

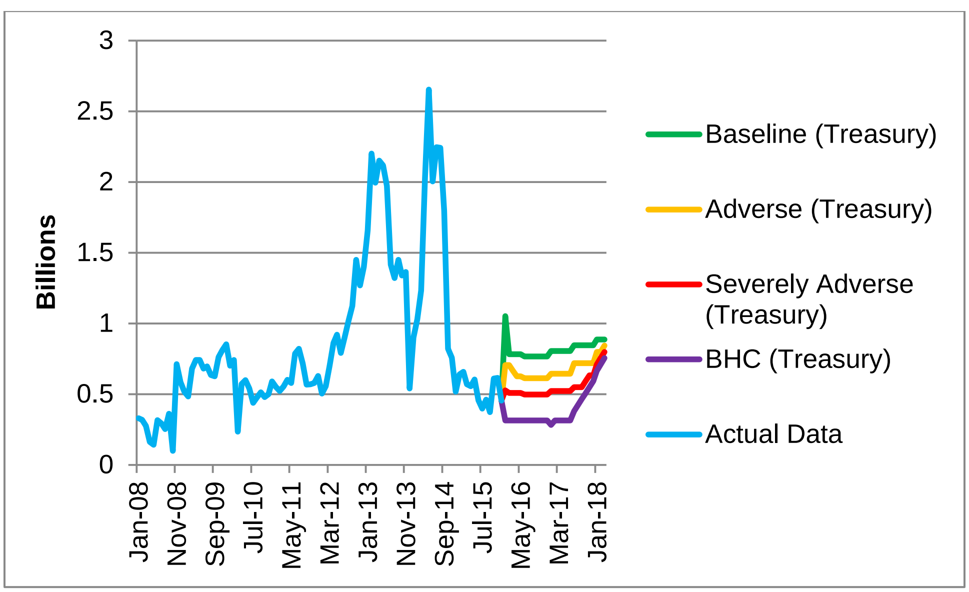
Figure 435: Historic Ratio of Capital Markets Trading Assets to Liabilities



This average ratio is then applied to the Trading Assets forecast based on a statistical model, in order to determine the monthly Trading Liabilities forecast:

Trading Liabilities Forecast = Trading Assets forecast / average historic ratio

Figure 505: Historical and forecast balances for Trading Liability (Capital Markets) based on Simple Model



10.16.4. Model limitations

The Trading Liabilities (Capital Markets) model will share the same limitations as the Trading Assets (Capital Markets) model, due to the selected forecasting approach.

10.17. Short-term borrowings: Broker-Dealer Payables and Customer Payables

10.17.1. Business overview

Payables to customers and broker-dealers represent funds awaiting re-investment and short sale proceeds payable on demand. Payables to customers and broker-dealers are driven by customer trading activity levels and market volatility.

10.17.2. Summary

A statistically sound model that is consistent with business intuition was found for Broker-Dealer Payables and Customer Payables segment. Some management scrutiny may be needed for stress forecasts to ensure that the projected movements in balances are not overly extreme given management expectations.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation of the total commitment time series for commercial loans, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 391: Coefficient estimates for selected model for Broker-Dealer and Customer Payables

Broker-Dealer and Customer Payables (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Market Volatility	First difference – MoM	Index	35.350	0.43
KBW Bank Index	Percent change – MoM	Index	17.237	0.25
Intercept	None (level)	$ MM	170.596	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – 30-day moving average of VIX, which measures implied volatility of S&P 500 index options

- **Equity Markets –** KBW Bank Index, a common benchmark of the banking sector performance

The intuition of these variables is as follows:

- The S&P volatility variable has a positive coefficient; when equity markets are more volatile, increased volume of trading activity may lead to higher volumes of payables
- KBW Bank Index variable has a positive coefficient; when there is improved performance in the banking sector, overall volume of trading activity may increase, which would lead to higher volumes of payables

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs, noting also that the bank's risk appetite would be a constraint on the overall total commitments.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 436: Candidate models for Broker-Dealer and Customer Payables

Broker dealer payables
Candidate models

	Candidate models			
Driver	**1**	**2**	**3**	**4**
General economic health				
Relative credit worthiness of BNYM				BNYM – peer group debt yield spread (Diff MoM, 1m lag)
Equity markets	KBW Bank Index (% MoM)			KBW Bank Index (% MoM)
Market volatility/ uncertainty	Market volatility (Diff MoM)	1 week LIBOR 1 week OIS spread (Diff MoM)	Market volatility (Diff MoM)	S&P volatility (% MoM)
Short-term rates				
R-squared (balances)	**92%**	**91%**	**92%**	**92%**
R-squared (differences)	**21%**	**17%**	**15%**	**14%**

Recommended model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results

- Sensitivity tests and results

10.17.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

10.17.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The total commitment time series for the Broker-Dealer and customer payables segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 392: Unit root tests and stationarity tests including a trend variable on balances

Broker-Dealer and Customer Payables – Unit root test with trend on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	1	-1.4	>0.10	Fail to reject unit root
Phillips-Perron	1	-1.7	0.74	Fail to reject unit root
KPSS	5	0.2	0.02	Reject stationarity

Table 393: Unit root tests and stationarity tests including a constant on first differences

Broker-Dealer and Customer Payables – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	0	-11	<0.01	Reject unit root
Phillips-Perron	1	-11	<0.01	Reject unit root
KPSS	2	0.19	0.3	Fail to reject stationarity

Stationarity tests for Broker-Dealer and Customer yield results that imply the series is non-stationary: The ADF and PP tests fail to reject a unit root while the KPSS test rejects stationarity. These results suggest the levels may be non-stationary. The monthly first difference series passes all three stationarity tests which implies that the series is stationary.

Based on these results, the Broker-Dealer and Customer are modeled on their first differences.

10.17.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Broker-Dealer and Customer Payables.

10.17.4. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 437: Summary of drivers for Broker-Dealer Payables and Customer Payables

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• Stronger macroeconomic conditions promote increased investment activity, which drives up payable volumes	US GDP growth, US unemployment rate
Financial economy	**Debt issuances**	• Higher debt issuances may lead to greater investment activity, e.g. in fixed income markets, which drives up payable volumes	Corporate debt outstanding, total bond issuance
	Equity markets	• Stronger equity markets lead to more trading activity and more broker-dealer payables and customer payables	DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Hedge fund index	• Stronger hedge fund performance leads to more trading activity and more broker-dealer payables and customer payables	HFRX index, Eurekahedge HF index, Eurekahedge FoF index
	Market volatility/ uncertainty (equity)	• Volatility and uncertainty may indicate greater trading activity, resulting in increased broker-dealer payables and customer payables	VIX, market volatility index
	Market volatility/ uncertainty (rates)		10-year US T-note volatility index
	Perceived credit risk	• Greater perceived credit risk leads to lower trading activity, which will lower the amount of broker-dealer and customer payables	Overnight LIBOR – 1-week OIS spread, 1-week LIBOR – 1-week OIS spread, TED spread
Rates	**Short-term rates**	• Increases in rates leads to less demand for risky assets and thereby potentially lowering the investment activity that correlates with payable volumes	Prime rate, Fed Funds target and effective rates, 1- and 3-month Treasury rate, overnight repo rate
	Long-term rates		1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year Treasury rates; mortgage rate
	Corporate credit		Baa corporate yield, Baa to Treasury spread

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

10.17.5. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Broker-Dealer and Customer Payables are statistically significant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section X on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 394: Statistical significance tests of model and variables for Broker-Dealer and Customer Payables

Broker-Dealer and Customer Payables (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Market Volatility	35.350	<1%	10%	Statistically significant
KBW Bank Index	17.237	<1%	10%	Statistically significant
Intercept	170.596	1%	10%	Statistically significant

10.17.6. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual

and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

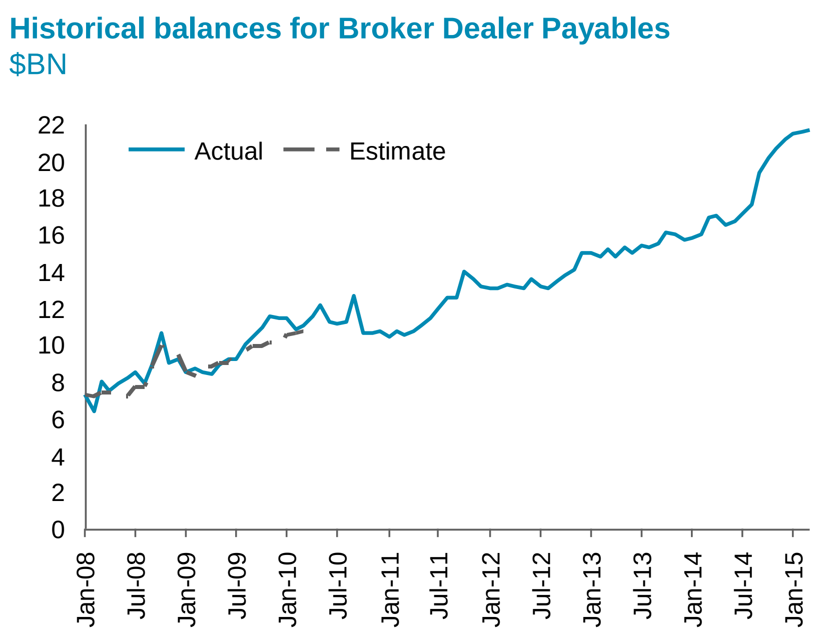
The diagnostic tests reviewed are exhibited below.

Table 395: Model Diagnostics for Broker-Dealer and Customer Payables

Broker-Dealer and Customer Payables (in USD MM) – Model diagnostics

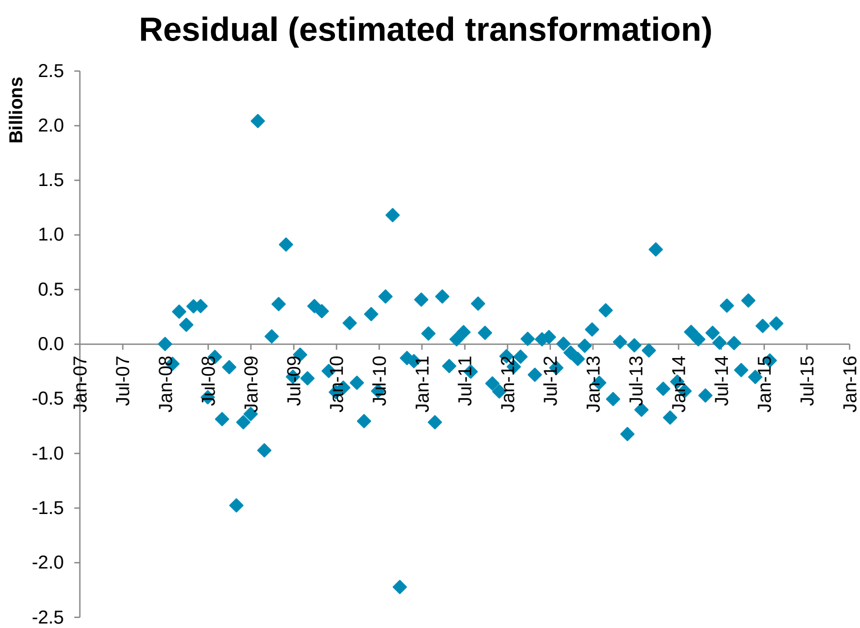
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	21%	-	-
	Adjusted R-squared	19%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.63	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	8%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.02	5	No multicollinearity
Linearity	RESET test	31%	10%	Linear specification appropriate

Figure 438: 9-quarter In-sample Prediction for Broker-Dealer and Customer Payables



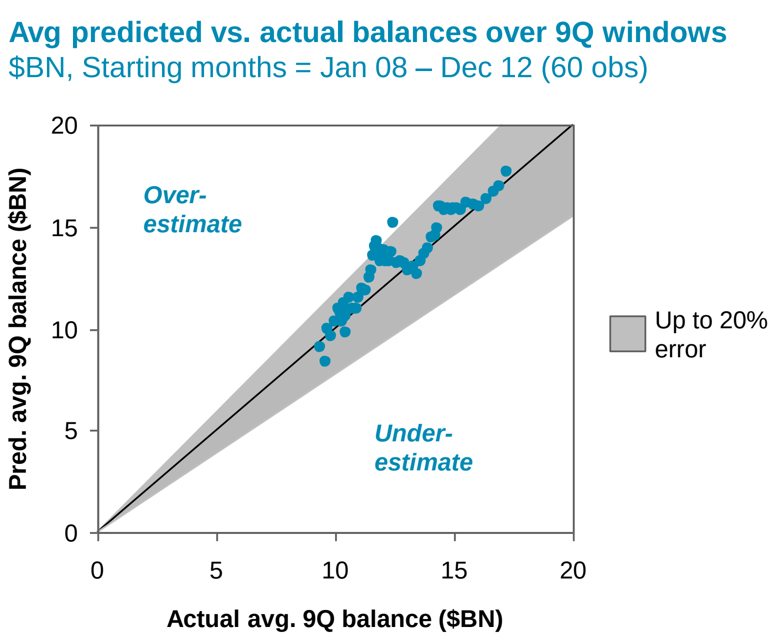
The in-sample back test of the model starting from January 2008 tracks very closely with the actual levels, capturing the correct directional behavior as well as the magnitude of changes.

Figure 439: Residual Plot for Broker-Dealer and Customer Payables ($ BN)



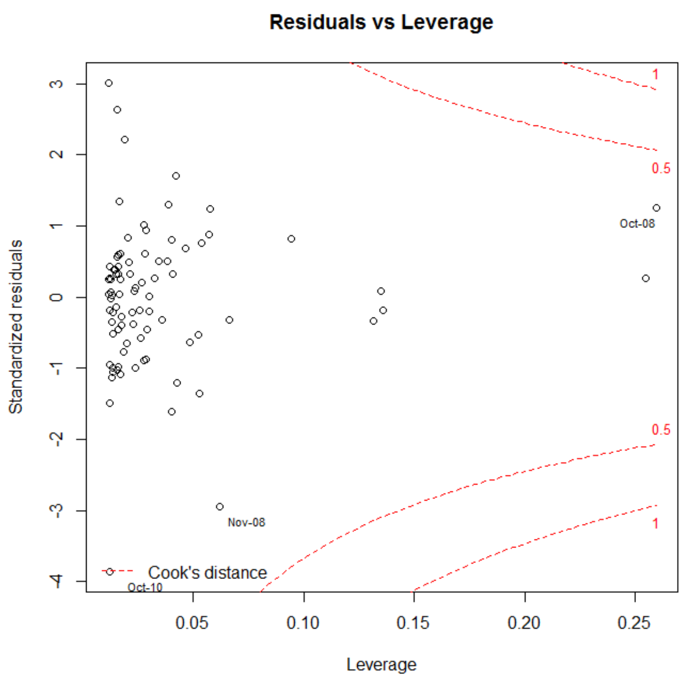
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 440: Estimation Scatterplot for Broker-Dealer and Customer Payables



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for different 9-quarter forecast windows, with most estimated average values within 20% of actual average values.

Figure 441: Broker dealer and customer payables



The segment does not contain any highly influential points.

10.17.7. Model sensitivity

10.17.7.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 396: Sensitivity to changes to independent variables for Broker-Dealer and Customer Payables

Broker-Dealer and Customer Payables – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Market Volatility	First difference – MoM	Index	0.43	7.185	0.26
KBW Bank Index	Percent change – MoM	Index	0.25	8.45	0.15
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the corporate debt outstanding variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the corporate debt outstanding variable results in a 0.43 standard deviation ($0.26 BN) increase in the predicted monthly change of the total commitment for Broker-Dealer and Customer Payables segment.

10.17.7.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. The market volatility variable, however, had a significant coefficient which could imply the model may not remain stable over time.

Table 397: Statistical sensitivity tests for Broker-Dealer and Customer Payables

Broker-Dealer and Customer Payables (in USD MM) – Statistical significance tests of model and variables

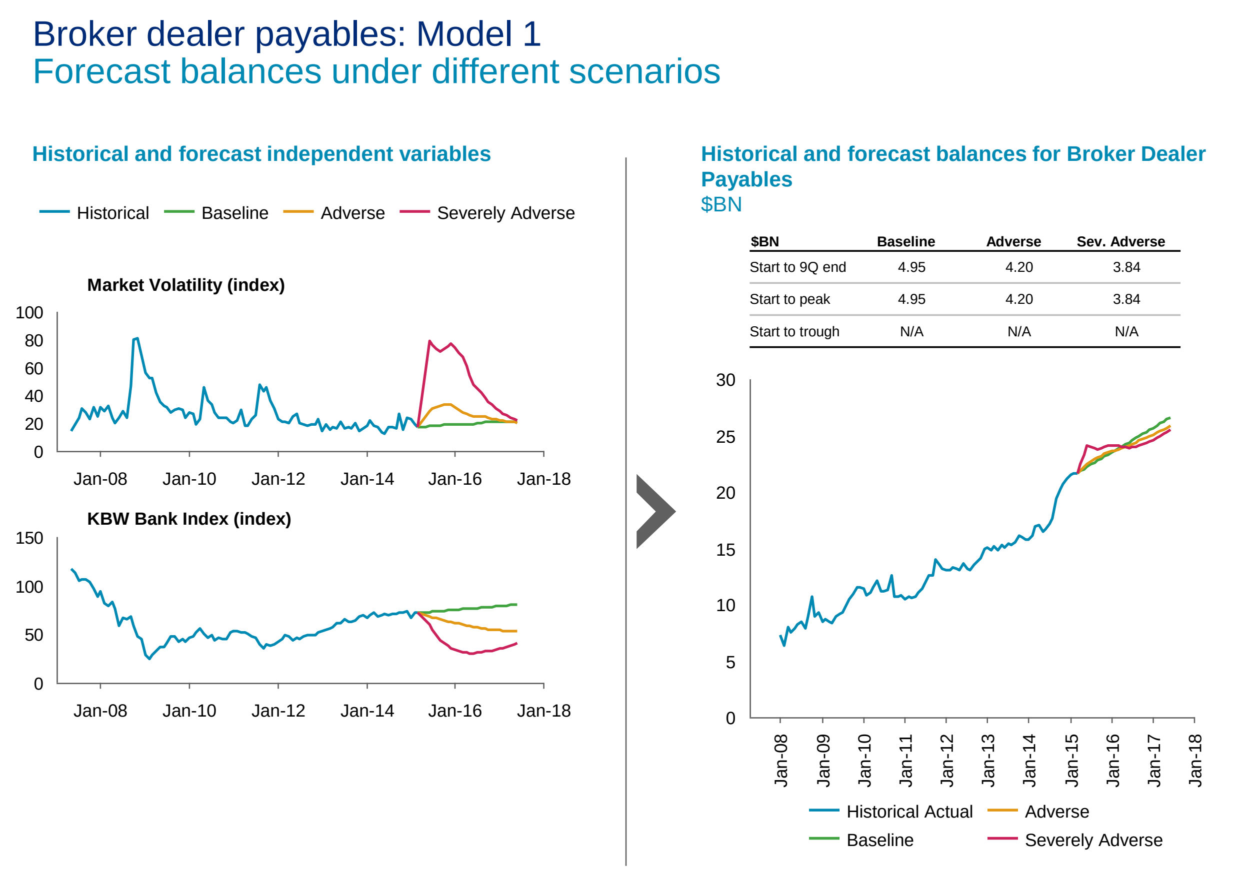
Tested independent variable	Original coefficient estimate	Sum of coefficients	HAC P-value of shortened period coefficient	Conclusion
Market Volatility	35.350	37.751	0.05	Statistically significant
KBW Bank Index	17.237	16.990	0.89	Statistically insignificant
Intercept	170.596		0.43	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.16	Statistically insignificant

10.17.7.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 442: Final model forecast for Broker-Dealer and Customer Payables



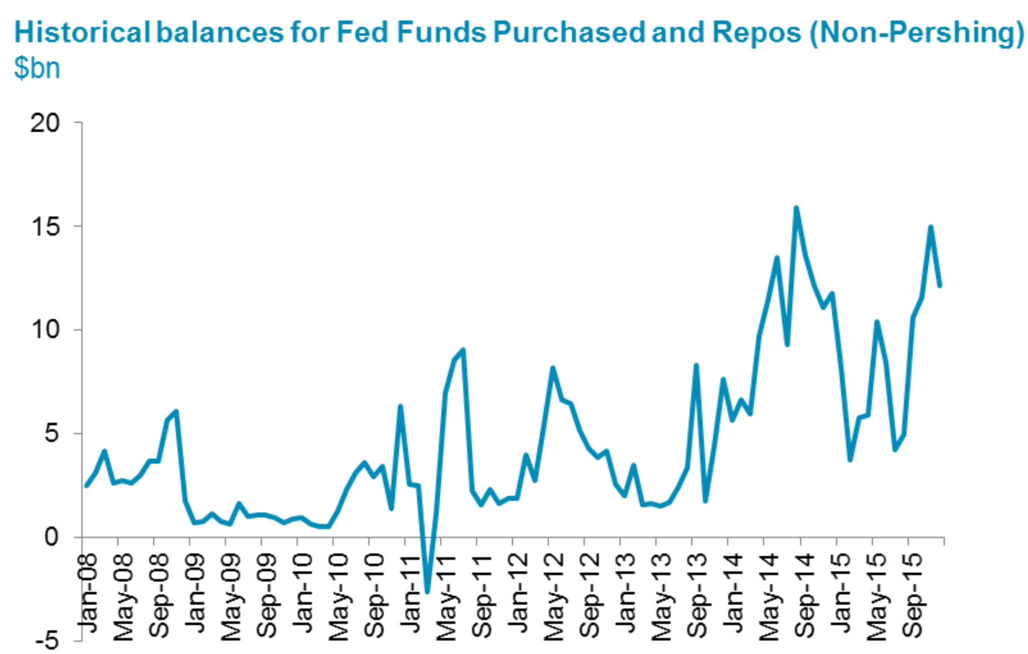
The Working Group considered the forecast behavior for the selected Broker-Dealer Payables and Customer Payables model as directionally intuitive. Some management review may be needed to ensure that forecasts are aligned with expectations and intuition

- **Severe recession (Severely Adverse) scenario:** The model predicts balances to initially rise, and then remain mostly flat. This is potentially intuitive under the rationale that at the beginning of a severe recession, there may be increased sales of securities, increasing the volume of payables
- **Interest rate shock (Adverse) scenario**: The model predicts balances will grow at a moderate rate consistent with observed historical growth
- **Baseline scenario**: The model predicts that total commitments will grow at a moderate rate consistent with observed historical growth

10.18. Short-term borrowings: Fed Funds Purchased and Repos (non-Pershing)

10.18.1. Historical data

Figure 443 Historical balances for STB: Fed Funds Purchased and Repos (non-Pershing)



However, the qualitative data does not require the use of historical data.

10.18.2. General data issues

The historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Fed Funds Purchased and Repos (non-Pershing). As discussed previously, the data was sourced from the Credit Risk Data Warehouse (CRDW), which is also used for regulatory reporting purposes.

10.18.3. Summary of approach

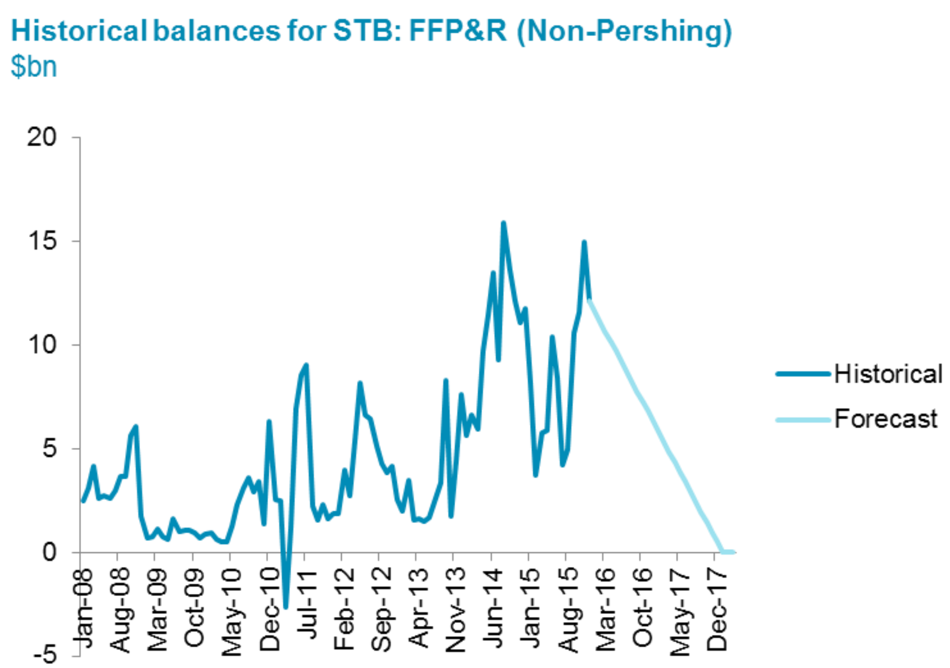
10.18.3.1. Approach

A qualitative framework is applied for the Fed Funds Purchased and Repos Influential point(non-Pershing) segment.

Under normal course of buisness, Corporate Treasury conducts repos to gain incremental NII by holding the cash at the Federal Reserve and earning an excess spread. This function will have come to an end in January 2018 when the new SLR regulation takes effect. As a consequence, the qualitative framework linearly interpolates from the balance at the beginning of the forecast period to zero in January 2018, and then holds the balance at zero until the end of the forecasting period.

However, if additional funding is needed during the forecast period, the amortization above is not to be programmed. Instead the decision tree as described in Investment Portfolio (Section 9) is applied period after period in which Fed Funds Purchased and Repos (non-Pershing) may serve as a source of additional funding.

Figure 444: Historical and forecast balances for STB: FFP&R (non-Pershing)



10.18.3.2. Previous Statistical approach

The modeling team first attempted to develop a statistical model for this segment. The Fed Funds Purchased and Repos (non-Pershing) model failed to capture the high volatility of the segment and had a relatively poor in-sample fit. Moreover, the segment's balances are management driven. The Corporate Treasury team that manages Corporate Treasury deposits and Fed Funds Purchased and Repos (non-Pershing) balances explained that balances are in large part solicited when there is room in the leverage ratio and Corporate Treasury decides to repo out securities or purchase deposits. These balances then earn incremental NII when they are left at the Federal Reserve and earn interest above the purchase price for deposits or the interest rate for repos, and have little to do with macroeconomic variables. Finally, the statistical model miss an important aspect of the future business outlook for both balances, namely, that they are expected to wind down in light of new, more restrictive regulation concerning the leverage ratio that takes effect in January 2018 (new SLR regulation). As more restrictive leverage ratio regulation takes effect in January 2018 and there is less room in the bank's leverage ratio, this activity is likely to come to an end in the upcoming years. Subsequently, a qualitative framework was developed.

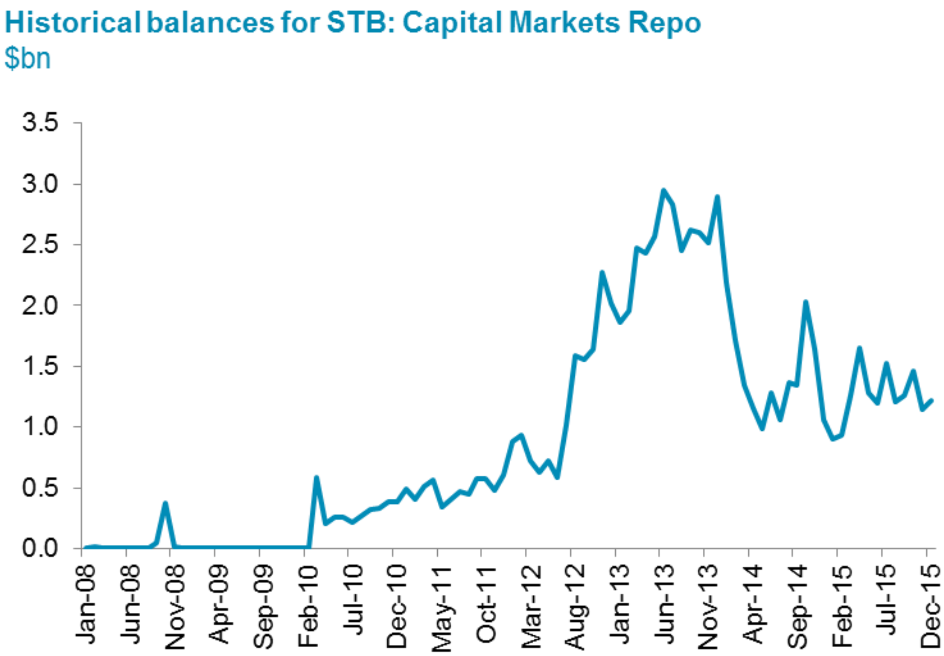
In addition, during CCAR 2016, Capital Market repo was broken out from Repos (Non-Pershing), as these balances do not serve the same purpose as described above. Rather, they fund Capital Markets activity. See Section 10.19 for more details.

10.19. Short-term borrowings: Capital Market repos

10.19.1. Business overview

Capital market repos fund Trading Assets: Capital Markets which are HQLA (government debt, agencies, and MBS), using these assets as collateral.

10.19.2. Historical data



10.19.3. General data issues

No data issues were observed in the historical time series for BNY Mellon capital market repo balances.

10.19.4. Summary of approach

At the time of model development, this balance model was consolidated in with Fed Funds Purchased and Repos (Non-Pershing), Section 10.18. Upon further investigation, Capital Markets repos are unlike Fed Funds Purchased other non-Pershing repos, which are largely managed by Treasury, fund the balance sheet and tactically uplift NII. Thus, a qualitative framework that separated out this segment was applied.

As Capital Market repos fund a portion of Trading Assets: Capital Markets activity, the approach holds Capital Market repo balances at the December 2015 ratio between Capital Market repos average balances and Trading Assets: Capital Markets balances. In December 2015, this ratio was 0.51.

10.20. Short-term borrowings: Repos (Pershing)

10.20.1. Business overview

As a broker dealer, Pershing LLC requires funding such that it can meet the funding needs of its customers. Pershing LLC's primary funding needs in the ordinary course of business are caused by margin loans to clients and introducing broker-dealers, as well as non-purpose loans to various parties. Repurchase agreements ("Repos"), in which Pershing sells securities with an agreement to buy them back at a later date, is one form of funding its liquidity needs. Repos are often used by Pershing to finance customer loans by rehypothecating client collateral.

This segment also includes securities lending balances. In securities lending transactions, similar to repos, Pershing lends stocks for cash to fund customer loans.

10.20.2. Summary

A statistically sound model that is consistent with business intuition was found for Pershing repos. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity**: the model is estimated on month-over-month differences in Pershing repos, which are found to be stationary
- **Statistical significance**: the coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests**: the model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 398: Coefficient estimates for selected model for Pershing repos

Pershing repos (in USD MM) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized Coefficient**
Market Volatility	% MoM	%	6.37	0.30
MSCI WORLD Index	% MoM	%	28.84	0.26
Total Bond Issuance (excl mortgage, treasuries)	Diff QoQ	$ BN	2.86	0.28
Intercept	None (level)	$ MM	48.48	N/A

The model contains the following drivers and variables:

- **Market volatility/uncertainty (equity)** – VIX, which measures implied volatility of S&P 500 index options
- **Equity markets** – MSCI World Index, a benchmark for global stock funds based on securities from 23 countries
- **Debt issuances** – total US bond issuance, excluding mortgages and Treasuries

The intuition of these variables is as follows:

- The S&P volatility variable has a positive coefficient; when equity markets are more volatile, more trading activity may take place, increasing the demand for repos to fund this activity
- The MSCI World Index has a positive coefficient, with the rationale that Pershing repo balances will increase as equity investments become more attractive, driving greater volume of investment activity

- Total Bond Issuance has a positive coefficient, with the rationale that as activity in fixed income markets increases, more trading activity may take place, increasing the demand for repos to fund this activity

In a review and challenge meeting, the line of business confirmed the intuitiveness of the variables and their coefficient signs.

The final model was selected following the model-based approach described in Section 3.3. The other shortlisted candidate models for this segment are listed in the figure below.

Figure 445: Candidate models for repos (Pershing)

	Candidate models			
Drivers Considered	**1**	**2**	**3**	**4**
General economic health				
Relative credit worthiness of BNYM				
Equity markets	MSCI WORLD Index (% MoM)		MSCI WORLD Index (Diff MoM)	Eurekahedge NA FoF Index (% MoM)
Market volatility/ uncertainty	Market Vol (% MoM)	Ovrnt LIBOR-1wk OIS spread (Diff MoM, 1M Lag)	Market Vol (Diff MoM)	Market Vol (% MoM)
Debt issuances	Total Bond Issuance (excl mortgage, treasuries) (Diff QoQ)	Total Bond Issuance (excl mortgage, treasuries) (Diff QoQ)	US Bond Issuance (ex MBS ex gov) (% QoQ)	Total Bond Issuance (Diff QoQ)
Short-term rates		T spread with Fed Funds (Diff MoM)		
Variation in balances explained through estimated first differences	**87%**	**79%**	**86%**	**87%**
R-squared (differences)	**11%**	**11%**	**11%**	**10%**

Final model

The following sections provide details on:

- Statistical tests necessary to determine the transformation of the dependent variable
- Statistical diagnostic tests and results
- Sensitivity tests and results

10.20.3. Dependent variable construction

Dependent variable construction consisted of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

10.20.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. The time series for the Pershing repos segment is tested as a growth variable, as there is a possibility that it could grow continuously. As a consequence, the balances are tested using unit root and stationarity tests including a time trend.

The first differences of the balances, i.e. the month-over-month changes, are tested using unit root and stationarity tests that do not include a time trend but a constant (drift term). The results are listed in the two tables below.

Table 399: Unit root tests and stationarity tests including a trend variable on balances

Pershing repos – Unit root test with trend on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	2	-2	>0.10	Fail to reject unit root
Phillips-Perron	1	-3.8	0.02	Reject unit root
KPSS	5	0.09	0.21	Fail to reject stationarity

Table 400: Unit root tests and stationarity tests including a constant on first differences

Pershing repos – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-10	<0.01	Reject unit root
Phillips-Perron	1	-12	<0.01	Reject unit root
KPSS	47	0.3	0.13	Fail to reject stationarity

Stationarity tests for Pershing Repos balances yield mixed results: The ADF failed to reject the presence of a unit root while the PP test rejected the presence of the unit root and the KPSS failed to reject stationarity. These results suggest the segment may be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Pershing Repos balances are modeled on their first differences.

10.20.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the historical values of the dependent variables were checked for possible outliers and data issues. Specifically, the historical data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No adjustments to data were necessary for Pershing repos.

10.20.4. Hypotheses and independent variable identification

In several discussions with the Working Group, the ALM team, Credit Risk, and the line of business, a list of driver hypotheses were developed and refined over time. The modeling team then collected a list of candidate variables that represent the drivers. During the development process, the Working Group gave feedback that sometimes resulted in changes to the set of variables. The final set of variables is included in the Appendix.

Figure 446: Summary of drivers for Pershing repos

Driver bucket	Driver	Hypotheses	Candidate variables
Real economy	**General economic health**	• A better performing economy will encourage clients to seek funding to make investments, increasing the demand for repos by Pershing to fund these clients	• Real GDP growth, US unemployment rate
Financial economy	**Equity markets**	• Strong market performance entices more investments and trading activity from clients resulting in greater demand for funding	• DJI, MSCI World Index, KBW Bank Index, FTSE 500, EURO STOXX 50 Index
	Debt issuances	• As activity in fixed income markets increase, the demand for repos to fund this activity increases	• Corporate debt outstanding, total bond issuance
	Relative credit worthiness of BNYM	• During times of stress where clients place money with BNY Mellon (as it is perceived as a relative "safe haven") the need for repos as a source of funding may decrease, although this effect may be diminished if the deposits are considered to not be "sticky"	• Spread between BNYM CDS and industry average CDS (North American, EU, UK bank indices), spread of BNYM debt rate to industry peer rate
	Market volatility/ uncertainty	• Higher market volatility results in more trading activity, increasing the demand for repos to fund this activity	• VIX, rates volatility, US LIBOR-OIS spread, equity indices, FDIC insurance on DDA dummy variable, Fed stress indices
Rates	**Short-term rates**	• As short term rates increase, there is less demand for risky assets, which lowers customer funding demand and in turn the demand for repos from Pershing	• Overnight LIBOR, Fed Funds rate, Treasury yields, SONIA, EONIA, Money Market fund yield indices, repo rates

The combined list of candidate variables served as the explanatory variable set used in the model estimation procedure as described in Section 3.3.3.2.

10.20.5. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated model.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the model for Pershing repos are statistically significant. The intercept is found to be statistically insignificant.

Serial correlation was detected in the residuals of this model (further discussed in the next section). As described in Section 3.3.3 on Methodology, all P-values in this section are therefore based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Table 401: Statistical significance tests of model and variables for Pershing repos

Pershing repos (in USD MM) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	HAC P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	2%	10%	Statistically significant
Market Volatility	6.37	1%	10%	Statistically significant
MSCI WORLD Index	28.84	2%	10%	Statistically significant
Total Bond Issuance (excl mortgage, treasuries)	2.86	<1%	10%	Statistically significant
Intercept	48.48	42%	10%	Statistically not significant

10.20.6. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in residuals, autocorrelation in residuals, multicollinearity of variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9-quarter in-sample fit (chart on levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter levels compared with actual average 9-quarter levels, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

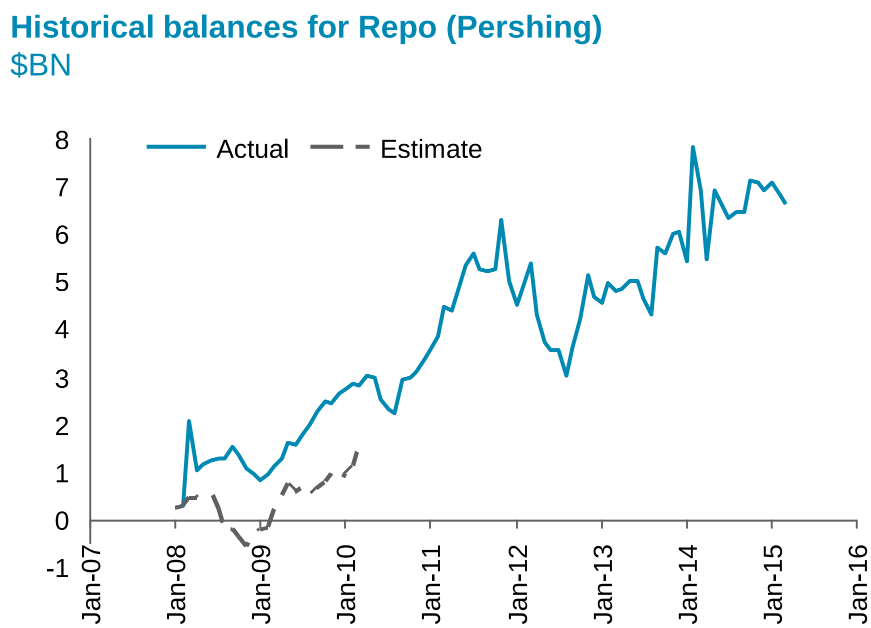
The diagnostic tests reviewed are exhibited below.

Table 402: Model Diagnostics for Pershing repos

Pershing repos (in USD MM) – Model diagnostics

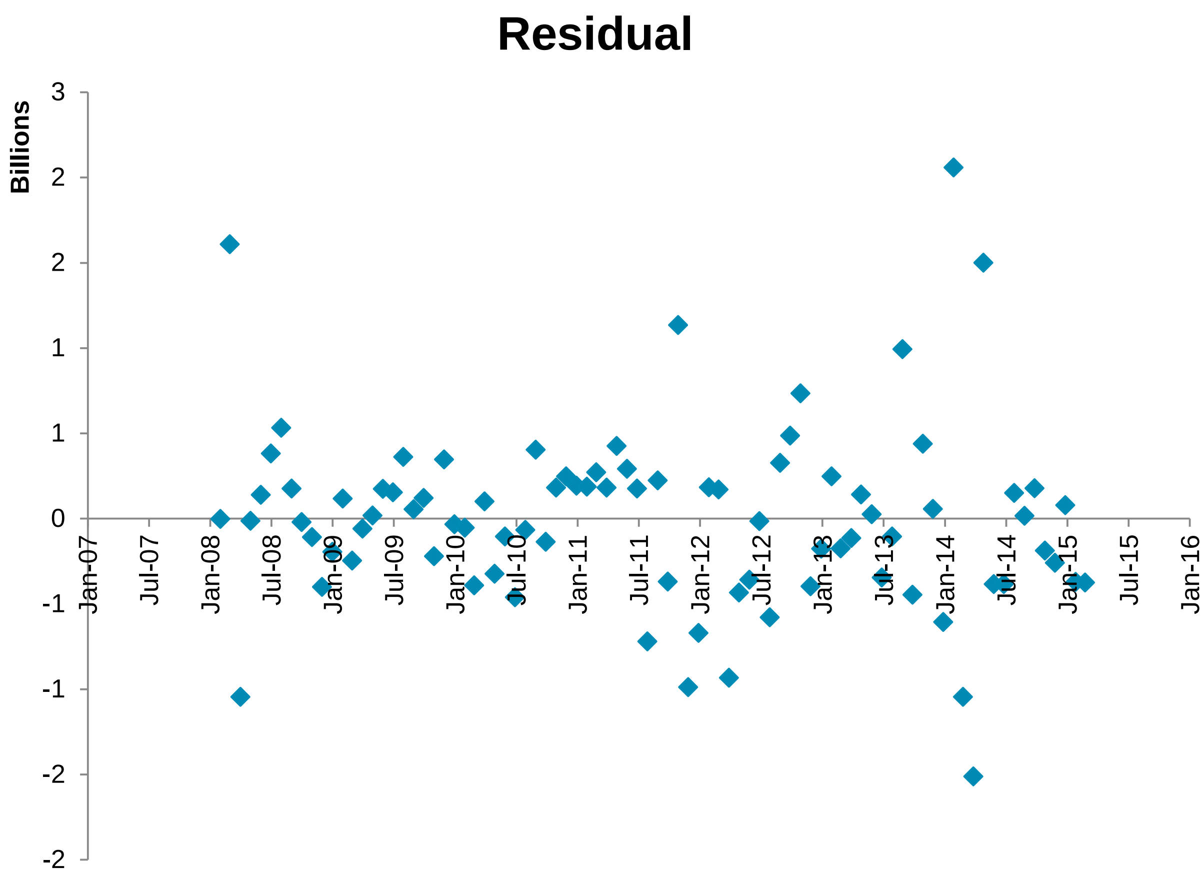
Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of Fit	R-squared	11%	-	-
	Adjusted R-squared	8%	-	-
Heteroskedasticity	Breusch-Pagan test (P-value)	82%	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum P-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.53	5	No multicollinearity
Linearity	RESET test	20%	10%	Linear specification appropriate

Figure 447: 9-quarter In-sample Prediction for Pershing repos



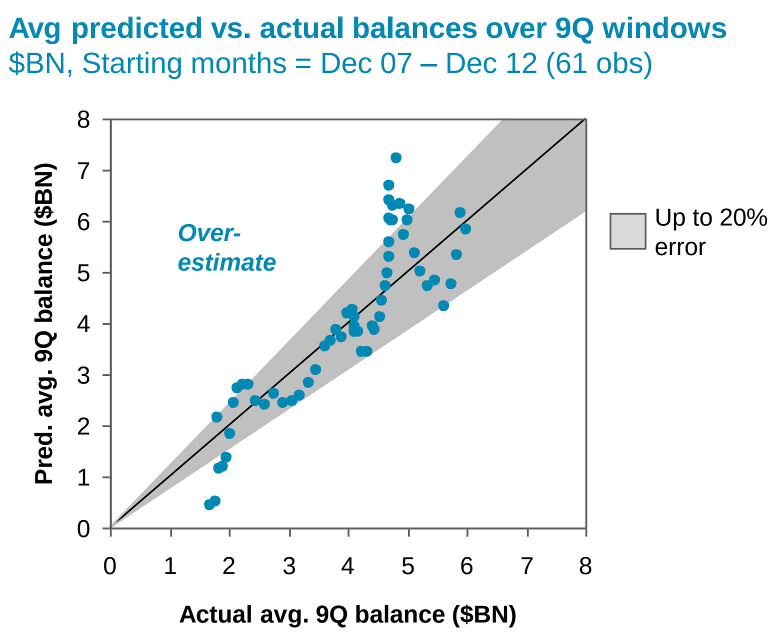
The in-sample back test of the model starting from January 2008 tracks the directional behavior of the balances, although does not capture the magnitude of changes arising from the high month-to-month volatility in the historical time series. In particular, the model does not capture an initial rise in balances, which leads to underestimation through the entire forecast window.

Figure 448: Residual Plot for Pershing repos ($ BN)



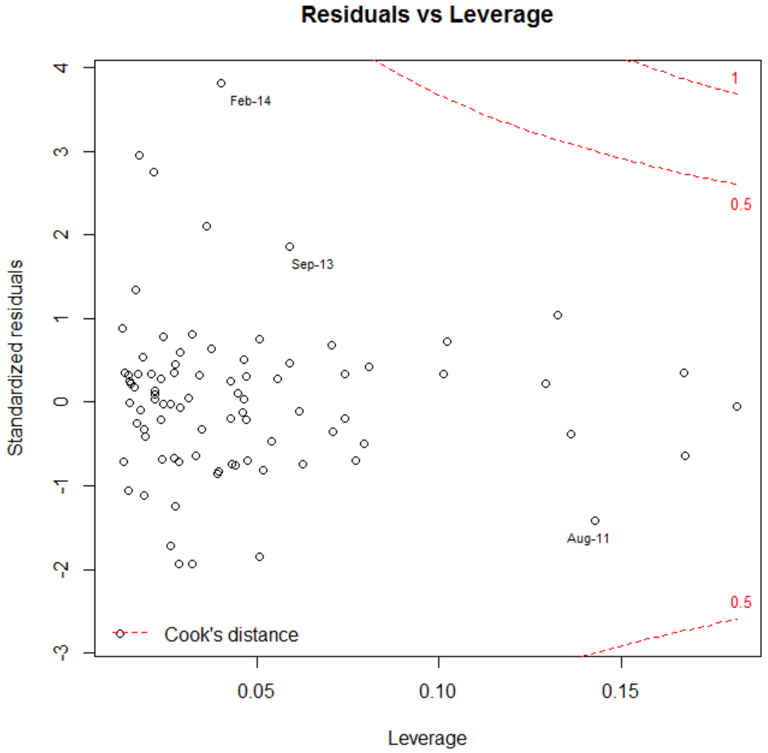
As expected, the residuals appear to be randomly distributed around the horizontal axis.

Figure 449: Estimation Scatterplot for Pershing repos



Estimated average 9-quarter levels tracked closely with actual average 9-quarter levels for some of the 9-quarter forecast windows. The model does not capture the high month-over-month volatility in the historical overdraft balances, which leads to some overestimation or underestimation over 9-quarter forecast windows, depending on which month is taken as the starting month of the forecast.

Figure 450: Influential points for Pershing repos



The segment does not contain any highly influential points.

10.20.7. Model sensitivity

10.20.7.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected model are shown in the table below. The standardized coefficient reported describes the change in the predicted balances due to a one standard deviation increase in an independent variable.

Table 403: Sensitivity to changes to independent variables for Pershing repos

Pershing repos – model sensitivity

Independent variable	Transformation	Unit	Standardized Coefficient	Std. dev of independent variable	Change in balances resulting from 1 std. dev change in the independent variable ($ BN)
Market Volatility	% MoM	%	0.30	26.66	0.17
MSCI WORLD Index	% MoM	%	0.26	5.02	0.15
Total Bond Issuance (excl mortgage, treasuries)	Diff QoQ	$ MM	0.28	58.26	0.16
Intercept	None (level)	$ MM	N/A	N/A	N/A

In the selected model, the Market Volatility variable has the standardized coefficient with the largest magnitude. A one standard deviation increase in the Market Volatility variable results in a 0.30 standard deviation ($0.17 BN) increase in the predicted monthly change of the total commitment for the FI loan segment.

10.20.7.2. Sensitivity to estimation period

To test the model for statistical sensitivity, a Chow test was conducted. The model was recalibrated together with shortened versions of the selected variables, setting the 24 most recent observations to zero. The coefficient estimates in the final model will be considered to be sensitive to a change in the model calibration period if the coefficients of the shortened versions of the variables are found to be statistically significant.

The results of the test are shown in the table below.

For the selected models, the coefficients of the shortened variables are statistically insignificant collectively. This suggests the model maintains stability when removing observations from the development data. In addition, all of the coefficients are insignificant individually.

Table 404: Statistical sensitivity tests for Pershing repos

Pershing repos (in USD MM) – Statistical significance tests of model and variables

Tested independent variable	Original coefficient estimate	Sum of Coefficients	HAC P-value of shortened period Coefficient	Conclusion
Market Volatility	6.37	4.79	0.32	Statistically insignificant
MSCI WORLD Index	28.84	17.9	0.14	Statistically insignificant
Total Bond Issuance (excl mortgage, treasuries)	2.86	2.57	0.56	Statistically insignificant
Intercept	48.48	-	0.22	Statistically insignificant
Chow-test on all shortened period coefficients	-	-	0.39	Statistically insignificant

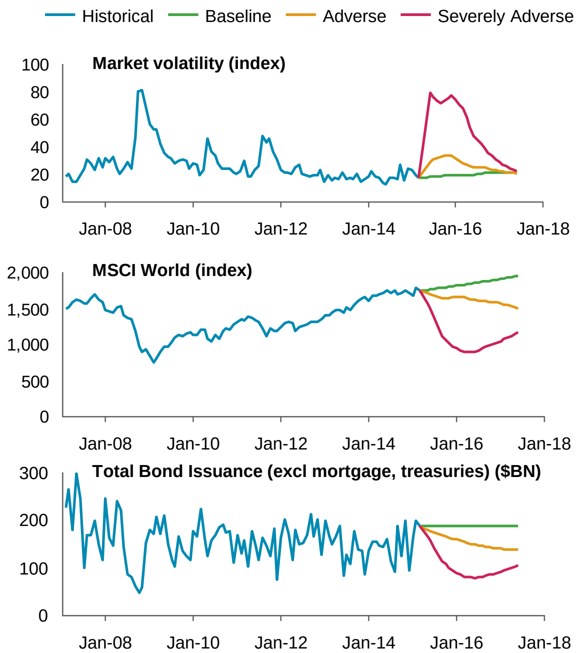
10.20.7.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

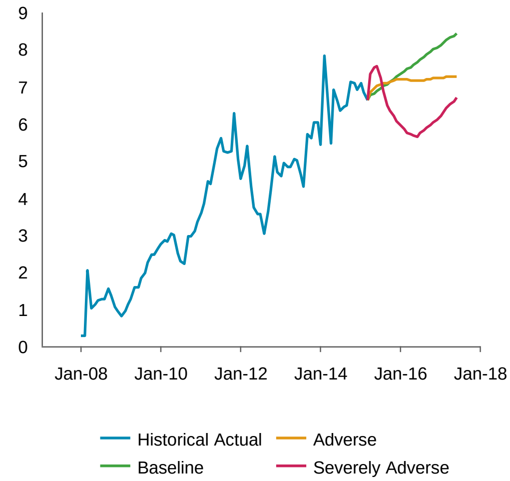
Figure 451: Final model forecast for Pershing repos

Historical and forecast independent variables



Historical and forecast balances for Repo (Pershing)
$BN

$BN (% of start)	Baseline	Adverse	Sev. Adverse	2008-2009
Start to 9Q end	1.8 (27%)	0.63 (9%)	0.08 (1%)	-
Start to peak	1.8 (27%)	0.63 (9%)	0.91 (14%)	2.37 (894%)
Start to trough	N/A	N/A	-0.98 (-15%)	0 (0%)



The Working Group considered the forecast behavior for the selected Pershing repos model as directionally reasonable. In normal business operation Pershing repos are used to finance customer debit, to finance concentrated positions, or to improve spreads on certain loan types (e.g. non-purpose loans).

- **Severe recession (Severely Adverse) scenario:** The model predicts an increase followed by a significant decline in Pershing repos, with an eventual gradual recovery in balances. In a review of the forecasts with the line of business, this was noted to be directionally consistent with expectations. The spike in balances at the start of the 9-quarter period is first being driven by the positive correlation on the market volatility variable. As equity markets go into crisis under the scenario, balances begin to come down, tracking the shape of the MSCI World Index
- **Interest rate shock (Adverse) scenario**: Business intuition is that Pershing repos decrease as rates rise due to a decreased desire for holding risky assets, and a corresponding decrease in the demand for funding through repos. This is seen in slow growth in the forecast relative to the baseline scenario
- **Baseline scenario**: The model predicts that Pershing repos will grow over the 9-quarter period. It would be expected that more trading activity would take place relative to a stressed macro-economy, thus increasing the demand for repos for additional funding

10.20.8. Model limitations

Any model based on macroeconomic factors would not be able to capture the high month-over-month volatility in the historical Pershing repo balances. Therefore, the model results should be interpreted as the general expected trend for the balances, without the volatility that arises from more idiosyncratic behavior.

10.21. Short-term borrowings: Commercial Paper

10.21.1. Business overview

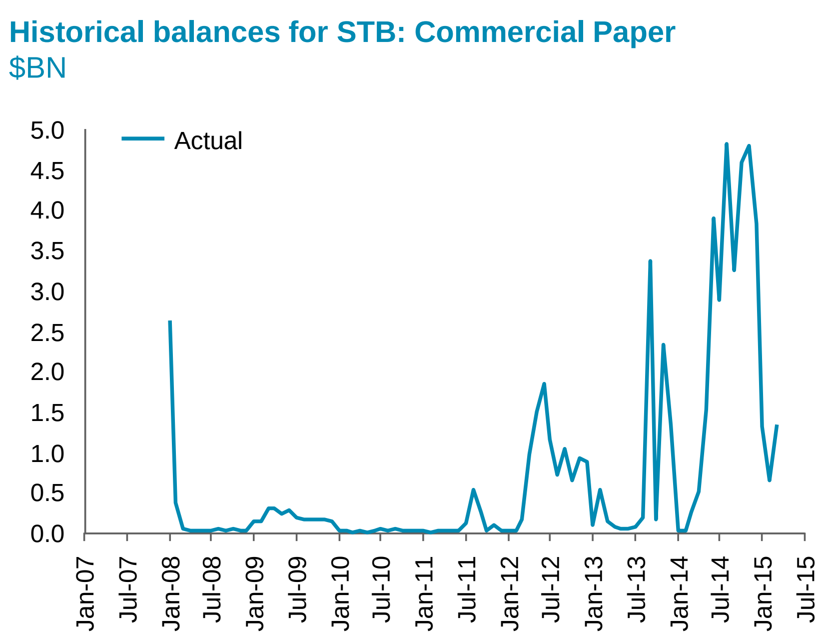
BNY Mellon uses short-term borrowings as a means of funding. Short-term borrowings consist of federal funds purchased and securities sold under repurchase agreements, payables to customers and broker-dealers, commercial paper and other borrowed funds.

Commercial paper consists of short-term unsecured promissory notes issued by BNY Mellon. Commercial paper issued by BNY Mellon matures within 397 days from date of issue and is not redeemable prior to maturity or subject to voluntary prepayment. Based on discussion with the business, commercial paper has a cap of a $4.8 BN on total balances.

Relatively recent regulatory requirements disallow BNY Mellon's holding company from issuing debt maturing in less than one year. Therefore, BNY Mellon does not intend to issue commercial paper over the 9-quarter forecast window. This decision, driven by management, is independent of macroeconomic factors.

10.21.2. Historical data

Figure 452: Average balances for short-term borrowings: commercial paper ($ BN)



The historical figure above shows the average balances for commercial paper at BNY Mellon. Based on discussions with the business, at various points in time, BNY Mellon took advantage of favorable rates to issue Commercial paper leading to the various sharp increases in the graph.

10.21.3. General data issues

No data issues were observed in the historical time series for BNY Mellon commercial paper balances.

10.21.4. Summary of approach

Relatively recent regulatory requirements disallow BNY Mellon's holding company from issuing debt maturing in less than one year. Therefore, forecasts for this segment will utilize a run-off approach. Outstanding commercial paper balances can be modeled using QRM, which contains all rates, balances, and maturities of commercial paper outstanding and can therefore forecast the run-off of these balances.

As of April 2015, the portfolio of Short-term Borrowings: Commercial Paper had a size of $1.74 BN, and a rate of 0.08.

10.21.5. Model limitations

The choice to issue commercial paper is strongly impacted by management decisions. The qualitative framework follows the BNY Mellon Working Group's assumption that that the Company has decided not to issue commercial paper during the 9-quarter period. Change to this decision will impact future balances, which may diverge from the original run-off assumptions.

10.22. Short-term borrowings: Other borrowings

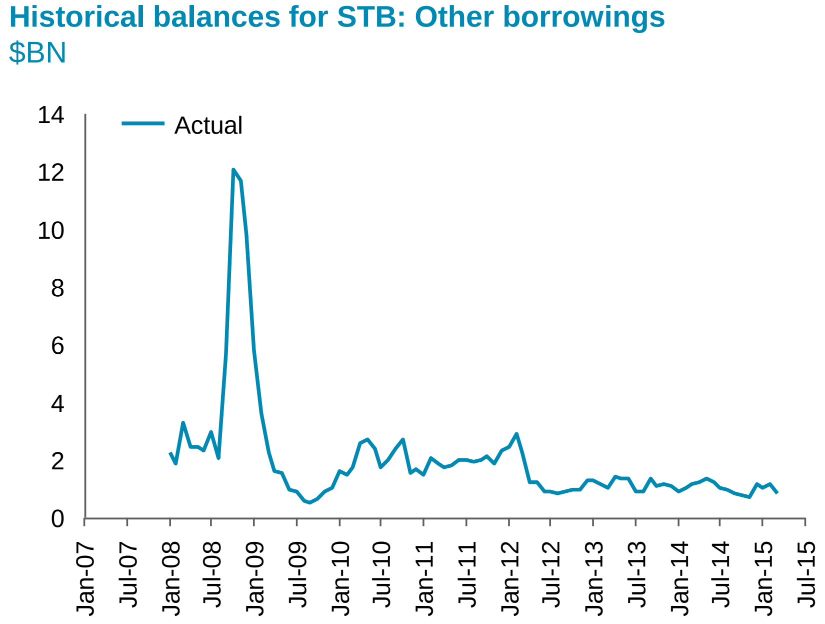
10.22.1. Business overview

BNY Mellon uses short-term borrowings (STB) as a means of funding. Short-term borrowings consist of federal funds purchased and securities sold under repurchase agreements, payables to customers and broker-dealers, commercial paper and other borrowed funds.

The "Short-term borrowings: Other borrowings" segment relates primarily to overdrafts of sub-custodian account balances in BNY Mellon's Investment Services businesses and borrowings under lines of credit by BNY Mellon's Pershing subsidiaries. Overdrafts typically relate to timing differences for settlements. This segment also includes purchases of Eurodollars to increase excess deposits placed at the Federal Reserve.

10.22.2. Historical data

Figure 453: Average balances for STB: Other borrowings ($ BN)



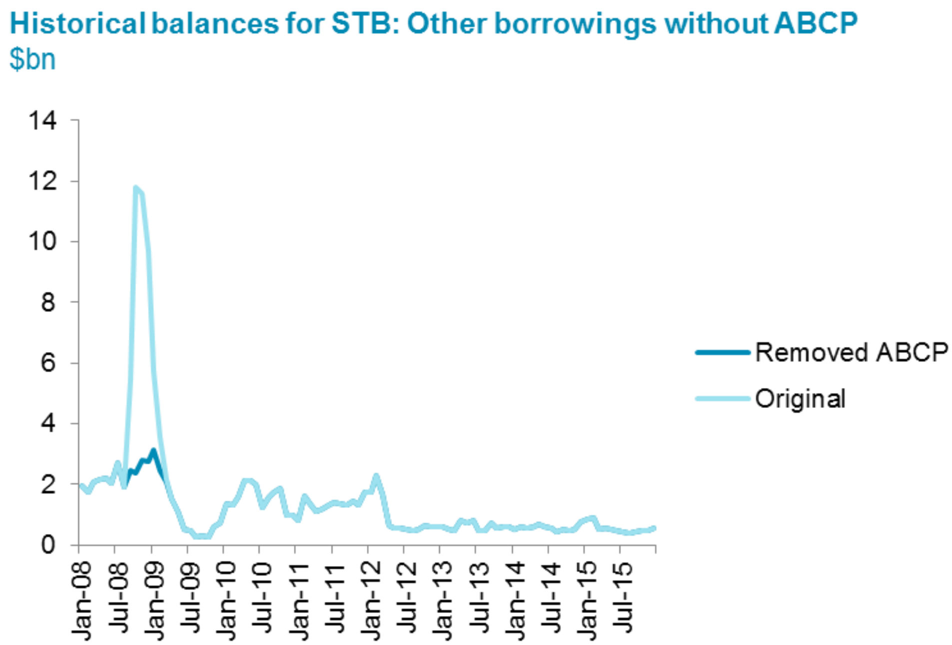
The historical figure above shows the average balances for other borrowings. This segment's balance was highest during Oct-Dec 2008 during the height of the 2008 financial crisis. Since 2012, balances have largely held flat, and as of April 2015 were less than $0.9 BN.

10.22.3. General data issues

There is a spike in balances in late 2008. This spike was due to borrowings from the Federal Reserve under the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (ABCP) program, which provided funding to U.S. depository institutions and bank holding companies to finance purchases of high-quality asset-backed commercial paper from money market mutual funds. This program began in September 2008, and ended in February 2010. The facility was established as a policy response to the increasing investor withdrawals from money market funds during the global financial crisis and was one of the Federal Reserve's instruments to stabilize the short-term debt markets. As a similar policy response is uncertain and cannot be assumed to be present in future crises, the approach does not consider the balances that were related to it.

Removing these borrowings from the total balances normalizes balances historically shows that balances have been fairly flat.

Figure 454 Historical balances for STB: Other borrowings without ABCP



10.22.4. Summary of approach

Based on discussion with the Working Group, other borrowings will be held flat to the latest month in the historical time series (March 2015 at the time this approach was developed).

10.22.5. Model limitations

The decision to hold flat to the latest month was discussed with and agreed to by the Working Group. Changes in future strategy and environment may cause divergence from the original flat assumptions over the 9-quarter forecast horizon. For example, if interest on excess reserves at the Federal Reserve drops below the costs of purchasing Eurodollars, BNY Mellon would stop purchasing Eurodollars.

10.23. Long-term debt

10.23.1. Business overview

Long-term debt issued by BNY Mellon consists of loans and financial obligations that are longer than 1 year in maturity. BNY Mellon primarily issues debt instruments that are either floating rate or swapped to floating rate.

Debt issuance and timing is driven by existing debt maturities, and is conducted in advance of anticipated contractual cash outflow.

As of April 2015, BNY Mellon had $21 BN of long-term debt outstanding.

Listed below are the credit ratings for The Bank of New York Mellon Corporation and its principal subsidiaries, The Bank of New York Mellon and BNY Mellon N.A., as well as the main banking subsidiary in continental Europe, The Bank of New York Mellon SA/NV as of September 16, 2015[44].

Table 405: Credit ratings for The Bank of New York Mellon and principal subsidiaries

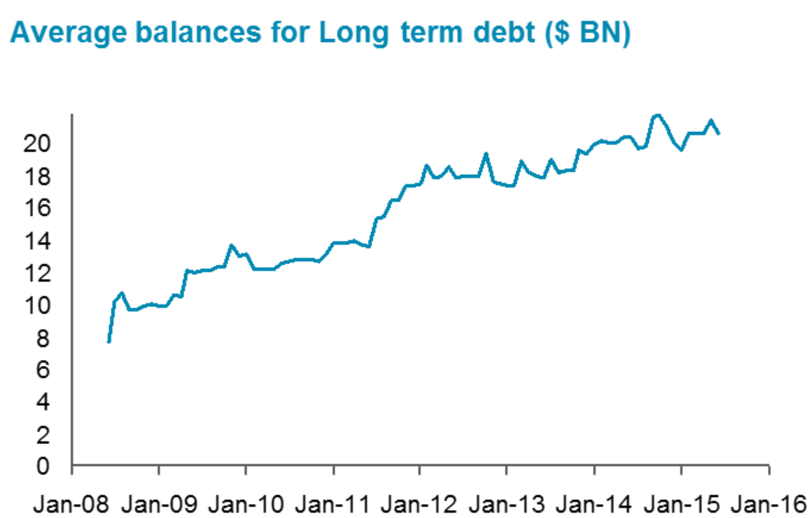
THE BANK OF NEW YORK MELLON CORPORATION	**MOODY'S**	**S&P**	**FITCH**	**DBRS**
Long-Term Senior Debt	A1	A+	AA-	AA (Low)
Subordinated Debt	A2	A	A+	A (High)
Preferred Stock	Baa1 (hyb)	BBB	BBB	A (Low)
Trust Preferred Securities	A3	BBB	BBB+	A (High)
Short-Term Debt/Commercial Paper	P1	A-1	F1+	R-1 (Middle)
Outlook	Stable	Negative	Stable	Stable (Long-Term) Stable (Short-Term)
THE BANK OF NEW YORK MELLON	**MOODY'S**	**S&P**	**FITCH**	**DBRS**
Long-Term Deposits	Aa1	AA-	AA+	AA
Long-Term Senior Debt	Aa2	AA-	AA	AA
Short-Term Deposits	P1	A-1+	F1+	R-1 (HIGH)
Outlook	Stable	Stable	Stable	Stable (Long-Term) Stable (Short-Term)

[44] https://www.BNY Mellonellon.com/us/en/investor-relations/credit-ratings.jsp

BNY MELLON N.A.	MOODY'S	S&P	FITCH	DBRS
Long-Term Deposits	Aa1	AA-	AA+	AA
Long-Term Senior Debt	Aa2	AA-	AA	AA
Short-Term Deposits	P1	A-1+	F1+	R-1 (HIGH)
Outlook	Stable	Stable	Stable	Stable (Long-Term) Stable(Short-Term)
The Bank Of New York Mellon SA/NV	**MOODY'S**	**S&P**	**FITCH**	
Long-Term Deposits/Issuer Default	Aa2	AA-	AA-	
Short-Term Deposits/Issuer Default	P-1	A-1+	F1+	
Outlook	Ratings Under Review (Positive)	Stable	Positive	

10.23.2. Historical data

Figure 455: Average balances for long-term debt ($ BN)



The historical figure above shows the average balances of long-term debt balances at BNY Mellon. Total dollar amount of outstanding issuances has climbed steadily since 2008. The historical data is used to determine a growth rate for the qualitative framework, as discussed in Section 10.23.4.

10.23.3. General data issues

No data issues were observed in the historical time series for BNY Mellon long-term debt balances.

10.23.4. Summary of approach

BNY Mellon is a highly creditworthy institution, and there is consistent market and demand for its debt. Based on discussion with the Working Group, BNY Mellon intends to continue its long-term debt issuances driven largely by management decisions independent of macroeconomic factors. As a result, macroeconomic variable regressions do not act as sufficient explanatory variables.

The long-term debt forecast is estimated in two components:

1. Debt outstanding
2. New issuances

The company's operating plan will be used to forecast both debt outstanding and new issuances. For debt outstanding, numbers are provided by the lines of businesses per capital actions on trust preferred securities and subordinated debt.

For forecasting new issuances, senior maturing issuances are embedded in QRM, and the remaining new issuances that have varied tenors such as 5Yr, 7Yr and 10Yr follow the holding company debt issuance plan.

10.23.5. Model limitations

Long term debt issuance is strongly impacted by management decisions. Though the general trend is anticipated to be captured in the company operating plan, management recommendation on the exact amount of debt to issue can change as a result of unforeseen business needs in addition to the needs assessed as part of the CCAR scenarios, which may diverge from the original planned issuances.

10.24. Non-interest bearing liabilities

10.24.1. Business overview

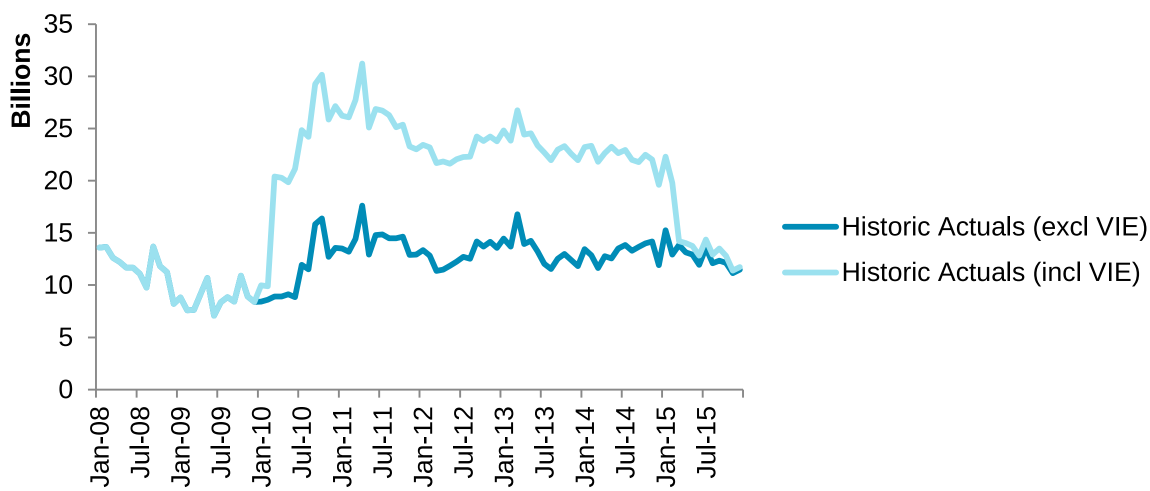
Non-interest bearing liabilities represent liabilities that do not accrue any interest expense for BNY Mellon. On BNY Mellon's balance sheet, these primarily consist of accounts payables and unpaid taxes that do not have payable interest.

Components of this segment include:

- Accounts Payable
- Accrued Interest Payable
- Accrued Expenses (Reserve for Taxes)
- Customer Payable
- Allowance for Credit Losses
- Fails to Receive
- MM Product Hedges
- Other NIBL segments
- VIE Liabilities

10.24.2. Historical data

Figure 456: Historic balances for Non-interest bearing liabilities ($BN)



The segment's historicalbalances are heavily driven by accounting convention. For example, a recent accounting change in 2015 with respect to treatment of VIEs resulted in a significant change in average balances. Specifically, this accounting change resulted in the deconsolidation of VIE liabilities from the BNY Mellon balance sheet, leading to a significant drop in the balance for this segment. Due to such data limitations, a statistical model was therefore not viewed as reasonable. Furthermore, based on the nature of this segment, there was no ex-ante expectation that balances would be sensitive to macroeconomic factors. Empirical analysis – specifically an attempt to build a statistical model – confirmed this ex-ante expectation of low correlation to any macroeconomic variable. An alternative approach was considered based on the initial hypothesis that overall balances for this segment were related to the overall balance sheet size of BNY Mellon. This hypothesis also was not supported by the data; analysis showed that while the BNY Mellon balance sheet had grown, this segment (excluding VIE) remained flat over the historical time period. Therefore, no relationship was possible between the segment and either macroeconomic variables or the overall BNY Mellon balance sheet. As a result a qualitative framework was suggested, specifically holding the forecast constant to the last available historical value (see below for further discussion).

10.24.3. Data issues

For additional details regarding the accounting changes, please refer to the section on Non-interest earning assets (excluding Goodwill and Intangibles).

10.24.4. Summary of approach

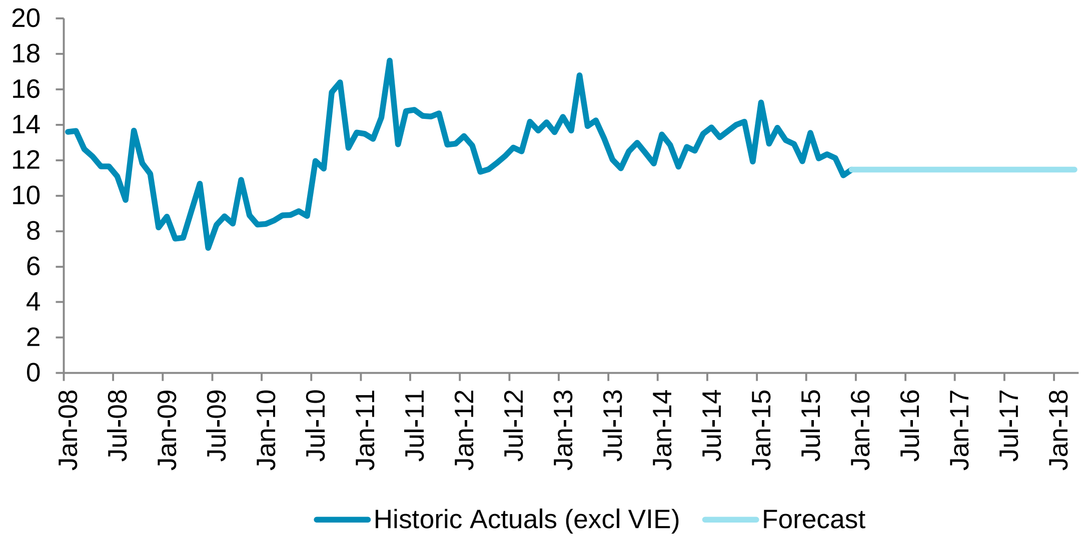
Due to the stability of the non-interest bearing liability segment and the fact that volatility in the segment arises primarily as a result of accounting policy changes, over the next nine quarters, the forecast will hold the entire segment constant to the December 2015 spot balance, excluding the remaining VIE liabilities that remain on the balance sheet in December 2015, as they are in run-off and expected to decrease to zero in the future.

Given this stability and the lack of an empirically observed relationship to either overall balance sheet size or individual macroeconomic factors (plus the lack of an ex-ante expectation regarding a relationship to macroeconomic factors), a qualitative framework to hold these balances flat was viewed as appropriate.

Additionally, the selected approach aligns with the forecasting methodologies of approaches for non-interest earning assets (excluding Goodwill and Intangibles).

The results hold the forecast at the December 2015 spot balance for the NIBL segment, excluding the remaining NIBL VIE liabilities still on the balance sheet. Because VIE liabilities were deconsolidated from the balance sheet in 2015 and do not impact the forecast, the graph below shows historic actuals without VIE liabilities included. The December 2015 spot balance (excluding VIE liabilities) was $11.5 billion:

Figure 457: Non-Interest Bearing Liabilities Balances Forecast ($BN)



10.24.5. Approach limitations

As of December 2015, the total balance for the Non-Interest Bearing Liabilities segment was $11.5 billion (excluding the remaining VIE liabilities on the balance sheet). Though the balances in this segment, excluding the one-time VIE liabilities accounting adjustments, tend to be steady, changes to accounting regulations can have a significant impact on the balances. However, advanced knowledge of these changes allows BNY Mellon to incorporate as many of the regulatory changes as possible, or hold to the most conservative assumption. In the case of CCAR, any such changes would either (a) already be known and thus incorporated into balance amounts for this segment at the appropriate time or (b) in the case of additional future changes (that are currently not known) would have to be hypothesized as part of scenario design.

11. Other balance sheet segment rates

11.1. Overview

This section discusses the rate forecasting approaches for balance sheet segment outside of deposits, loans, and the Investment Portfolio. The segmentation used for rates matches the segmentation used for balances; see Section 3.1.3 for further details on this segmentation. The tables below show the segmentation, along with the type of forecasting method used to forecast rates for each segment.

Table 406: “Other balance sheet” segments – Assets

#	Other assets	Description	Apr’15	Rate

			Balance ($ BN)	forecasting method
1	Central bank deposits: Fed deposits	Central bank deposits at the US Federal Reserve	71	Qualitative
2	Central bank deposits: Foreign Central Bank deposits	Central bank deposits at foreign central banks	29	Qualitative
3	Placements: Nostro	Short-term unsecured deposits at foreign non-central bank accounts in foreign currency	5.1	Qualitative
4	Placements: Pershing	Short-term unsecured deposits held by Pershing at non-central banks	5.7	Qualitative
5	Placements: Treasury	Short-term unsecured deposits held by branches and subsidiaries of BNY Mellon at non-central banks, excluding Pershing and Nostro placements	9.5	Qualitative
6	Fed funds sold and reverse repos (Non-Pershing)	Fed funds sold and reverse repos of BNY Mellon excluding Pershing	0.5	Qualitative
7	Securities Borrowing & Reverse repos (Pershing)	Securities borrowing and reverse repos conducted by Pershing	11	Model
8	Securities financing: ABCP, SF loans, Reverse repo	Term loans collateralized by investment securities; includes loans, reverse repos, and asset-backed commercial paper	24	Qualitative
9	Trading assets (Global Markets)	Debt, equity, and derivative instruments not designated as hedging instruments and held for short-term trading by Global Markets business	6.6	Qualitative
10	Trading assets (Capital Markets)	Debt, equity, and derivative instruments not designated as hedging instruments and held for short-term trading by Capital Markets business	3.0	Model
11	Non-interest earning assets (excl. Goodwill, Intangibles)	Assets that do not accrue interest, excluding goodwill and intangibles	33	N/A
12	Non-interest earning assets: Goodwill	Goodwill resulting from acquisitions	18	N/A
13	Non-interest earning assets: Intangibles	Intangible assets with a finite useful life	4.0	N/A

*Investment Portfolio not included here, as its rate forecasts are treated in a separate OCI project

Table 407: “Other balance sheet” segments – Liabilities

#	Other liabilities	Description	Apr’15 Balance ($ BN)	Rate forecasting method
1	Trading liabilities (Global Markets)	Trading liabilities generated by the Global Markets business	6.6	Model
2	Trading liabilities (Capital Markets)	Trading liabilities generated by the Capital Markets business	0.6	Model
3	Short-term borrowings: Broker dealer customer payables	Funds awaiting re-investment and short sale proceeds payable on demand to Pershing clients	23	Model
4	Short-term borrowings: Fed funds, Repos (Treasury)	Fed funds and repos held by BNY Mellon excluding Pershing	8.6	Qualitative
5	Short-term borrowings: Capital market repos	Repos used to fund HQLA Capital Markets activity	1.2	Qualitative
6	Short-term borrowings:	Repos made by Pershing	6.4	Model

	Repos (Pershing)			
7	Short-term borrowings: Commercial Paper	Commercial paper issued by BNY Mellon	4.8	Qualitative
8	Short-term borrowings: Other borrowed funds	Short-term borrowings other than Fed funds, repos, customer payables, and commercial paper; primarily consisting of Eurodollar deposits	1.1	Qualitative
9	Long term debt	Long term debt issued by BNY Mellon	21	Qualitative
10	Non-interest bearing liabilities	Liabilities that do not accrue interest	14	N/A

The rate models follow the approach discussed in Section 3.5, where the independent variables used in the regressions are underlying reference rates for each segment. The table below shows a summary of the models selected for the modeled rate segments, with the independent variables used.

Table 408: Summary of rate models of other Balance Sheet segments

Product	Variable 1	Variable 2
Securities Borrowing & Reverse repos (Pershing)	Overnight Repo (diff QoQ, 1-month lag)	
Securities Financing	USD 1-month Libor (diff MoM, 1-month lag)	USD 6-month Libor (diff MoM, 3-month lag)
Trading Assets (Capital Markets)	Overnight Libor (diff MoM, 1-month lag)	
Trading Liabilities (Global Markets)	Treasury 10 year yield (diff QoQ, 1-month lag)	
Trading Liabilities (Capital Markets)	USD 1-month Libor (diff MoM, 1-month lag)	
Short-term borrowings: Broker dealer customer payables	Fed funds target rate (diff QoQ)	
Short-term borrowings: Repos (Pershing)	USD 1-month Libor (diff QoQ, 1-month lag)	

The rate models are discussed in further detail within the following sections.

For segments that did not ultimately use a statistical model, qualitative frameworkes were applied in several cases:

- Segments where no statistically valid model could be found
- Segments where historical data was not available
- Segments where the forecast rate was judged to align to a variable that could be forecast directly by Moody's Analytics
- Segments where a more precise approach was used to capture heterogeneity within the segment, e.g. for long-term debt where new issuances are treated separately from existing issuances

The rationales and exact forecast methodology for the qualitative frameworkes are discussed in further detail within the following sections.

11.2. Central bank deposits: Fed deposits

11.2.1. Historical data

The qualitative method does not require the use of historical data.

11.2.2. General data issues

Not applicable as historical data was not used for approach development.

11.2.3. Summary of approach

BNY Mellon receives interest for both required balances and excess deposits, at the interest rate on required reserves (IORR rate), and the interest rate on excess reserves (IOER rate), respectively. For CCAR, required balances are not calculated explicitly, but have historically made up a small part of BNY Mellon's balances at the Fed and are expected to make up a small part of deposits in all scenarios.

As an approximation, the IOER will be applied on the total Fed balances. If the IOER is not available, the Fed Funds Target rate will be used as an approximation.

11.3. Central bank deposits: Foreign Central Bank deposits

11.3.1. Historical data

The qualitative method does not require the use of historical data.

11.3.2. General data issues

Not applicable as historical data was not used for approach development.

11.3.3. Summary of approach

For European Central Bank (ECB) and Bank of England balances the required balances make up a small percentage of the total balances held. The rate forecast will utilize rate forecasts for interest paid on deposits at the ECB and the Bank of England. The ECB deposit facility rate will be used for the total ECB reserves. The BOE official bank rate will be used for BOE reserves. The interest rates will be applied on the respective forecasted balances by currency.

11.4. Nostro Placements

11.4.1. Historical data

Historical data was unavailable at the time of approach development. A qualitative framework that does not require historical data was developed.

11.4.2. General data issues

Not applicable as historical data was not available at time of approach development.

11.4.3. Summary of approach

The Nostro Placements rates model derives its rate from the Asset Servicing IB rates model. That is, the rate forecasted in the AS IB rates model will be used as the forecasted rate for the Nostro Placements rates model.

Other approaches were explored, such as the use of overnight LIBOR (forecasted by Moody's Analytics) as a proxy rate. These attempted approaches were ultimately rejected as they resulted in rates higher than suggested by business intuition. For example, the use of overnight LIBOR would result in rates higher than expected for the Nostro Placement which can be considered similar in nature to unsolicited balances at other banks. Instead, the rate paid on unsolicited balances at BNY Mellon was chosen as a benchmark. As the bank's largest segment, the Asset Servicing IB Rates model was selected as it reflects the largest portion of the bank's balances. In addition, the decision to move from the overnight LIBOR to tying the Nostro Placements rate to the AS IB rates model is conservative as it effectively assumes no net interest income generated by the balances that fund these placements (i.e. rate earned is equal to rate paid).

11.4.4. Approach limitations

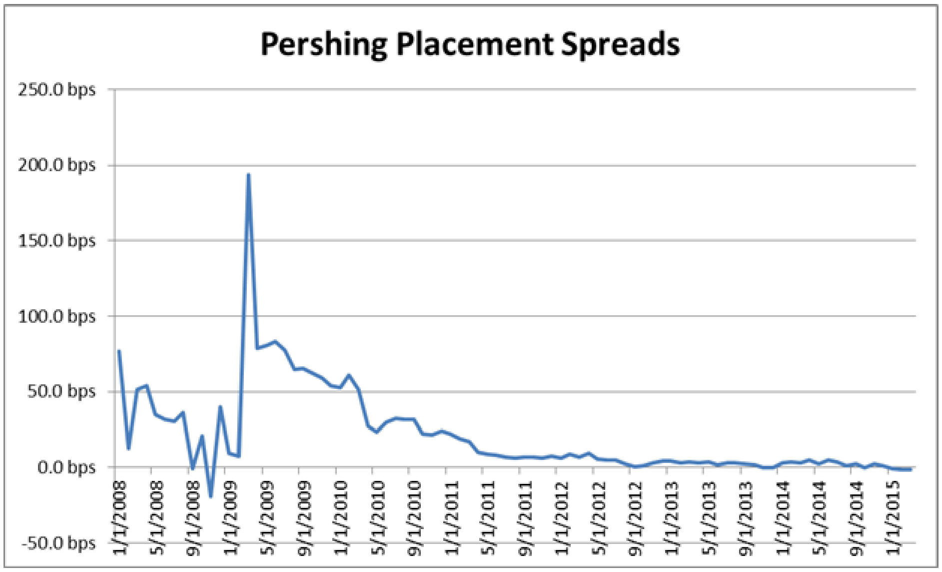
The same limitations of the AS IB rate model, if any, apply.

11.5. Pershing Placements

11.5.1. Historical data

Figure 1 shows the historical data for this business. Starting from 2011, the spread of rate to Fed Fund Target Rate is very close to zero. Historical balances do not have a relationship to the macroeconomic environment that could be captured by a model. Thus, a qualitative framework that does not require historical data was developed.

Figure 458: Pershing Placements Spreads



11.5.2. Summary of approach

The qualitative framework here is to use Fed Fund Target Rate plus the historical lowest spread to Fed Fund Target Rate after last great recession. These placements are short-term unsecured deposits held at non-central banks, so this qualitative framework would be the reasonable proxy and conservative. The current spread is approximately 1bp.

11.6. Treasury Placements

11.6.1. Historical data

Historical data was unavailable at the time of approach development. A qualitative framework that does not require historical data was developed.

11.6.2. General data issues

Not applicable as historical data was not available at time of approach development.

11.6.3. Summary of approach

Market interest rates as forecasted by Moody's Analytics plus a spread are used as the rate for Treasury Placements. BNY Mellon effectively provides liquidity to other banks with these funds and can demand a higher rate than for other types of placements, such as the Nostro Placements. The rate that BNY Mellon demands on the placements is calculated as follows:

- For placements that are made as of December 31, 2015, the contractual terms are used for the rates.

- For reinvested funds, the rates will equal the market interest rate as forecasted by Moody's plus a spread. The spread will be equal to the spread between
  - weighted average coupon of placements in a single currency in the portfolio as of December 31, 2015, and
  - a short-term interest rate closest in maturity to the weighted average maturity of placements in a given currency in the portfolio as of December 31, 2015.

Only the placements of desks that reinvest placements in the company's plan are used in the weighted average maturity and rate calculations. The rate that is used to calculate the spread and the spreads are as follows:

- USD placements: 1-month USD LIBOR, 5 bps
- CAD placements: 1-month CAD swap rate, -10 bps
- AUD placements: 3-month AUD swap rate, -74 bps
- HKD placements: 3-month HKD swap rate, -2 bps
- SGD placements: 1-month SGD swap rate, -93 bps
- Other placements: 1-month USD LIBOR, 159 bps

11.7. Fed Funds Sold and Reverse Repos (Non-Pershing)

11.7.1. Historical data

Historical data was not available to the modeling team at the time of model development. No historical rate data is used as part of the selected qualitative forecasting method.

11.7.2. General data issues

Historical data was not available to the modeling team at the time of model development.

11.7.3. Summary of approach

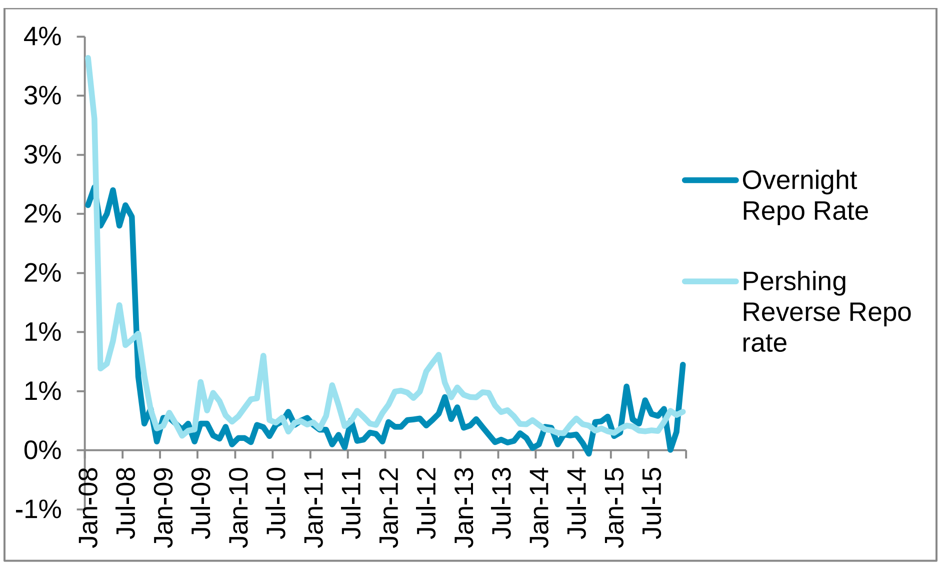
Due to the short-term nature and security of the investments in this segment, the overnight repo rate forecasted by Moody's Analytics will be used for the Fed CCAR scenarios as the rate for the Fed Funds Sold and Reverse Repos. This rate was viewed to be the most appropriate rate by the modelling team and Working Group, supported by line of business feedback that any activity in this segment going forward is likely to be in the form of reverse repos – for which the repo rate can serve as a proxy – as opposed to Fed Funds sold. The choice of the repo rate also allows the modelling team to leverage the scenario forecasts provided by Moody's as part of the CCAR process.

11.8. Securities Borrowing and Reverse Repos (Pershing)

11.8.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with one of the selected short-term reference rates. The historical Reverse Repo (Pershing) rate data displays significant volatility, but generally follows the directional movement of the reference rate.

Figure 459: Historical rates for overall Reverse Repo (Pershing) segment



11.8.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Reverse Repo (Pershing) rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary

- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests except for serial correlation as described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 409: Coefficient estimates for the Reverse Repo (Pershing) rates model

Rate – Reverse Repo (Pershing) (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Overnight repo rate	First difference – QoQ, 1-month lag	%	0.247	0.0628
Intercept	None (level)	%	-0.00963	0.0278

The model uses one factor: a transformation of the overnight repo rate, with a positive coefficient. The Working Group confirmed the intuition of this variable and its sign. Positive coefficients were required to match business intuition that the segment rate should be positively correlated with the reference rates.

11.8.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

11.8.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the other Balance Sheet segment rates using the same methodology as for the other Balance Sheet segment balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 410: Unit root tests and stationarity tests including a trend variable on balances

Rate – Reverse Repo (Pershing) – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	10	-8.46	<0.0001	Reject unit root
Phillips-Perron	1	-8.91	<0.0001	Reject unit root
KPSS	4	0.58	0.0239	Reject stationarity

Table 411: Unit root tests and stationarity tests including a constant on first differences

Rate – Reverse Repo (Pershing) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	9	-3.15	0.0267	Reject unit root
Phillips-Perron	1	-8.24	<0.0001	Reject unit root
KPSS	3	0.36	0.0944	Fail to Reject stationarity

Stationarity tests for Reverse Repo (Pershing) rate levels yield mixed results: The ADF test rejects a unit root, while the PP tests rejects a unit root and the KPSS test fails reject stationarity. This implies that the levels are not robustly stationary. Because of this the modeling team looked at the first differences. And the first differences passed all the three tests.

Therefore, the modeling team uses first difference transformations for the other Balance Sheet segment rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

11.8.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Reverse Repo (Pershing) rates data shows significant volatility, particularly in 2009. However, to preserve the integrity of the data, no changes were made to the underlying data.

11.8.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Reverse Repo (Pershing) rates model are statistically significant.

Table 412: Statistical significance tests of model and variables for Reverse Repo (Pershing) rates

Rate – Reverse Repo (Pershing) (in %) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant
Overnight repo rate	0.247	<1%	10%	Statistically significant
Intercept	-0.0096	73%	10%	Statistically not significant

11.8.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable

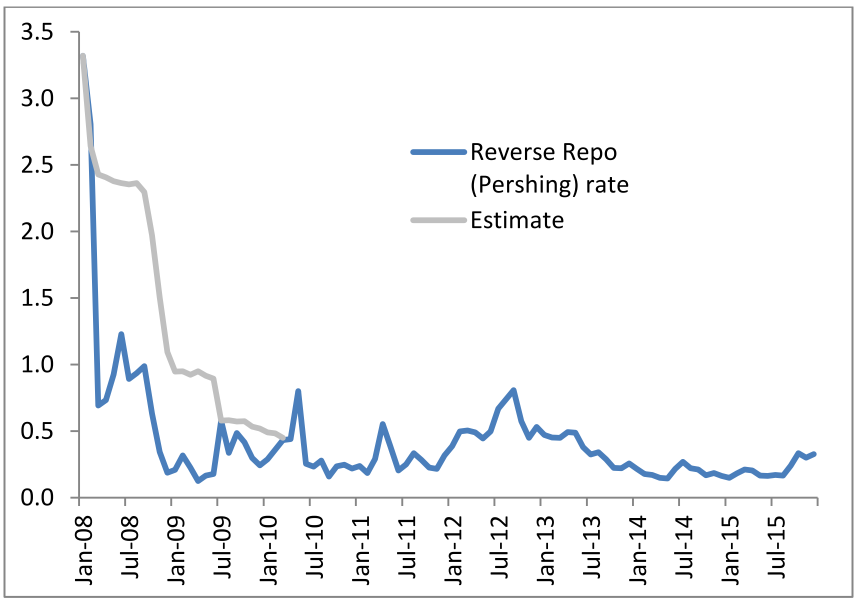
The results for the diagnostic tests reviewed are exhibited below.

Table 413: Reverse Repo (Pershing) rate model diagnostics

Rate – Reverse Repo (Pershing) – Model diagnostics				
Assessment	**Statistic or test**	**Result**	**Threshold**	**Conclusion**
Goodness of fit	R-squared	16%	-	-
	Adjusted R-squared	15%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	8%	10%	Heteroskedasticity present
Autocorrelation	White(p-value)	56%	10%	No Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	26%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity

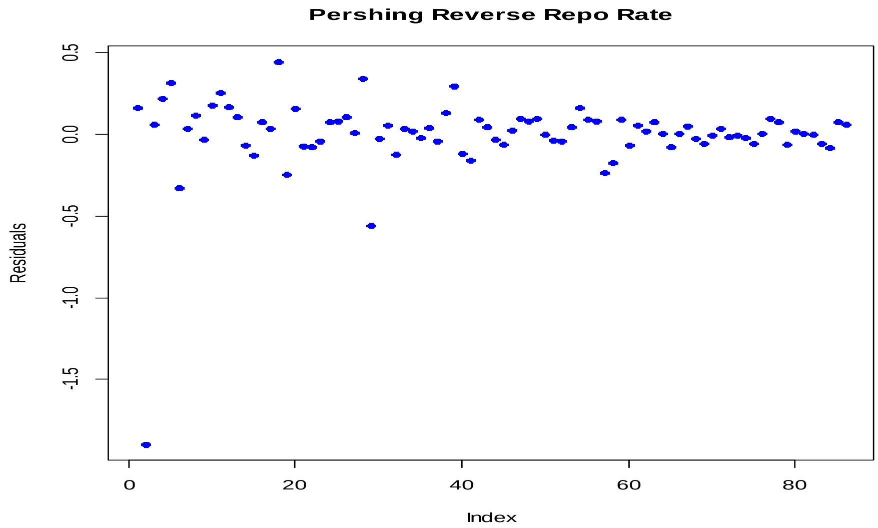
The selected model for this segment passed all statistical tests.

Figure 460: Reverse Repo (Pershing) rate 9Q in-sample prediction (%)



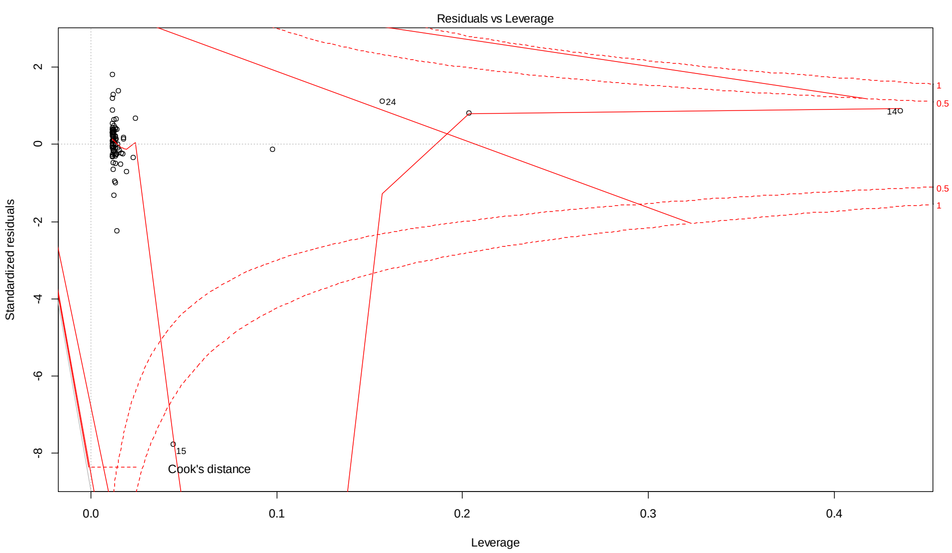
In the select 9Q in-sample prediction, the model captures the decline in rates, but fails to capture the full magnitude of the decrease. In addition, the timing of the decrease is not aligned to the actual rates, with the decrease in actual rates occurring several months before the estimate. Given the poor historical fit of this model, management scrutiny is recommended for its results.

Figure 461: Reverse Repo (Pershing) rate residual plot (%)



The residuals appear to be randomly distributed around the horizontal axis, with a few outliers due to the poor historical fit of the model.

Figure 462: Influential points for Reverse Repo (Pershing) rates



For this segment March 2008 is a highly influential point. However, this is not surprising because the volatility in rates during the crisis and does not invalidate the model

11.8.6. Model sensitivity

11.8.6.1. Sensitivity to changes in independent variables

Given the Reverse Repo (Pershing) rates model only contains one type of independent variable (i.e. one or more transformations of the benchmark rate), the sensitivity can be directly interpreted from the coefficient estimates.

11.8.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

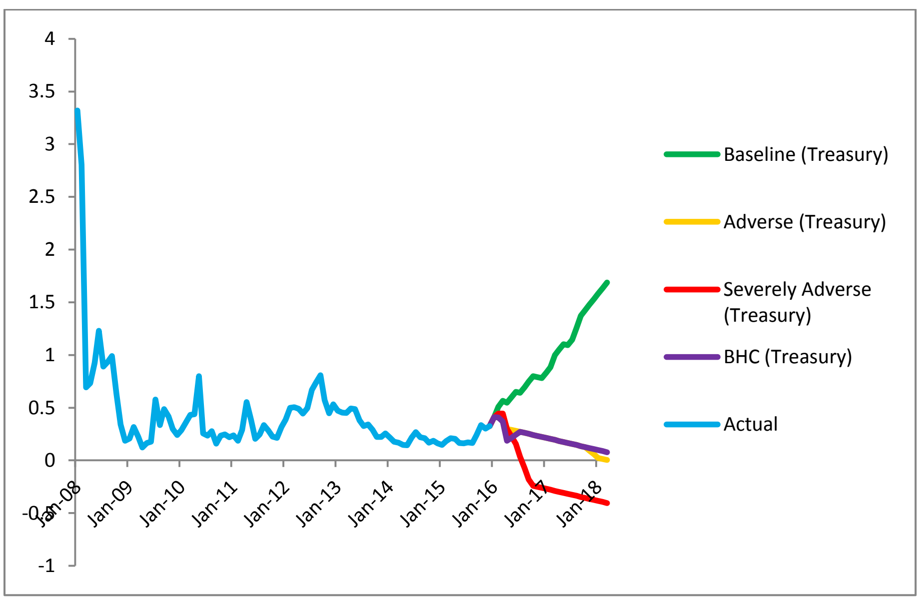
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

11.8.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 463: Reverse Repo (Pershing) rates model forecast (%) (Using CCAR 2016 Scenario)



The Working Group and Line of Business both considered the forecast behavior for the selected Reverse Repo (Pershing) rates model as reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts continued low rates, in line with the overall interest rate environment in this scenario
- **Adverse scenario**: The model predicts a slight decrease in reverse repo rate. This is in line with business intuition
- **Baseline scenario**: The model predicts a rise in segment rates. This is in line with business intuition, but management review is recommended to ensure the magnitude of the increase is consistent with expectations

11.8.7. Model limitations

The historical series for dependent variable is limited because data prior to the merger of Bank of New York and Mellon in 2008 is not available to the modeling team. The model shown above is not trained on a long set of historical data with varying interest rates, and thus would require management attention when forecasting rates under scenarios with rising interest rates.

11.9. Securities Financing

11.9.1. Influential pointBusiness overview

BNY Mellon's Securities Financing is a new business that began in early 2011. As part of the Securities Financing program, BNY Mellon enters in Term Reverse Repos, originates Securities Financing Loans and purchases Collateralized Commercial Paper (CCP).

11.9.2. Data issues

A statistical model was originally attempted for this segment, but the results were not reasonable or intuitive so a structural approach was developed. Feedback from the Securities Financing Line of Business (LOB) indicates that the Securities Financing rates are highly management driven, while the forecasting outputs from the attempted model were not aligned to business intuition. For example, in baseline scenario the attempted model forecasted a rate increase from 0.93% to 5.54% over the forecasting horizon, which represents an implied change in spreads from 28 bps to 285 bps above the 3-month USD LIBOR. This spread cannot be supported by business intuition: It is significantly higher than any spread observed historically and it is significantly higher than what is expected by the LOB; and in the severely adverse scenario, the rates implied from the original model forecast go negative in some months, which is highly unlikely in light of LOB feedback. The LOB expects that in the Severely Adverse Scenario, pricing will increase and rates will remain positive due to a heightened risk aversion and the requirement of maintaining a return on loans. Specifically, if rates were to go negative, the bank would likely choose to purchase Treasury bills rather than issue new Securities Financing products, as the expected returns would be higher in a negative rates environment. Due to the difference between the LOB's expected rates, the historically observed rates, and the original model rate output, the rate in the Severely Adverse scenario will be calculated using the qualitative framework described in the Approach section below.

Due to the under-performance of the attempted quantitative model, a qualitative approach was thus adopted.

11.9.3. Summary of approach

The proposed qualitative framework here for the Securities Financing rate model is based on expert feedback from the Line of Business. Specifically:

The line of business prices products with spreads against LIBOR rates matching the tenor of the product. Compared to historical spreads, the original model forecasts rates instead of spreads, an approach that does which is not aligned with business insight under the Securities Financing rate. Furthermore, the original model did not consider products' tenor and instead forecasts in a mixed rate across all products. Furthermore, the Securities Financing rates are highly management driven. This is approved due to several meetings with the line of business.

The original model also allows negative forecasting outputs. The Line of Business, however, strongly indicates that it would not lend at a negative rate due to the nature of the product. Even under stress scenarios, the Line of Business's plans are to keep pricing at positive rates due to higher risk aversion, strained market liquidity and the requirement to maintain a return on loans.

As such, a qualitative framework which uses spreads based on historical data is more reasonable for the Securities Financing rate projection. The qualitative framework here is to use LIBOR rates plus a 45bps spread. Historically, the portfolio's rates have ranged between a maximum of 1.42% in March 2011 and a minimum of 0.63% in January 2015. The 45bps spread corresponds to the average spread from January 2013 to December 2015 in the Securities Financing Portfolio to 3-month LIBOR rate and aligns with feedback from the line of business regarding pricing strategies for Securities Financing products. The LIBOR rate that will be applied references to corresponding maturities of the securities. For new volumes the maturities of the transactions are assigned proportionally to the existing portfolio.

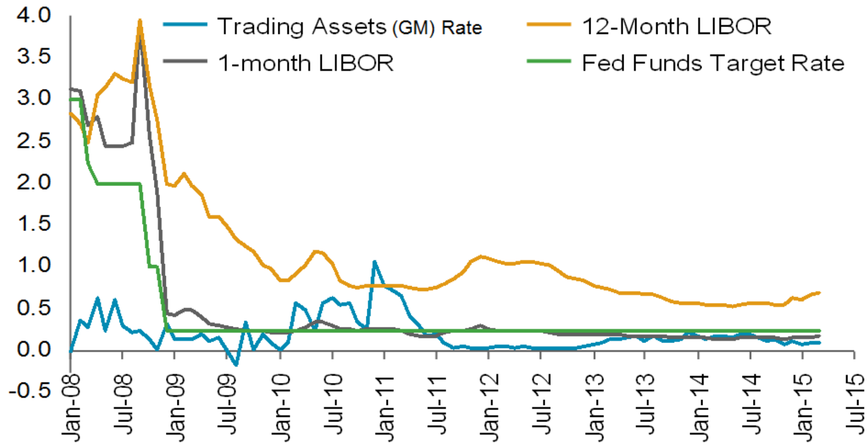
The decision to use a spread of 45bps plus LIBOR matching the tenor of the product aligns with business pricing strategies and historical data.

11.10. Trading Assets (Global Markets)

11.10.1. Historical data

Historical data for Trading Assets (Global Markets) was retrieved via MAQ and are presented in the figure below, along with potential reference rates.

Figure 464: Trading Assets (Global Markets) Rates



The historical rates data for the segment is shown in the figure above. The historical Trading Asset Global Markets rate data displays significant volatility, especially from 2008 to 2011. From 2012 onwards, the Trading Asset Capital Markets group rates tend to track closely to the reference rates. However, the historical segment rate does not show the higher levels before the 2008–2009 financial crisis that the reference rates show.

11.10.2. General data issues

One negative point in August 2009 existed in the dataset. Because this point had limited impact on the series, it was left in during the initial modeling attempts. In order to maintain the dataset as closely as possible to MAQ historical actuals, the final qualitative framework selected also included this observation due to its limited impact.

11.10.3. Summary of approach

During the model development phase for Trading Assets (Global Markets) Rates, the Working Group found that business intuition provided only a small number of hypotheses that could be used to develop a model using macroeconomic variables (such as interest rate variables).

Trading Assets (Global Markets) consist primarily of Global Markets derivatives transactions, but also equity and debt. The Working Group suggested a wide range of rates as independent variables, which included the following: 1-month, 3-month, 6-month, 12-month LIBOR rates, Fed funds target and effective rates, 1-month and 3-month Euro LIBOR rates, 1-month and 3-month GBP LIBOR rates, Overnight LIBOR rates, Overnight Repo rates, Treasury 10-year rates and exchange rates.

Using these variables, the modeling team was unable to produce a statistically significant result that had intuitive signs in the coefficients. Thus, a qualitative framework was employed.

The historical rates of Trading Assets (Global Markets) were not sensitive to the aforementioned referenced rates and variables. As such, a qualitative framework that uses the historical average of the Trading Assets (Global Markets) rates from January 2008 to December 2015 will be used. The rate derived from the historical average is 0.20% and will be used for the 9-

quarter CCaR forecast period in all scenarios. This is consistent with the observation that rates did not react in any specific way to the global financial crisis in 2008 and 2009.

11.10.4. Approach limitations

Both the business and Working Group had little intuition for interest rate variables that can explain the rate variability of Trading Assets (Global Markets). The Trading Assets portfolio includes a range of debt, equity, and derivative instruments in constantly changing proportions. Much of the volatility is driven by the constant change in portfolio mix. The rate is calculated by dividing the balance by interest income, and since only debt earns interest income, the portfolio mix change can contribute heavily to volatility in the rates. For instance, if equity instruments are traded heavily during a certain period, the balances (denominator) will increase without change in interest income (numerator), driving down the overall rate for this segment.

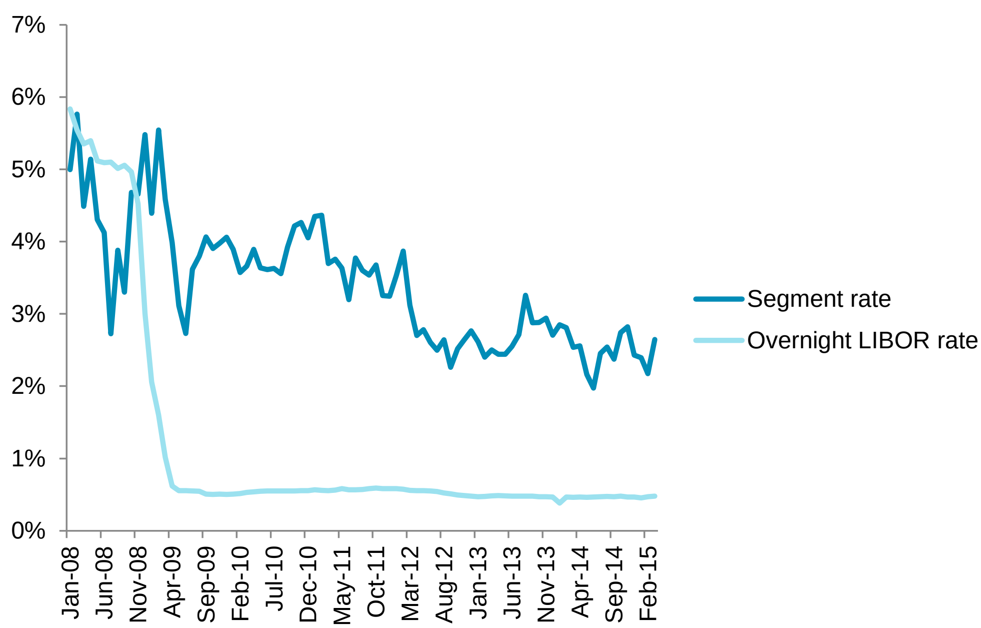
For these reasons, close attention from management is likely required to potentially adjust the forecasts from the model.

11.11. Trading Assets (Capital Markets)

11.11.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with one of the identified reference rates. The historical Trading Asset (Capital Markets) rates data displays a significant level of volatility with a general downward trend. In contrast, the reference rate remains relatively flat at a low level from mid-2009 onwards.

Figure 465: Historical rates for overall Trading Asset (Capital Markets) rates



11.11.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Trading Asset (Capital Markets) rates segment. However, given the volatile nature of the historical dependent variable time series, and the inability of reference rates to capture the diverse products within the segment, a high level of management scrutiny is recommended.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests except for serial correlation as described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 414: Coefficient estimates for the Trading Asset (Capital Markets) rates model

Rate – Trading Asset (Capital Markets) (in %) – Selected model

Independent variable	Transformation	Unit	Coefficient estimate	Standardized coefficient
Overnight LIBOR rate	First difference – MoM, 1 month lag	%	0.396	0.18
Intercept	None (level)	%	-0.002	N/A

Trading Asset (Capital Markets) portfolio holds a diverse of mix of instruments, including debt, equity and derivatives. Given the diversity within the portfolio, the Working Group suggested using a wide range of rates as independent variables, which included the following: 1-month, 3-month, 6-month, 12-month LIBOR rates, Fed funds target and effective rates, 1-month and 3-month Euro LIBOR rates, 1-month and 3-month GBP LIBOR rates, Overnight LIBOR rates, Overnight Repo rates and Treasury 10-year rates.

Of various transformations of the variables mentioned above, the modeling team selected a model that used a transformation of the Overnight LIBOR rates. The variable has a positive coefficient. The Working Group confirmed the intuition of its sign. Positive coefficient was required to match business intuition that the segment rate should be positively correlated with the reference rate.

11.11.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

11.11.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the other Balance Sheet segment rates using the same methodology as for the other Balance Sheet segment balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 415: Unit root tests and stationarity tests including a trend variable on balances

Rate – Trading Asset (Capital Markets) – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	4	-2.3	0.18	Fail to Reject unit root
Phillips-Perron	1	-2.7	0.08	Reject unit root
KPSS	5	1.34	<0.01	Fail to Reject stationarity

Table 416: Unit root tests and stationarity tests including a constant on first differences

Rate – Trading Asset (Capital Markets) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	3	-5.1	<0.01	Reject unit root
Phillips-Perron	1	-14	<0.01	Reject unit root
KPSS	3	0.04	0.94	Fail to Reject stationarity

Stationarity tests for Trading Asset (Capital Markets) rates on level suggest that the series may not be stationary: the PP test rejects the unit root and the KPSS test fails to reject stationarity, but the ADF test rejects the unit root. In contrast, the first differences series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Trading Asset (Capital Markets) rates are modeled on their first differences.

There is, however, a limitation to these tests. The other Balance Sheet segment rates data spans less than one full rate cycle. Therefore, tests on stationarity may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable shows stationary behavior, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[45].

Therefore, the modeling team uses first difference transformations for the other Balance Sheet segment rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

[45] “Real Interest Rate Persistence: Evidence and Implications” Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

11.11.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Trading Asset (Capital Markets) rates data showed a high degree of volatility, owing to the fact that it includes a wide mix of products ranging from debt, equity to derivatives. The changing mix of instruments in the portfolio affects the level of the historical rates. However, to preserve the integrity of the data, no changes were made to the underlying data.

11.11.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. The coefficient estimates of Overnight LIBOR rates and the joint f-test are both statistically significant. The intercept is found to be statistically insignificant.

Table 417: Statistical significance tests of model and variables for Trading Asset (Capital Markets) rates

Rate – Trading Asset (Capital Markets) (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	6%	10%	Statistically significant
Overnight LIBOR rate	0.396	6%	10%	Statistically significant
Intercept	-0.002	96%	10%	Statistically not significant

11.11.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

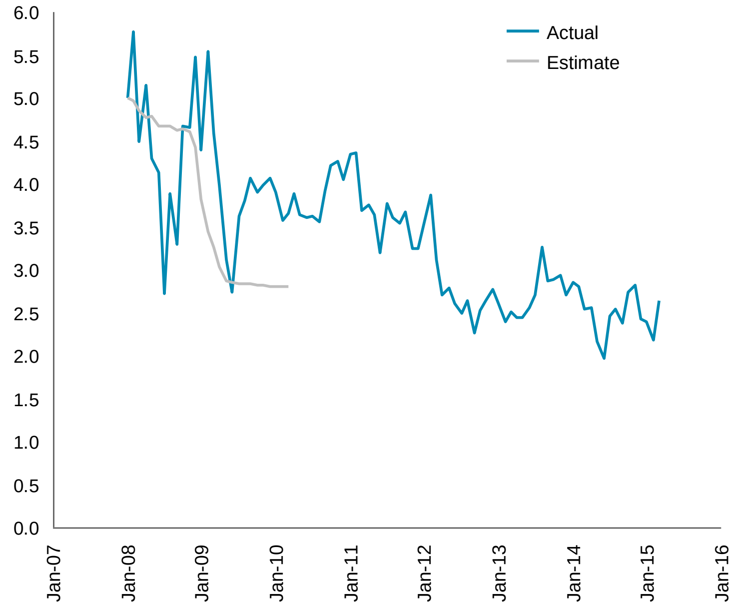
Table 418: Trading Asset (Capital Markets) rate model diagnostics

Rate – Trading Asset (Capital Markets) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	3%	-	-
	Adjusted R-squared	2%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	0.02%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	94%	10%	Linear specification appropriate

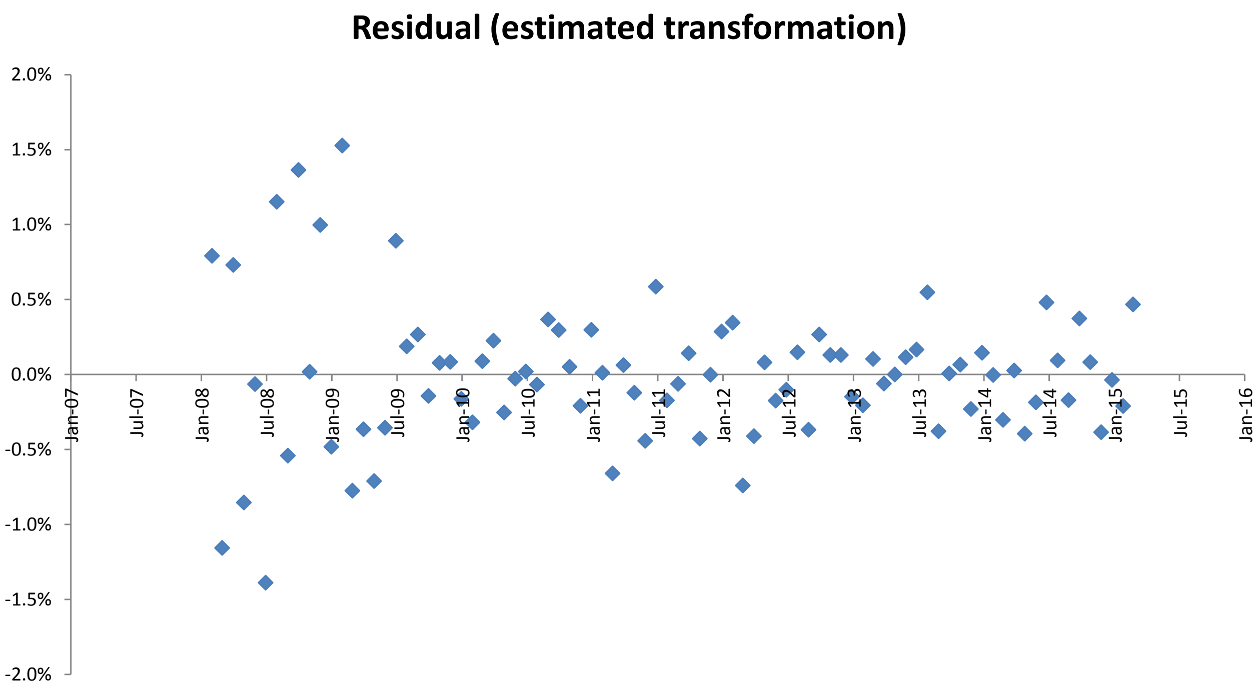
Serial correlation was detected in the residuals of this model. As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Figure 466: Trading Asset (Capital Markets) rate 9Q in-sample prediction (%)



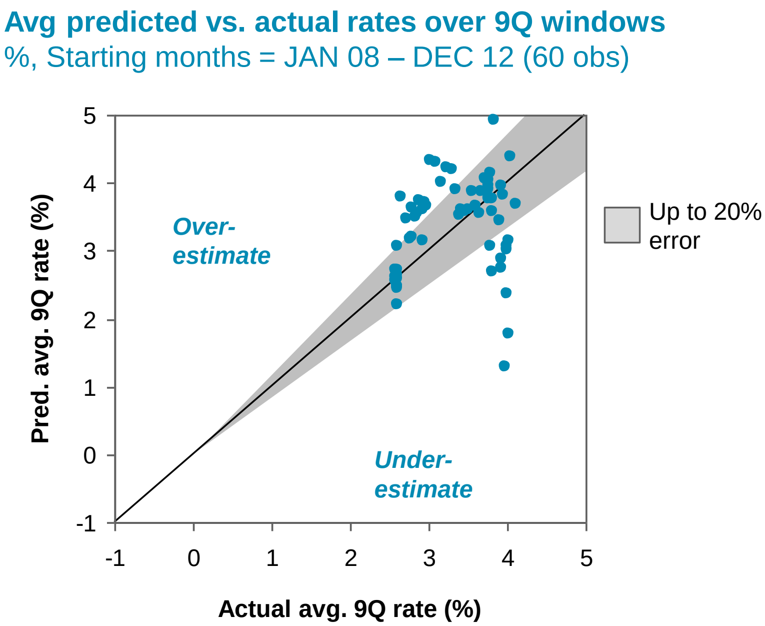
In the select 9Q in-sample prediction, the model is unable to pick up the dip in 2008–2009, but it does predict the decrease from mid-2009 to 2010 with some lag. In general, the model is unable to capture historical volatility during the 9-quarter period since 2008. While the actual balance continues to undergo volatile movements from 2009 onward, the reference rate remains flat. Given the varied portfolio mix within this segment, the relative weakness of the model is not unexpected. A close management scrutiny is required with the usage of this model.

Figure 467: Trading Asset (Capital Markets) rate residual plot (%)



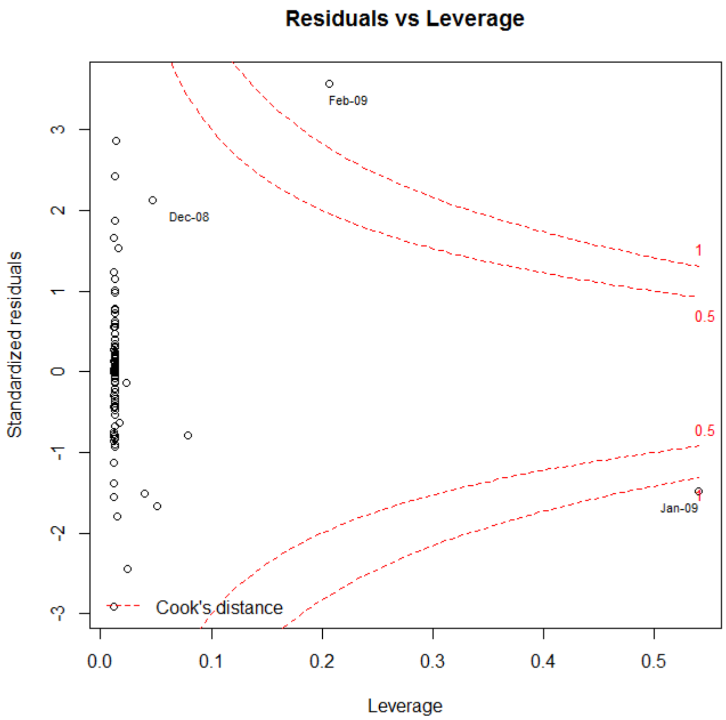
As seen in the figure above, the residuals are randomly distributed around the horizontal axis.

Figure 468: Trading Asset (Capital Markets) rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels result in certain overestimations and underestimations of Trading Asset (Capital Markets) rates. The model does not pick up the significant dip during the financial crisis, and also remains flat from 2009 onwards while the actual balances undergo volatile changes. Thus, the model will serve as a starting point while expert knowledge will also be used in the review for balance sheet forecasting.

Figure 469: Influential points for Trading assets (Capital Markets) Rates



For this segment January and February 2009 are highly influential points. However, this is not surprising because these were due to the financial crisis and does not invalidate the model

11.11.6. Model sensitivity

11.11.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in the table below. The standardized coefficient reported describes the standard deviation change in the predicted rates due to a one standard deviation increase in an independent variable.

Table 419: Trading Asset (Capital Markets) Model Sensitivity

Rate – Trading Asset (Capital Markets) (in %) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in rates resulting from 1 std. dev change in the independent variable (%)
Overnight LIBOR rate	First difference – MoM, 1 month lag	%	0.18	0.26	0.15
Intercept	None (level)	%	N/A	N/A	N/A

In the Trading Asset (Capital Markets) rates model, a one standard deviation increase in the Overnight LIBOR rates result in a 0.18 standard deviation (0.15%) increase in the predicted monthly change of the Trading Asset (Capital Markets) rates.

11.11.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

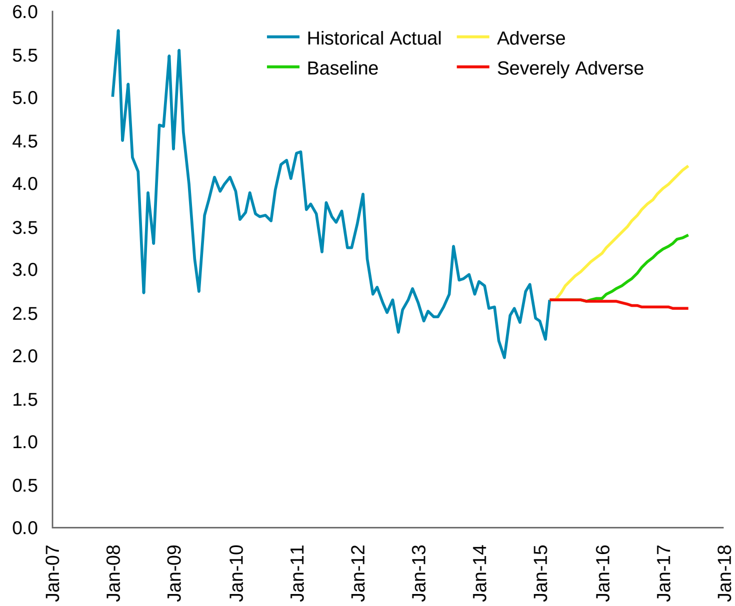
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

11.11.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 470: Trading Asset (Capital Markets) rates model forecast (%)



The Working Group considered the forecast behavior for the selected Trading Asset (Capital Markets) model as requiring scrutiny during management review, given the high volatility in this rates segment resulting from the portfolio mix and the weaknesses of the model.

- **Severe recession (Severely Adverse) scenario:** The model predicts minimal change in rates. Given the historical volatility of the Trading Asset (Capital Markets) rates, management overview is recommended for this segment
- **Interest rate shock (Adverse) scenario**: The model predicts a steep rise in segment rates. Although the magnitude of the increase is in line with historical data, management overview is recommended for this segment given the historical volatility of the Trading Asset (Capital Markets) rates
- **Baseline scenario**: The model predicts a moderate increase in segment rates. Although the magnitude of the increase is in line with historical data, given that the model is unable to capture the wide range of products in the segment, management attention and review are recommended

11.11.7. Model limitations

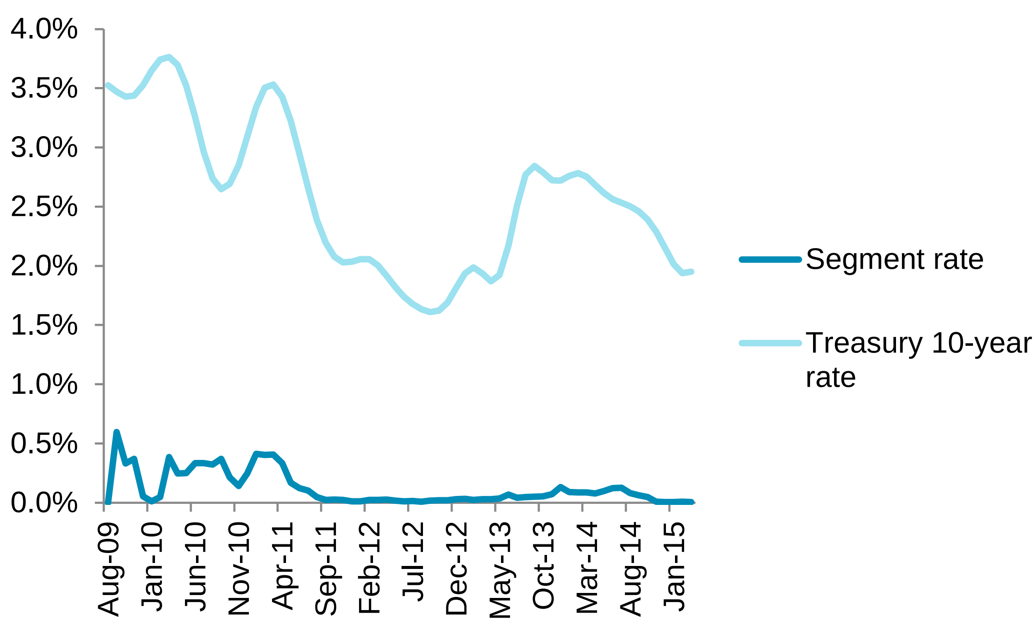
The key limitation to this model is its inability to capture the variety of underlying assets that are being traded. The Trading Assets portfolio includes a range of debt, equity, and derivative instruments in constantly changing proportions. This results in two limitations to the modeling approach: first, no single reference rate will be applicable to all the assets in the portfolio. Second, much of the volatility is driven by the constant change in portfolio mix. The rate is calculated by dividing the balance by interest income, and since only debt earns interest income, the portfolio mix change can contribute heavily to volatility in the rates. For instance, if equity instruments are traded heavily during a certain period, the balances (denominator) will increase without change in interest income (numerator), driving down the overall rate for this segment. For these reasons, close attention from management is likely required to adjust the forecasts from the model.

11.12. Trading Liabilities (Global Markets)

11.12.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with one of the identified reference rates. The historical Trading Liabilities (Global Markets) rate data displays some degree of volatility from 2009 to 2011, and has remained relatively flat since then. Compared to the segment rate, the reference rate has shown more volatility.

Figure 471: Historical rates for overall Trading Liabilities (Global Markets) portfolio



11.12.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Trading Liabilities (Global Markets) rates segment. However, given the inability of reference rates to capture the diversity and changing mix of products within the segment, a high level of management scrutiny is recommended.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary upon manual review
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests except for serial correlation as described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 420: Coefficient estimates for the Trading Liabilities (Global Markets) rates model

Rate – Trading Liabilities (Global Markets) (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Treasury10 year rate	First difference – QoQ, 1 month lag	%	0.048	0.16
Intercept	None (level)	%	0.003	N/A

Trading Liabilities (Global Markets) portfolio holds a diverse of mix of instruments, including debt, equity and derivatives. Given the diversity within the portfolio, the Working Group suggested using a wide range of rates as independent variables, which included the following: 1-month, 3-month, 6-month, 12-month LIBOR rates, Fed funds target and effective rates, 1-month and 3-month Euro LIBOR rates, 1-month and 3-month GBP LIBOR rates, Overnight LIBOR rates, Overnight Repo rates and Treasury 10-year rates.

Of various transformations of the variables mentioned above, the modeling team selected a model that used a transformation of the Treasury 10-year rate. The variable has a positive coefficient. The Working Group confirmed the intuition of its sign. Positive coefficient was required to match business intuition that the segment rate should be positively correlated with the reference rates.

11.12.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3.
- Historical data review to identify and address any detected anomalies in the data.

11.12.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the other Balance Sheet segment rates using the same methodology as for the other Balance Sheet segment balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 421: Unit root tests and stationarity tests including a trend variable on balances

Rate – Trading Liabilities (Global Markets) – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	8	-2.6	0.1	Fail to Reject unit root
Phillips-Perron	1	-13	<0.01	Reject unit root
KPSS	2	0.06	0.84	Fail to Reject stationarity

Table 422: Unit root tests and stationarity tests including a constant on first differences

Rate – Trading Liabilities (Global Markets) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	10	-2.6	0.11	Fail to Reject unit root
Phillips-Perron	1	-19	<0.01	Reject unit root
KPSS	0	0.08	0.67	Fail to Reject stationarity

Stationarity tests for Trading Liabilities (Global Markets) rate levels yield mixed results: The ADF test fails to reject unit root, while the PP test fails to reject unit root and the KPSS test fails to reject stationarity. Since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be non-stationary.

The monthly first difference series also yields mixed results: The first differences passes two out of the three stationarity tests – the KPSS and PP tests. Since the KPSS test is the primary test reviewed for first differences, the Trading Liabilities on first differences is determined to be stationary.

However, because the monthly first differences series failed the ADF test, the modeling team also manually reviewed the series and confirmed that first difference series appear to be stationary. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables for levels, but stationary for first differences.[46]

Therefore, the modeling team uses first difference transformations for the other Balance Sheet segment rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

11.12.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Trading Liabilities (Global Markets) rates data showed significant noise, especially during the first year and a half from 2008 when the data showed unreasonable large negative values or zeroes. After reviewing the data, the modeling team decided to remove data points up to August 2009 as a data correction. However, to preserve the integrity of the data, no further changes were made to the underlying data.

11.12.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

[46] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

- **Statistical significance of the model –** The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates –** The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. The coefficient estimates of Treasury 10-year rate and joint f-test are statistically significant. The intercept is found to be statistically insignificant.

Table 423: Statistical significance tests of model and variables for Trading Liabilities (Global Markets) rates

Rate – Trading Liabilities (Global Markets) (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	7%	10%	Statistically significant
Treasury10 year rate	0.048	6%	10%	Statistically significant
Intercept	0.003	81%	10%	Statistically not significant

11.12.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

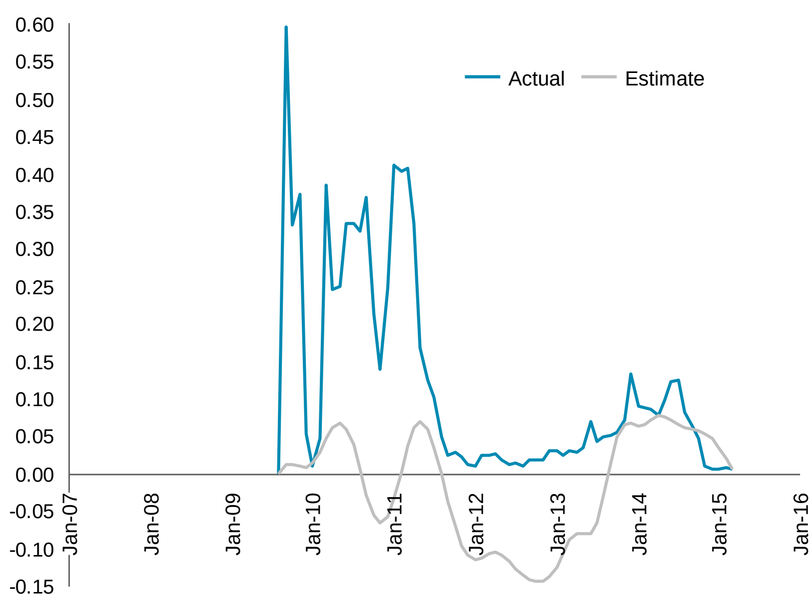
Table 424: Trading Liabilities (Global Markets) rate model diagnostics

Rate – Trading Liabilities (Global Markets) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	3%	-	-
	Adjusted R-squared	1%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.32	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	1.63%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	99%	10%	Linear specification appropriate

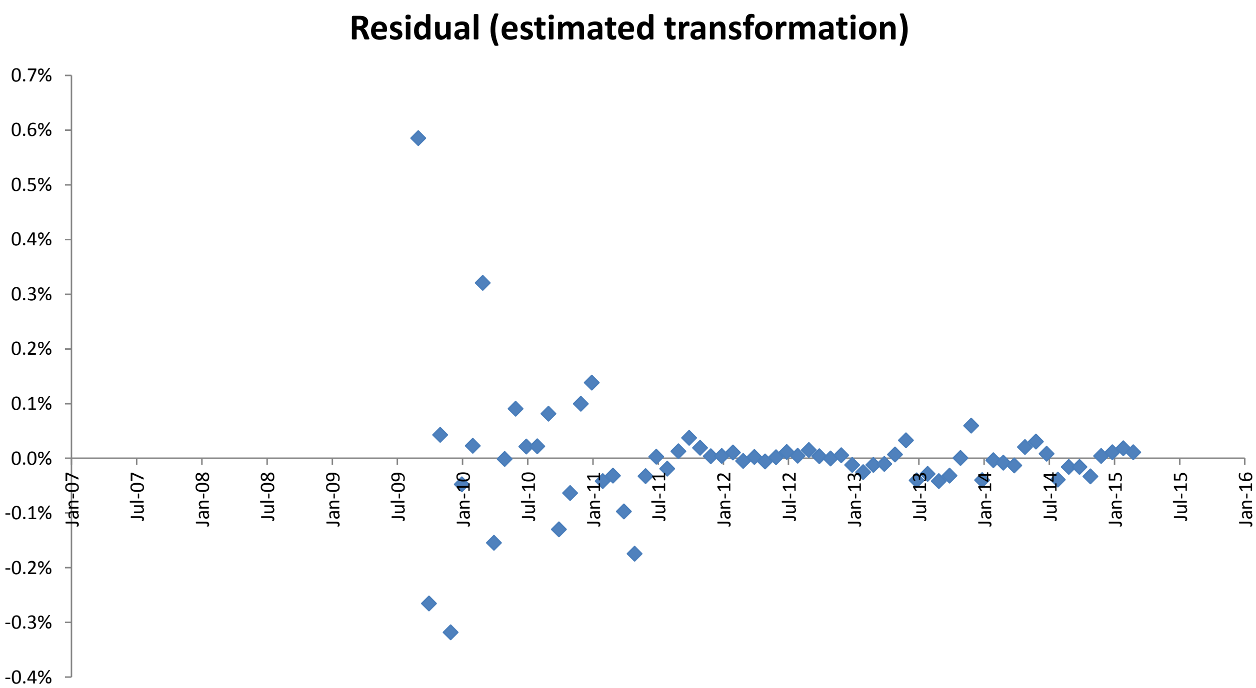
Serial correlation was detected in the residuals of this model. As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Figure 472: Trading Liabilities (Global Markets) rate 9Q in-sample prediction (%)



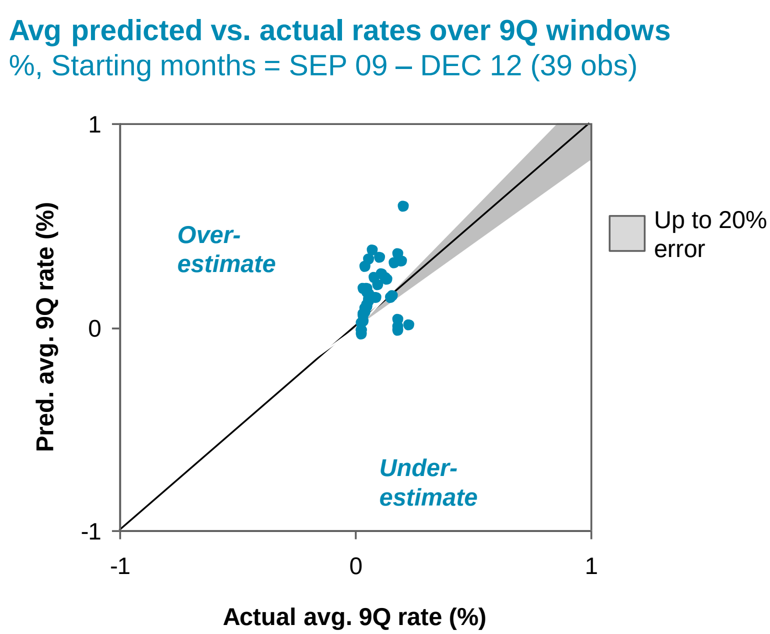
In the select 9Q in-sample prediction, the model is weak in its ability to track historical data. The model is not able to pick up the spike in late 2009, and only roughly follows the spikes in 2010, 2011, and 2014. The model is unable to capture the historical volatility during the 9-quarter period. Given the variety and volatile nature of the portfolio mix within this segment, the relative weakness of the model is not unexpected. A close management scrutiny is required for the usage of this model.

Figure 473: Trading Liabilities (Global Markets) rate residual plot (%)



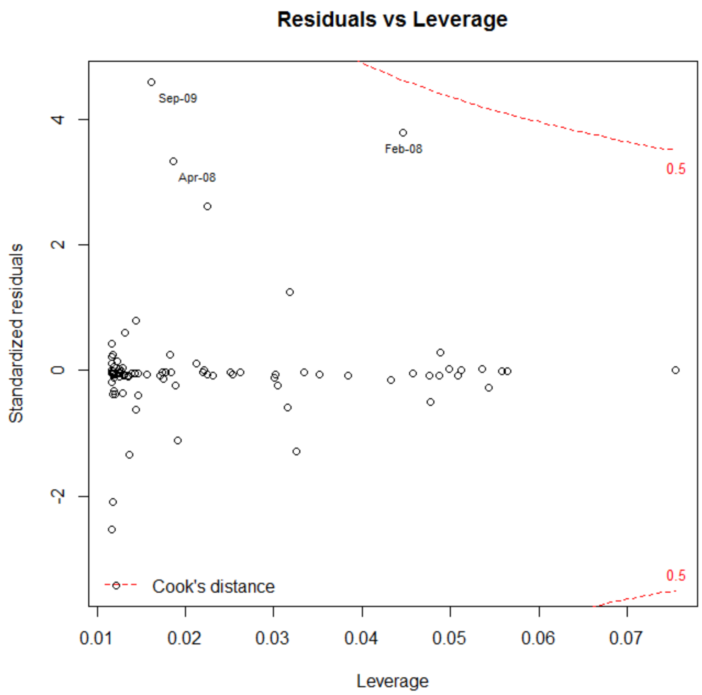
As seen in the figure above, the residuals are randomly distributed around the horizontal axis. Starting from 2011, the residuals are close to 0, since the historic rates have remained close to 0 as well.

Figure 474: Trading Liabilities (Global Markets) rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels result in a wide range of overestimation and underestimation of Trading Liabilities (Global Markets) rates. This is because the model is unable to capture the high level of volatility in historicals, resulting in a wide discrepancy between the actual and estimated data. The model will serve as a starting point while expert knowledge will also be used in the balance sheet forecasting review.

Figure 475: Influential points for Trading liabilities (Global Markets)



The segment does not contain any highly influential points.

11.12.6. Model sensitivity

11.12.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in the table below. The standardized coefficient reported describes the standard deviation change in the predicted rates due to a one standard deviation increase in an independent variable.

Table 425: Trading Liabilities (Global Markets) Model Sensitivity

Rate – Trading Liabilities (Global Markets) (in %) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in rates resulting from 1 std. dev change in the independent variable (%)
Treasury10 year rate	First difference – QoQ, 1 month lag	%	0.16	0.40	0.02
Intercept	None (level)	%	N/A	N/A	N/A

In the Trading Liabilities (Global Markets) rates model, a one standard deviation increase in Treasury 10-year rate results in a 0.16 standard deviation (0.02%) increase in the predicted monthly change of the Trading Liabilities (Global Markets) rates.

11.12.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

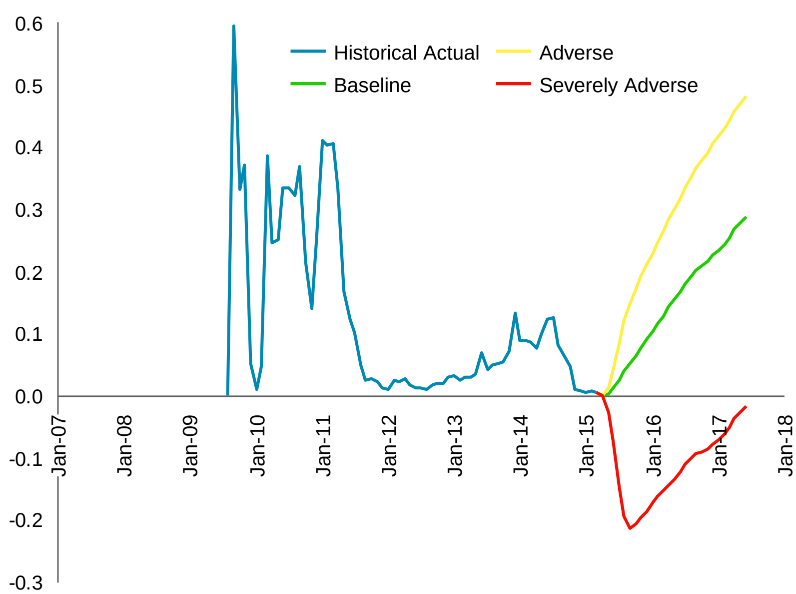
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

11.12.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 476: Trading Liabilities (Global Markets) rates model forecast (%)



The Working Group considered the forecast behavior for the selected Trading Liabilities (Global Markets) model as requiring a high level of scrutiny during management review, due to the high volatility in this rates segment and both the positive and negative magnitude of the forecasts.

- **Severe recession (Severely Adverse) scenario:** The model predicts a sharp decline into negative rates, and a gradual increase.
- **Interest rate shock (Adverse) scenario**: The model predicts a very steep rise in segment rates. Given that the model is unable to capture the wide range of products in the segment, a high level of management attention and review are highly recommended
- **Baseline scenario**: The model predicts an increase in segment rates. Although the magnitude of the increase is in line with historical data, given that the model is unable to capture the wide range of products in the segment, management attention and review are recommended

11.12.7. Model limitations

A key limitation to this model is historical data adjustment. Due to the high historical volatility in this segment, the model will be heavily affected by how much of the data the modeling team chooses to correct. The model will behave differently depending on when the starting date of the model is. Therefore, management scrutiny is required on the forecast results.

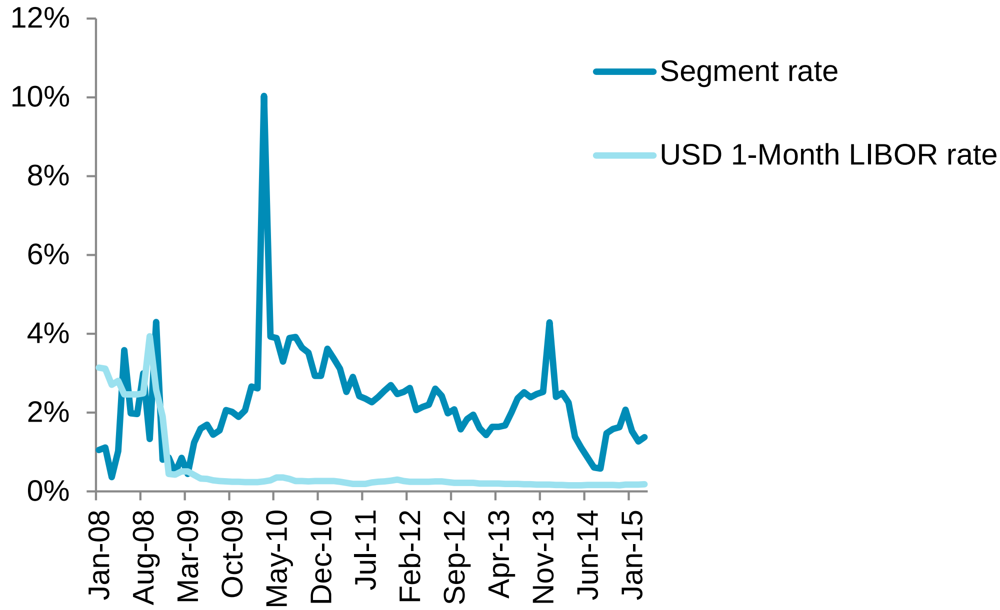
Another key limitation to this model is its inability to capture the changing nature of underlying assets that are being traded. The mix of portfolio, which is made up of various financial instruments, is bound to be dynamic. Portfolio diversity has largely two implications to the modeling procedure: first, no one reference rate will be able to fully capture the assets being traded under the Global Markets group. Second, much of the volatility is driven by the constant change in portfolio mix. The rate is calculated by dividing the balance by interest expense, and since only debt requires interest expense, the portfolio mix change contributes heavily to rates volatility. For instance, if equity instruments are traded heavily during a certain period, the balances (denominator) will increase without change in interest expense (nominator), driving down the rates significantly. For these reasons, a close attention from management is required to adjust the forecasts from the model.

11.13. Trading Liabilities (Capital Markets)

11.13.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with one of the identified reference rates. The historical Trading Liabilities (Capital Markets) rate data displays a high level of volatility throughout the series, with an especially sharp spike in Q1 2010. Compared to the segment rate, the reference rate has remained relatively flat and low since 2009.

Figure 477: Historical rates for overall Trading Liabilities (Capital Markets) portfolio



11.13.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Trading Liabilities (Capital Markets) rates segment. However, given the inability of reference rates to capture the diversity and changing mix of products within the segment, a high level of management scrutiny is recommended.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests except for serial correlation as described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 426: Coefficient estimates for the Trading Liabilities (Capital Markets) rates model

Rate – Trading Liabilities (Capital Markets) (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
USD 1-month LIBOR rate	First difference – MoM, 1 month lag	%	1.113	0.28
Intercept	None (level)	%	0.061	N/A

Trading Liabilities (Capital Markets) portfolio holds a diverse of mix of instruments, including debt, equity and derivatives. Given the diversity within the portfolio, the Working Group suggested using a wide range of rates as independent variables, which included the following: 1-month, 3-month, 6-month, 12-month LIBOR rates, Fed funds target and effective rates, 1-month and 3-month Euro LIBOR rates, 1-month and 3-month GBP LIBOR rates, Overnight LIBOR rates, Overnight Repo rates and Treasury 10-year rates.

Among various transformations of the variables mentioned above, the modeling team selected a model that used a transformation of the USD 1-month LIBOR rate. The variable has a positive coefficient. The Working Group confirmed the intuition of its sign. Positive coefficient was required to match business intuition that the segment rate should be positively correlated with the reference rates.

11.13.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

11.13.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the other Balance Sheet segment rates using the same methodology as for the other Balance Sheet segment balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 427: Unit root tests and stationarity tests including a trend variable on balances

Rate – Trading Liabilities (Capital Markets) – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	1	-3.5	0.01	Reject unit root
Phillips-Perron	1	-5.4	<0.01	Reject unit root
KPSS	4	0.24	0.21	Fail to Reject stationarity

Table 428: Unit root tests and stationarity tests including a constant on first differences

Rate – Trading Liabilities (Capital Markets) – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	0	-16	<0.01	Reject unit root
Phillips-Perron	1	-16	<0.01	Reject unit root
KPSS	9	0.11	0.56	Fail to Reject stationarity

Trading Liabilities (Capital Markets) rate levels pass all unit root and stationarity tests. Similarly, the first difference series also passes all unit root and stationarity tests. Given these results, both the level and first differences seem to be stationary. First differences were used to maintain consistency with other segments.

There is, however, a limitation to these tests. The other Balance Sheet segment rates data spans less than one full rate cycle. Therefore, tests on stationarity may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable shows stationary behavior, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[47].

Therefore, the modeling team uses first difference transformations for the other Balance Sheet segment rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

11.13.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Trading Liabilities (Capital Markets) rates data showed significant level of volatility, which is mostly attributed to its dynamic, diverse portfolio mix. However, to preserve the integrity of the data, no further changes were made to the underlying data.

[47] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

11.13.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. The coefficient estimates of USD 1-month LIBOR rate and joint f-test are statistically significant. The intercept is found to be statistically insignificant.

Table 429: Statistical significance tests of model and variables for Trading Liabilities (Capital Markets) rates

Rate – Trading Liabilities (Capital Markets) (in %) – Statistical significance tests of model and variables				
Tested independent variable(s)	**Coefficient estimate**	**P-value**	**Threshold**	**Conclusion**
Joint test of all variables (F-test)	-	1%	10%	Statistically significant
USD 1-month LIBOR rate	1.113	2%	10%	Statistically significant
Intercept	0.061	66%	10%	Statistically not significant

11.13.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

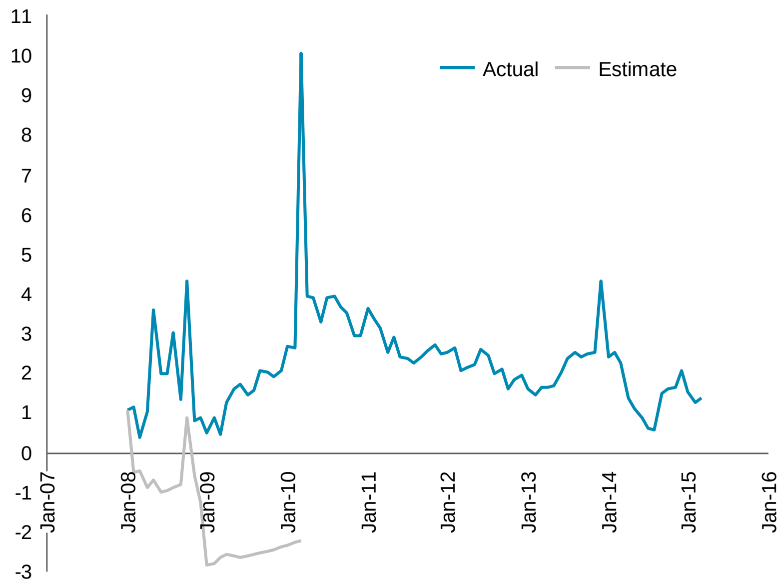
Table 430: Trading Liabilities (Capital Markets) rate model diagnostics

Rate – Trading Liabilities (Capital Markets) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	8%	-	-
	Adjusted R-squared	6%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0.91	10%	No heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<0.01%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	23%	10%	Linear specification appropriate

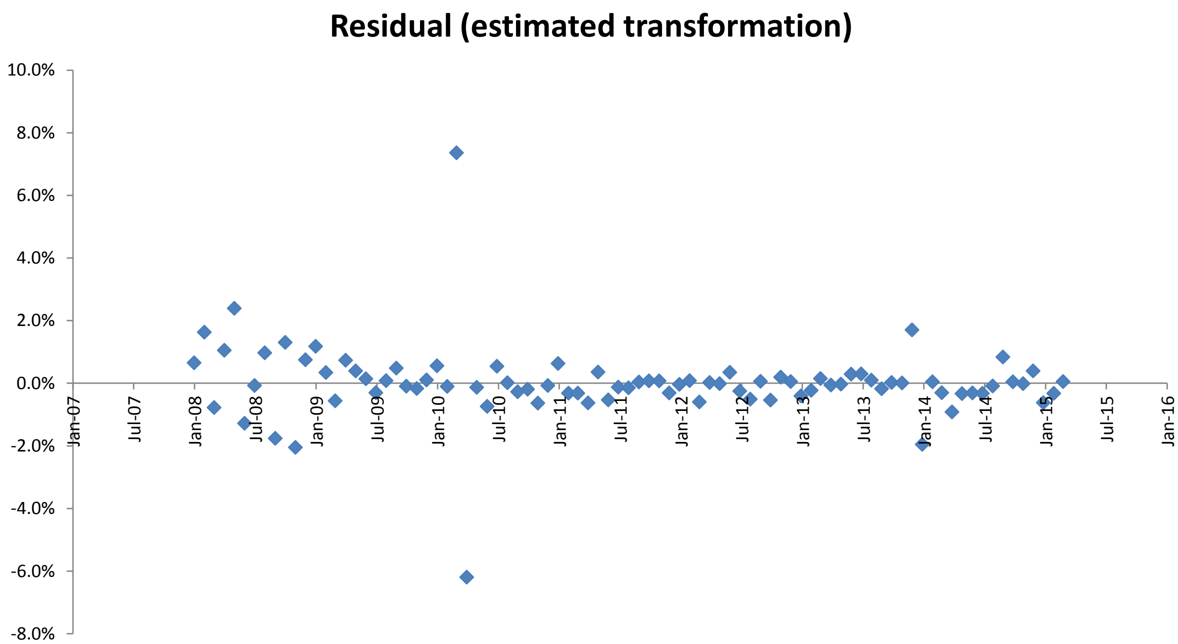
Serial correlation was detected in the residuals of this model. As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Figure 478: Trading Liabilities (Capital Markets) rate 9Q in-sample prediction (%)



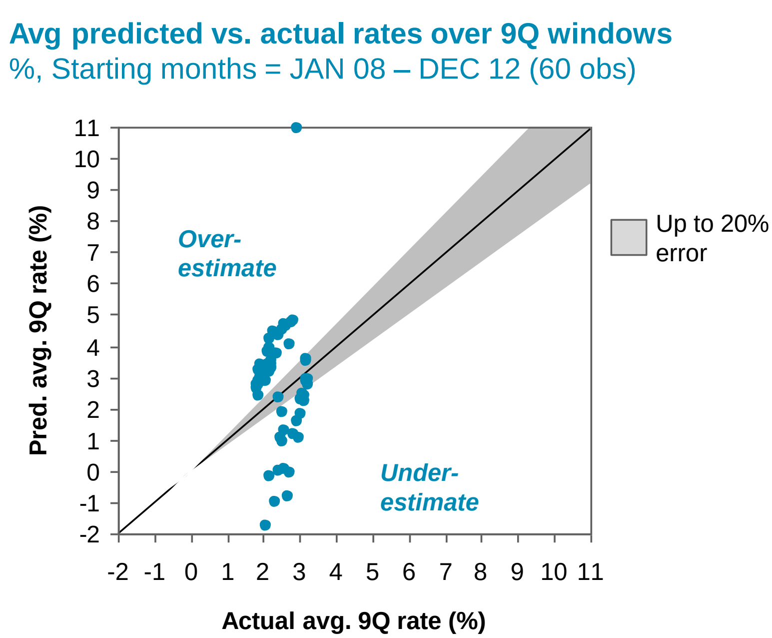
In the select 9Q in-sample prediction, the model is able to follow the general historic trend, but the estimated rates become negative values, which are against business intuition. Furthermore, the model is unable to pick up the first two spikes in 2008, and does not capture the magnitude of increase from 2009 to 2010. Given the variety and volatile nature of the portfolio mix within this segment, the relative weakness of the model is not unexpected. A close management scrutiny is required to adjust the output of the model by setting a floor for negative values.

Figure 479: Trading Liabilities (Capital Markets) rate residual plot (%)



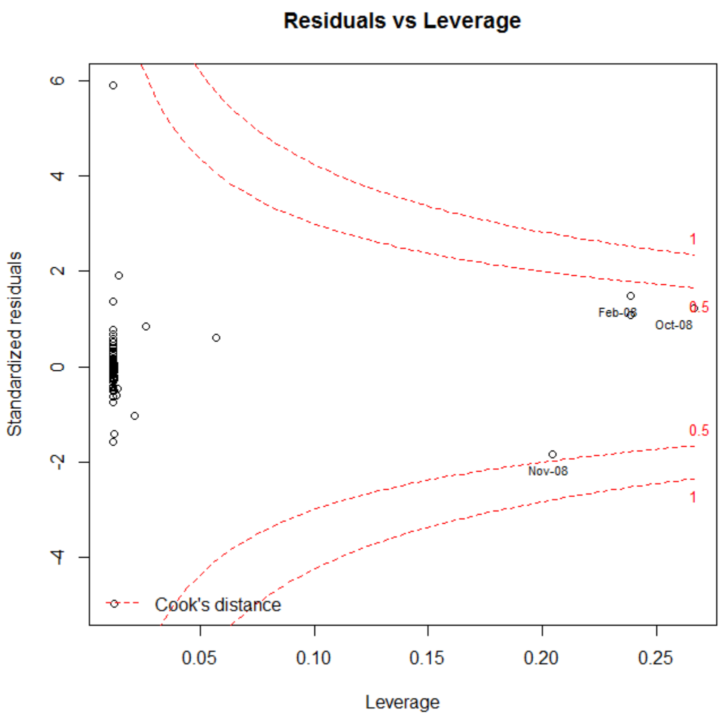
As seen in the figure above, the residuals are randomly distributed around the horizontal axis.

Figure 480: Trading Liabilities (Capital Markets) rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels result in a wide range of overestimation and underestimation of Trading Liabilities (Capital Markets) rates. This is because the model is unable to capture the high level of volatility in historicals, resulting in a wide discrepancy between the actual and estimated data. The model will serve as a starting point while expert knowledge will also be used in the balance sheet forecasting review.

Figure 481: Influential points for Trading Liabilities (Capital Markets) rates



The segment does not contain any highly influential points.

11.13.6. Model sensitivity

11.13.6.1. Sensitivity to changes in independent variables

The standardized coefficients of the selected models are shown in the table below. The standardized coefficient reported describes the standard deviation change in the predicted rates due to a one standard deviation increase in an independent variable.

Table 431: Trading Liabilities (Capital Markets) Model Sensitivity

Rate – Trading Liabilities Markets Group (in %) – model sensitivity

Independent variable	Transformation	Unit	Standardized coefficient	Std. dev of independent variable	Change in rates resulting from 1 std. dev change in the independent variable (%)
USD 1-month LIBOR rate	First difference – MoM, 1 month lag	%	0.28	0.32	0.34

Intercept	None (level)	%	N/A	N/A	N/A

In the Trading Liabilities (Capital Markets) rates model, a one standard deviation increase in the USD 1-month LIBOR rate results in a 0.28 standard deviation (0.34%) increase in the predicted monthly change of the Trading Liabilities (Capital Markets) rates.

11.13.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

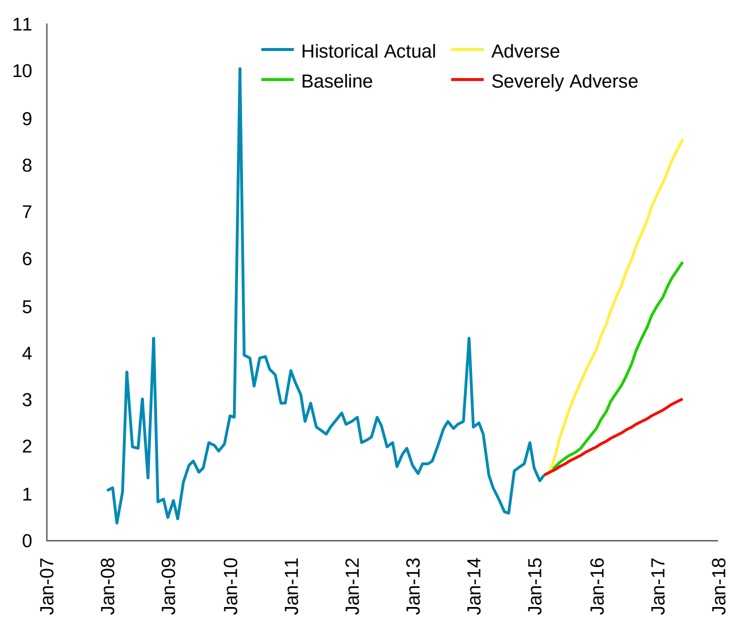
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

11.13.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 482: Trading Liabilities (Capital Markets) rates model forecast (%)



The Working Group considered the forecast behavior for the selected Trading Liabilities (Capital Markets) model as requiring a high level of scrutiny during management review, due to the high volatility in this rates segment.

- **Severe recession (Severely Adverse) scenario:** The model predicts a modest increase, similarly to how the historical data behaved during the 2009-2010 period. Since the model is not able to pick up the month-to-month volatility, a close management scrutiny is recommended
- **Interest rate shock (Adverse) scenario**: The model predicts a very steep rise in segment rates. Although there has been a similar historical incident in Q1 2010, such a drastic increase warrants a high level of management attention and review
- **Baseline scenario**: The model predicts a steep increase in segment rates. Although the magnitude of the increase is in line with historical data, given that the model is unable to capture the wide range of products in the segment, management attention and review are recommended

11.13.7. Model limitations

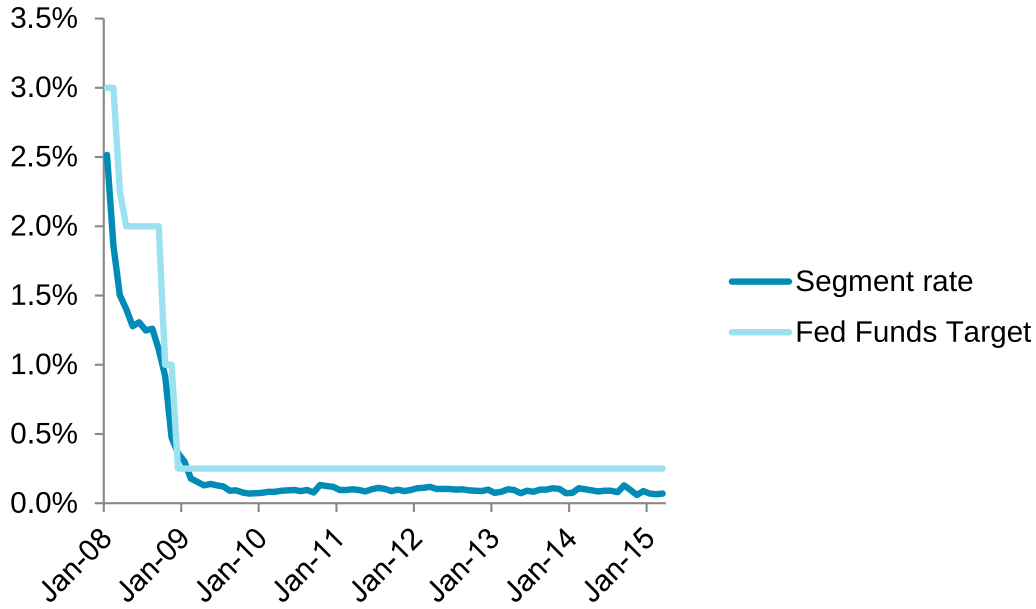
A key limitation to this model is its inability to capture the changing nature of underlying assets that are being traded. The mix of portfolio, which is made up of various financial instruments, is bound to be dynamic. Portfolio diversity has largely two implications to the modeling procedure: first, no one reference rate will be able to fully capture the assets being traded under the Capital Markets. Second, much of the volatility is driven by the constant change in portfolio mix. The rate is calculated by dividing the balance by interest expense, and since only debt requires interest expense, the portfolio mix change contributes heavily to rates volatility. For instance, if equity instruments are traded heavily during a certain period, the balances (denominator) will increase without change in interest expense (nominator), driving down the rates significantly. For these reasons, a close attention from management is required to adjust the forecasts from the model.

11.14. Short-term borrowings: Broker-Dealer Payables and Customer Payables

11.14.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with one of the selected short-term reference rates. The historical Broker Dealer payables rate data displays relatively low volatility, and follows the directional movement of the reference rate.

Figure 483: Historical rates for overall Broker Dealer payables segment



11.14.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Broker Dealer payables rates segment. The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests except for serial correlation as described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 432: Coefficient estimates for the Broker Dealer payables rates model

Rate – Broker Dealer payables (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
Fed Funds target rate	First difference – QoQ	%	0.197	0.783
Intercept	None (level)	%	-0.003	N/A

The model uses one factor: a transformation of the Fed Funds target rate, with a positive coefficient. The Working Group confirmed the intuition of this variable and its sign. Positive coefficients were required to match business intuition that the segment rate should be positively correlated with the reference rates.

11.14.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

11.14.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the other Balance Sheet segment rates using the same methodology as for the other Balance Sheet segment balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 433: Unit root tests and stationarity tests including a trend variable on balances

Rate – Broker Dealer payables – Single mean unit root test on level series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	8	-9.3	<0.01	Reject unit root
Phillips-Perron	1	-9.7	<0.01	Reject unit root
KPSS	5	0.69	0.01	Reject stationarity

Table 434: Unit root tests and stationarity tests including a constant on first differences

Rate – Broker Dealer payables – Single mean unit root test on first difference series				
Test	**Lags**	**Tau**	**Pr > Tau**	**Conclusion**
Augmented Dickey-Fuller	8	-4.9	<0.01	Reject unit root
Phillips-Perron	1	-9.1	<0.01	Reject unit root
KPSS	4	0.78	<0.01	Fail to Reject stationarity

Stationarity tests for Broker Dealer payables rate levels yield mixed results: The ADF and PP tests reject a unit root while the KPSS test rejects stationarity. Since the ADF and PP tests are the primary tests reviewed for levels, the series is determined to be stationary; however, the monthly first difference series yields more definitive results.

The monthly first difference series passes all three stationarity tests: the ADF and PP tests reject a unit root, while the KPSS tests fails to reject stationarity. The first differences time series is therefore determined to be stationary.

Given these results, the modeling team chose to model these rates on first differences.

There is, however, a limitation to these tests. The other Balance Sheet segment rates data spans less than one full rate cycle. Therefore, tests on stationarity may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable shows stationary behavior, given the limited variation the rate environment has experienced in the past 5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[48].

Therefore, the modeling team uses first difference transformations for the other Balance Sheet segment rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

11.14.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

No changes were made to the underlying Broker Dealer payables rates data.

11.14.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Broker Dealer payables rates model are statistically significant.

Table 435: Statistical significance tests of model and variables for Broker Dealer payables rates

Rate – Broker Dealer payables (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	<1%	10%	Statistically significant

[48] "Real Interest Rate Persistence: Evidence and Implications" Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

Fed Funds target rate	0.197	<1%	10%	Statistically significant
Intercept	-0.003	64%	10%	Statistically not significant

11.14.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable
- Error of average 9-quarter rates compared with actual average 9-quarter rates, where each point on the chart represents the average actual and predicted 9-quarter period starting on a different month. The purpose of this analysis is to mirror performance against actual results over the 9-quarter window used for CCAR. Large deviations between actual and predicted were highlighted and investigated to ensure the modeling team understood the reason for the deviation

The results for the diagnostic tests reviewed are exhibited below.

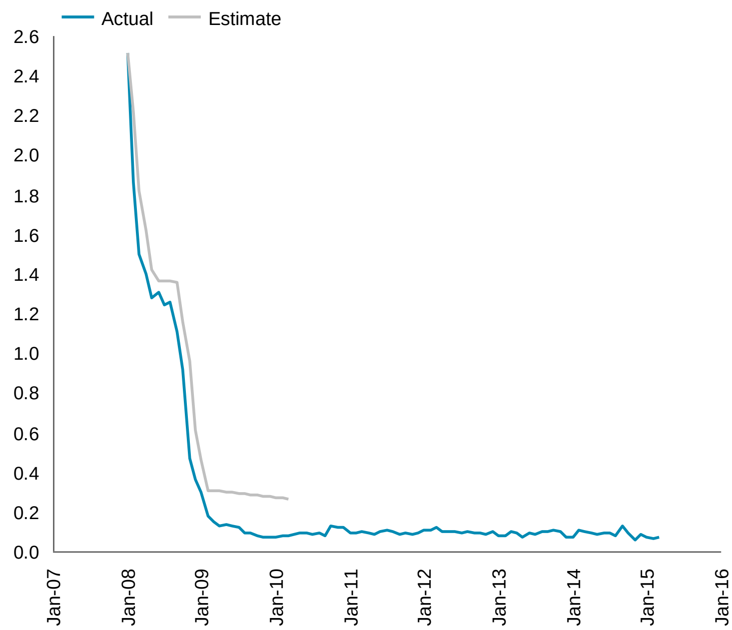
Table 436: Broker Dealer payables rate model diagnostics

Rate – Broker Dealer payables – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	61%	-	-
	Adjusted R-squared	61%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	<1%	10%	Heteroskedasticity
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	<1%	10%	Serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	44%	10%	Linear specification appropriate

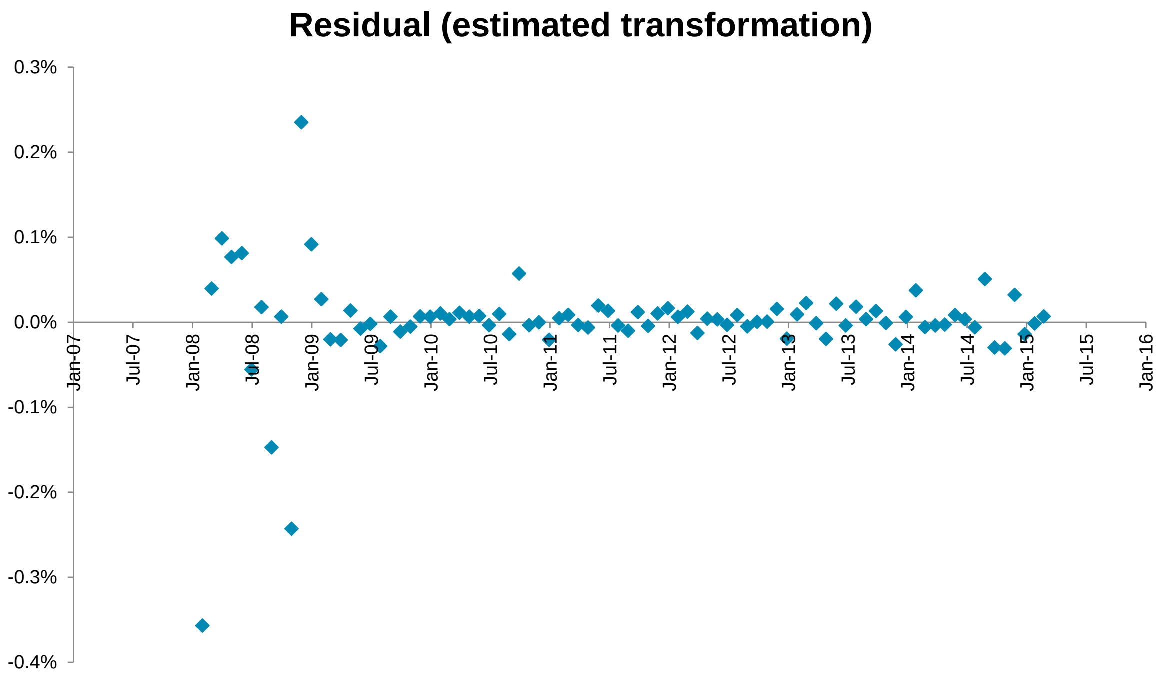
Heteroskedasticity and serial correlation detected in the residuals of this model. As described in Section 3.3.3 on Methodology, all P-values in this section are therefore are based on a heteroskedasticity and autocorrelation consistent estimator of the standard error of the regression.

Figure 484: Broker Dealer payables rate 9Q in-sample prediction (%)



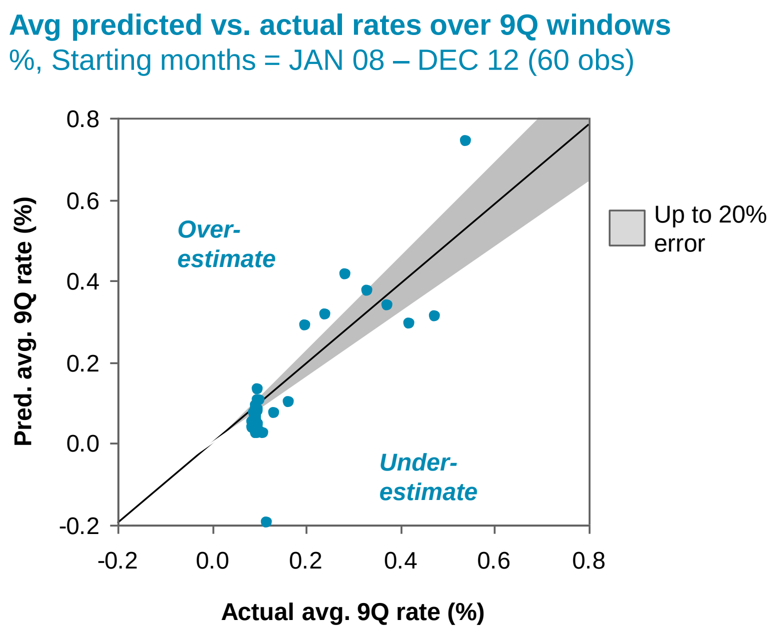
In the select 9Q in-sample prediction, the model picks up most of the movement in the actual rate, in terms of direction, timing, and magnitude. The model does not capture the full decrease in rates following the 2008–2009 financial crisis, which leads to overestimation in the last several months of the estimate.

Figure 485: Broker Dealer payables rate residual plot (%)



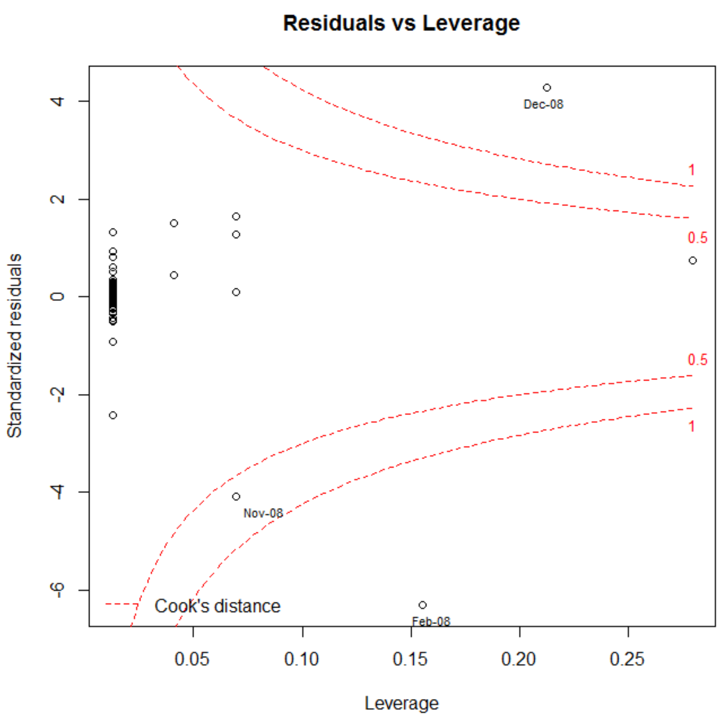
As seen in the figure above, the residuals are randomly distributed around the horizontal axis.

Figure 486: Broker Dealer payables rate estimation scatterplot



As seen in the figure above, estimated average 9-quarter levels generally tracks the actual average 9-quarter levels closely for different 9-quarter forecast windows, with a few outliers arising from the model not being able to capture the full magnitude of the drop in rates in 2008–2009.

Figure 487: Influential points for Broker Dealer Payables rates



For this segment December and February are highly influential points. However, this is not surprising because there are large increases and decreases in rates at these points due to the financial crisis and does not invalidate the model

11.14.6. Model sensitivity

11.14.6.1. Sensitivity to changes in independent variables

Given the Broker Dealer payables rates model only contains one type of independent variable (i.e. one or more transformations of the benchmark rate), the sensitivity can be directly interpreted from the coefficient estimates.

11.14.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

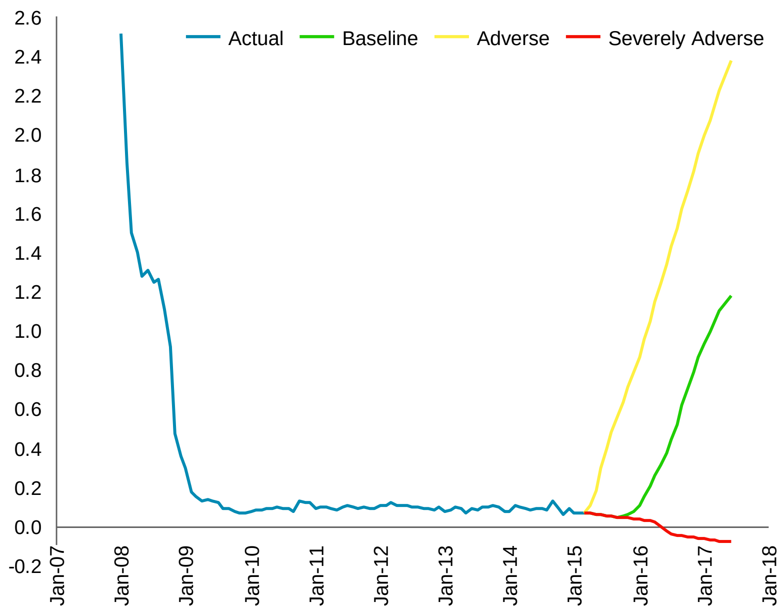
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

11.14.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2015 scenarios.

Figure 488: Broker Dealer payables rates model forecast (%)



The Working Group considered the forecast behavior for the selected Broker Dealer payables rates model as reasonable.

- **Severe recession (Severely Adverse) scenario:** The model predicts continued low rates; due to the negative intercept of the model, the forecast becomes negative in later months of the forecast.
- **Interest rate shock (Adverse) scenario**: The model predicts a steep rise in segment rates. This is in line with business intuition, but management review is recommended to ensure the magnitude of the increase is consistent with expectations

- **Baseline scenario**: The model predicts a rise in segment rates. This is in line with business intuition, but management review is recommended to ensure the magnitude of the increase is consistent with expectations

11.14.7. Model limitations

The historical series for dependent variable is limited because data prior to the merger of Bank of New York and Mellon in 2008 is not available to the modeling team. The model shown above is not trained on a long set of historical data with varying interest rates, and thus would require management attention when forecasting rates under scenarios with rising interest rates.

11.15. Short-term borrowings: Fed Funds Purchased and Repos (non-Pershing)

11.15.1. Historical data

The short-term borrowings are split into five different segments that correspond to different businesses that they relate to, these are 1. Broker Dealer customer payables from Pershing, 2. Fed funds purchased and repurchase transactions by the Corporate Treasury, 3. Repurchase transactions by Pershing, 4. Commercial paper, and 5. Other short-term borrowings.

Repo transactions are one of several ways of sourcing funds when the bank is in need of liquidity after Central Bank deposits, Placement balances, the Securities Financing Portfolio (taking into account contractual maturities) are run off and certain securities are sold.

Repo transactions are also used to generate incremental NII on a discretionary basis. If transaction and borrowing costs for repos are favorable in comparison to the IOER, and if BNY Mellon has room in its leverage ratio to do so, it would borrow funds through repo transactions to deposit them as Excess Reserves.

At the time of development of the Balance and Rate Forecasting Model, no historical data was available for this segment; therefore a structural approach was determined.

11.15.2. General data issues

Not applicable as historical data was not available at time of approach development.

11.15.3. Summary of approach

The overnight repo rate as forecasted by Moody's Analytics will be used as the rate for this segment. This approach relies on the assumption that BNY Mellon is participating in transactions with prices that are not systematically different from market prices.

This assumption is supported by the fact that transactions are collateralized and executed by a large number of financial institutions, and BNY Mellon's collateral is not significantly different from those of the market. Moreover, such transactions are often conducted without knowing the precise counterparty, which means that there should be no preference for BNY's repos over that of others in the market. This is especially the case because historically, BNY Mellon has traded through the Fixed Income Clearing Corporation (FICC), which aggregates many brokers and dealers and other entities that trade U.S. government securities and automates comparison and settlement services. Subsequently, BNY Mellon's rate is likely to receive the market rate, even in idiosyncratic stress scenarios.

Where BNY Mellon must borrow unsecured funds, as in Bank Holding Company Idiosyncratic for CCAR 2016, due to limits on repo borrowing, the rate will be set to overnight LIBOR, to reflect the additional cost incurred from uncollateralized funding, for the unsecured (Fed Funds Purchased) segment only. Repos will continue to cost at the overnight repo rate, as discussed above.

11.16. Short-term borrowings: Capital Market Repos

11.16.1. Historical data

Historical data was not available for this segment at time of approach development.

11.16.2. General data issues

Not applicable, as historical data was not available.

11.16.3. Summary of approach

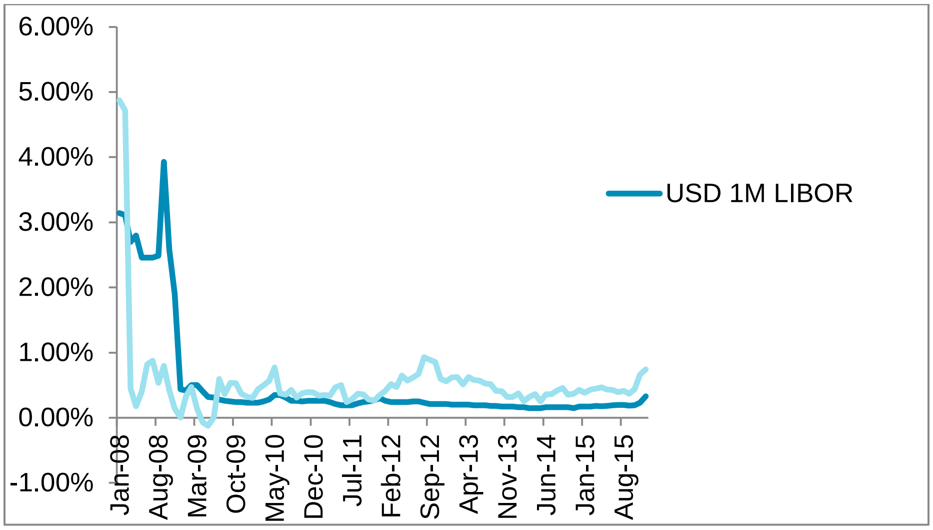
The overnight repo rate as forecasted by Moody's Analytics is used as the rate for this segment.

11.17. Short-term borrowings: Repos (Pershing)

11.17.1. Overview of historical data

The historical rates data for the segment is shown in the figure below, along with one of the identified reference rates. The historical Repos (Pershing) rate data displays significant volatility, but roughly follows the directional movement of the reference rates, with several months of lag.

Figure 489: Historical rates for overall Repos (Pershing) portfolio



11.17.2. Model summary

A statistically sound model that is consistent with business intuition was found for the Repos (Pershing) rates segment. However, given the volatile nature of the historical dependent variable time series, management scrutiny is recommended.

The model exhibits statistical robustness across all of the statistical tests conducted:

- **Stationarity:** The model is estimated on a month-over-month transformation, which is found to be stationary
- **Statistical significance:** The coefficient estimates are both individually and collectively statistically significant
- **Diagnostic tests:** The model passes all statistical diagnostic tests described in Section 3.3.3 on Methodology and exhibits stability in its in-sample model fit

The coefficient estimates are displayed in the table below.

Table 437: Coefficient estimates for the Repos (Pershing) rates model

Rate – Repo Pershing (in %) – Selected model				
Independent variable	**Transformation**	**Unit**	**Coefficient estimate**	**Standardized coefficient**
1-month LIBOR rate	First difference – QoQ, 1 month lag	%	0.23845	0.08476
Intercept	None (level)	%	-0.01251	0.052N/A

The model uses one factor, which is a transformation of the USD 1-month LIBOR. The variable has a positive coefficient. The Working Group confirmed the intuition of the variable and its sign. A positive coefficient was required to match business intuition that the segment rate should be positively correlated with the reference rate.

11.17.3. Dependent variable construction

Dependent variable construction consists of two main steps:

- Stationarity testing, per the estimation strategy described in Section 3.3.3
- Historical data review to identify and address any detected anomalies in the data

11.17.3.1. Stationarity testing

To minimize the risk of spurious regressions, the adopted estimation strategy requires stationary variables. Section 3.3.3 on the Methodology outlines the stationarity testing procedure. Stationarity testing is conducted for the other Balance Sheet segment rates using the same methodology as for the other Balance Sheet segment balances.

The stationarity tests results for the rates are shown in the two tables below.

Table 438: Unit root tests and stationarity tests including a trend variable on balances

Rates – Repos (Pershing) – Single mean unit root test on level series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	8	-2.8	0.05861	Fail to Reject unit root
Phillips-Perron	1	-7.2	<0.0001	Reject unit root
KPSS	3	0.27	0.16	Fail to Reject stationarity

Table 439: Unit root tests and stationarity tests including a constant on first differences

Rates – Repos (Pershing) – Single mean unit root test on first difference series

Test	Lags	Tau	Pr > Tau	Conclusion
Augmented Dickey-Fuller	4	-8.50	<0.0001	Reject unit root
Phillips-Perron	1	-3.70	0.0058	Reject unit root
KPSS	3	0.2942	0.1046	Fail to Reject stationarity

Repos (Pershing) rates on level only passes two out three stationarity or unit roots tests: the PP test rejects unit root and KPSS fails to reject stationarity, but the ADF test fails to reject unit root. These results suggest the Repos (Pershing) rates on level are likely to be non-stationary. In contrast, the monthly first difference series passes all three tests for stationarity. These results strongly suggest that the first differences series is stationary.

Based on these results, the Repos (Pershing) rates are modeled on their first differences.

There is, however, a limitation to these tests. The other Balance Sheet segment rates data spans less than one full rate cycle. Therefore, tests on stationarity may not be representative of the long-term behavior of the variable, i.e. it could just be a coincidence that the variable shows stationary behavior, given the limited variation the rate environment has experienced in the past

5 years. Furthermore, in academic literature, there are numerous studies that argue interest rates are non-stationary variables[49].

Therefore, the modelling team uses first difference transformations for the other Balance Sheet segment rates models for an additional precautionary measure of generating spurious relationships from non-stationary variables.

11.17.3.2. Historical data review

In addition to checking for stationarity of dependent variables, the modeling team also examined the historical values of the dependent variables for possible outliers and data issues. Specifically, the historical rates data was reviewed for any uncharacteristically large, sudden movements. If any potential data issues were found, they were discussed with the lines of business, ALM team, and data experts to understand their cause.

The Repos (Pershing) rates data showed significant noise, especially during the first quarter of 2008 when the data showed unreasonable large negative values. However, to preserve the integrity of the data, no changes were made to rest of the underlying data.

11.17.4. Significance tests

A number of tests are performed to assess the statistical soundness and predictive power of the estimated models.

- **Statistical significance of the model** – The coefficient estimates in the models is tested jointly to determine whether the model is statistically significant using an F-test. The test result is presented as a P-value against a null hypothesis that all variables in the model are equal to 0 (the constant is not included in this test), and the model is considered statistically significant if the P-value is below the 10% threshold
- **Individual statistical significance of coefficient estimates** – The coefficient estimates in the models are also tested individual using standardized two-sided t-tests. The test results are presented as P-values and the variables are considered statistically significant if their P-values are below a significance level of 10%

The table below reports the results of the significance tests. All of the coefficient estimates in the Repos (Pershing) rates model are statistically significant.

Table 440: Statistical significance tests of model and variables for Repos (Pershing) rates

Rate – Repos Pershing (in %) – Statistical significance tests of model and variables

Tested independent variable(s)	Coefficient estimate	P-value	Threshold	Conclusion
Joint test of all variables (F-test)	-	0.6%	10%	Statistically significant
1-month LIBOR rate	0.23845	0.6%	10%	Statistically significant
Intercept	-0.01251	81%	10%	Statistically not significant

[49] “Real Interest Rate Persistence: Evidence and Implications” Neely and Rapach, FEDERAL RESERVE BANK OF ST. LOUIS REVIEW, November/December 2008.

11.17.5. Diagnostic tests

A number of tests are used to detect potential violations of model requirements and assumptions. The model was tested for goodness of fit, heteroskedasticity in their residuals, autocorrelation in their residuals, multicollinearity of their variables, and violations of the linearity assumption. The tests used are described in Section 3.3.3 on Methodology.

For each model, four sets of diagnostic tests were reviewed:

- Model diagnostic statistics
- Select 9Q in-sample fit (chart on rate levels), which shows the in-sample back-test results over the 2008–2009 financial crisis for the model
- Residual plot (on estimated first differences), which shows the distribution of residual errors in the model's dependent variable

The results for the diagnostic tests reviewed are exhibited below.

The results for the diagnostic tests reviewed are exhibited below.

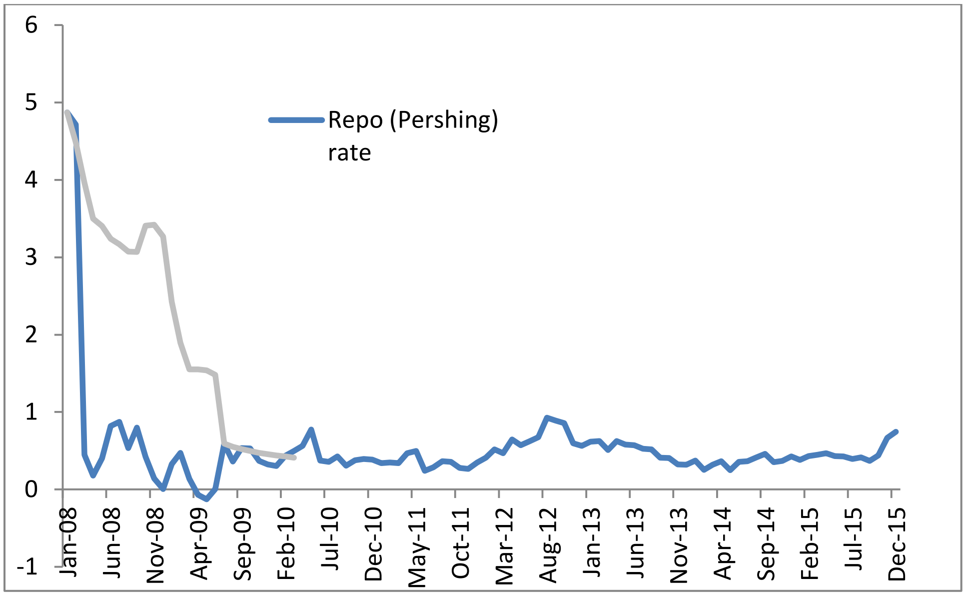
Table 441: Repos (Pershing) rate model diagnostics

Rate – Repos (Pershing) – Model diagnostics

Assessment	Statistic or test	Result	Threshold	Conclusion
Goodness of fit	R-squared	9%	-	-
	Adjusted R-squared	8%	-	-
Heteroskedasticity	Breusch-Pagan test (p-value)	0	10%	Heteroskedasticity Present
Autocorrelation	Breusch-Godfrey test (minimum p-value up to 4 lags)	26%	10%	No serial correlation
Multicollinearity	Variance inflation factor (maximum VIF across all variables)	1.00	5	No multicollinearity
Linearity	RESET test	91%	10%	Linear specification appropriate

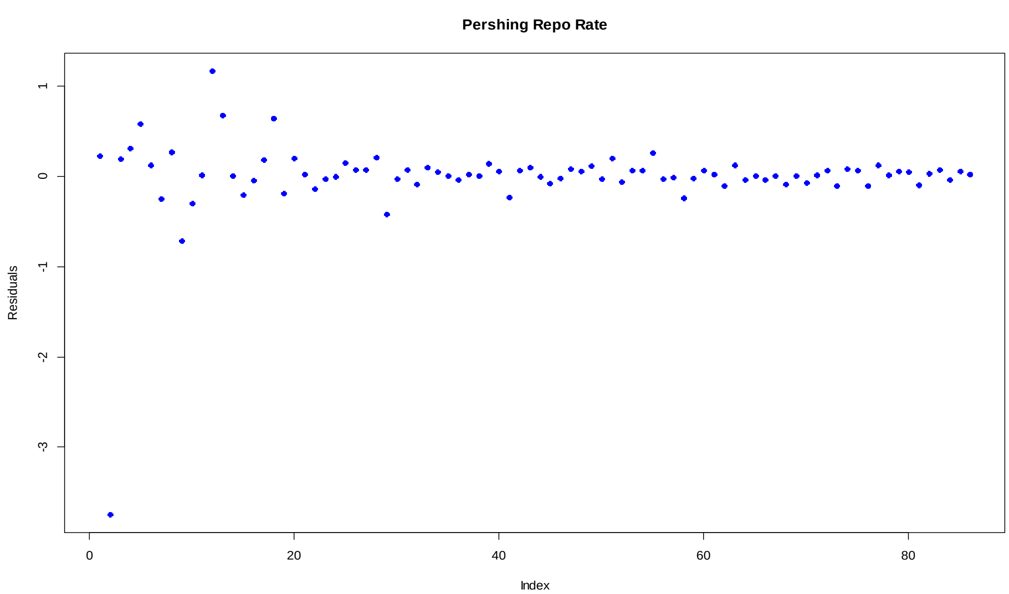
The model passes all model diagnostic tests that were evaluated except Heterokedasticity.

Figure 490: Repos (Pershing) rate 9Q in-sample prediction (%)



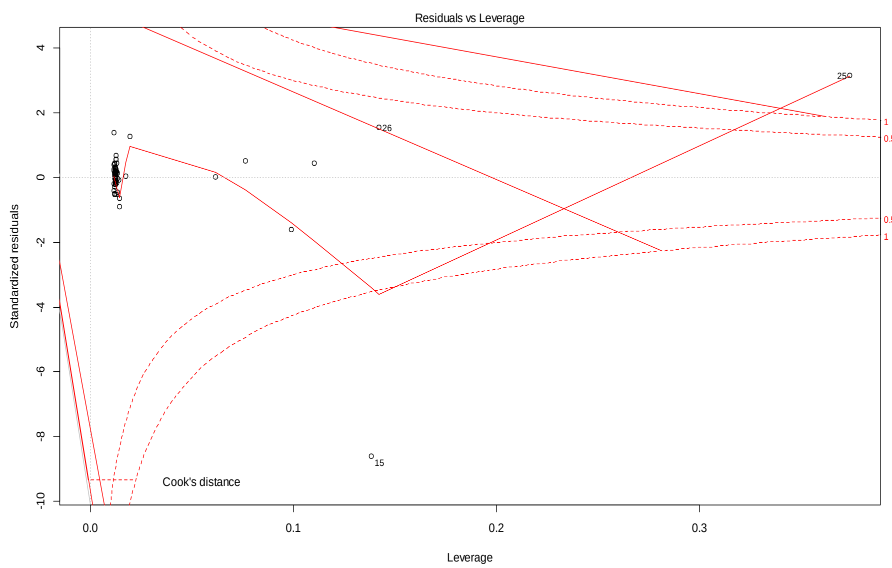
In the select 9Q in-sample prediction, the model picks up the general decline shown in the historical data from 2008–2009 to later years. However, the model does not capture the volatility of the segment rate: it fails to predict the rapid decrease in mid-2008, which causes overestimation during this period. The model also fails to pick up the sharp increase and subsequent decrease in mid-2009.

Figure 491: Repos (Pershing) rate residual plot (%)



As seen in the figure above, the residuals are randomly distributed around the horizontal axis.

Figure 492: Influential points for Pershing Repo rates



For this segment March 2008 and January 2009 are highly influential points. However, this is not surprising because of the volatility in rates during the financial crisis and does not invalidate the model

11.17.6. Model sensitivity

11.17.6.1. Sensitivity to changes in independent variables

Given the Repos (Pershing) rates models only contain one type of independent variable (i.e. one or more transformations of the benchmark rate), the sensitivity can be directly interpreted from the coefficient estimates.

11.17.6.2. Sensitivity to estimation period

The modeling team used a Chow-test to assess the statistical sensitivity of the balance models to the estimation period, which involves recalibrating the model together with shortened versions of the selected variables, setting the 24 most recent observations to zero. For the rate models, the shortened variables that would need to be used in the test are perfectly collinear with the explanatory variables in the model as the benchmark rates have not had any changes over the last six years. The test is therefore omitted.

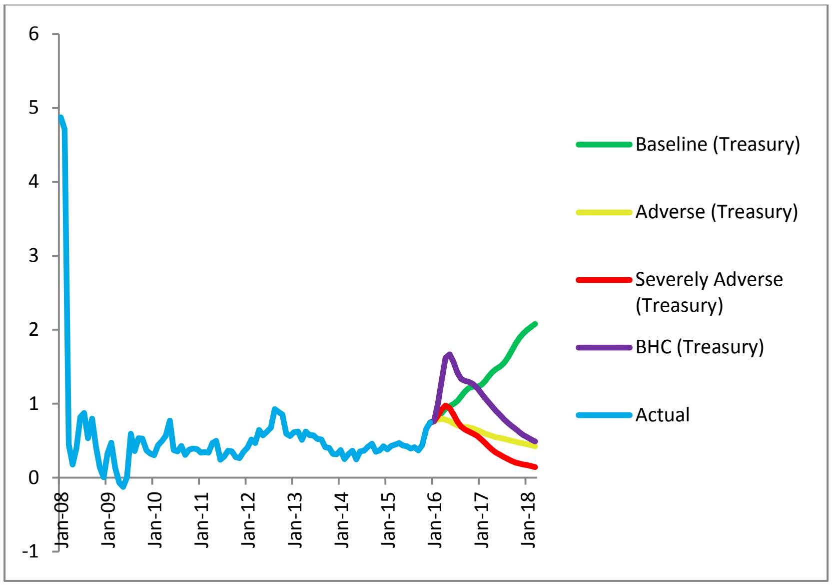
The modeling team strongly recommends, however, the re-estimation of the rates models as more observations in higher rate environments are obtained.

11.17.6.3. Sensitivity to stressed independent variable scenarios

Out of sample testing could not be conducted, as all available data points were used in the model development given the limited data availability.

The figure below illustrates the forecast behavior of the selected model. Forecasts were created based on CCAR 2016 scenarios.

Figure 493: Repos (Pershing) rates model forecast (%) (Using CCAR 2016 Scenarios)



The model forecasts for the scenarios are directionally in line with the rate and spread environment of the scenarios.

- **Severe recession (Severely Adverse) scenario:** The model predicts a decrease in Repo rate.
- **Adverse scenario**: The model predicts a rate slightly decreased.
- **Baseline scenario**: The model predicts a solid increase in segment rates in line with the expected baseline rise in interest rates

11.17.7. Model limitations

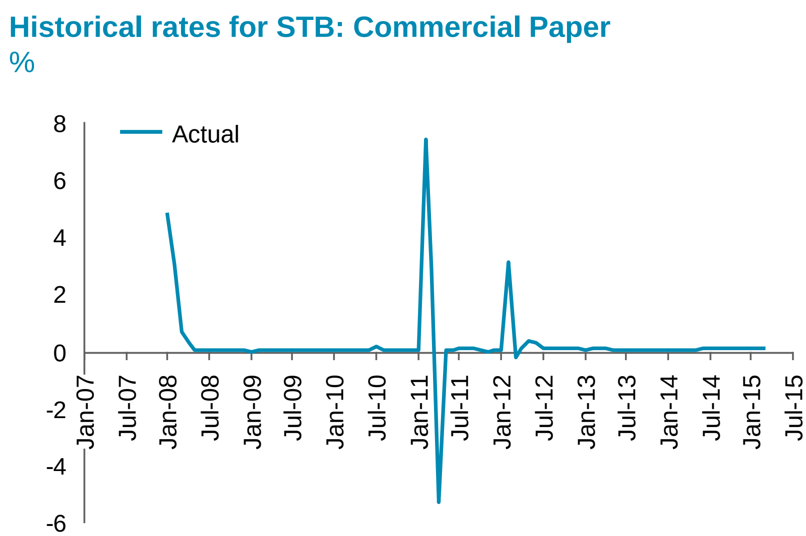
There are two key data limitations to this model: first, the historical series for dependent variable is limited because data prior to the merger of Bank of New York and Mellon in 2008 is not available to the modeling team. Second, short-term interest rates post-2008 have been low and constant due to US monetary policy.

These data limitations have two important implications for model limitations: first, the model shown above is not trained on a long set of historical data with varying interest rates, and thus would require close management attention when forecasting rates under scenarios with rising interest rates. Second, the model is not able to pick up the high month-over-month volatility in the historical Repos (Pershing) rates, because the US Libor 1-month rate has been largely flat post-crisis. Therefore, the model results should be interpreted as the general expected trend for the rates, without the volatility that arises from more idiosyncratic short-term behavior.

11.18. Short-term borrowings: Commercial Paper

11.18.1. Historical data

Figure 494: Average historical rates for Short-term borrowings: Commercial paper (%)



Generally, historical rates on commercial paper have been very low as a result of the short-term nature of commercial paper, and the historically low interest rate environment for the period covered by the development data. A few outliers exist that will be further discussed in the next section.

11.18.2. General data issues

Though rates over the course of the historical period have generally held steady, a few highly positive and negative points were observed during the historical time period in February 2011, March 2011, April 2011, and February 2012. However, the run-off approach used does not require the input of historical rates, and data cleansing was not required.

11.18.3. Summary of approach

Relatively recent regulatory requirements disallow BNY Mellon's holding company from issuing debt maturing in less than one year. Therefore, forecasts for this segment will utilize a run-off approach. To align with the balance forecast approach for this segment, rates for commercial paper outstanding will be modeled using QRM, which contains all rates, balances, and maturities of debt outstanding and can therefore forecast the run-off of these balances.

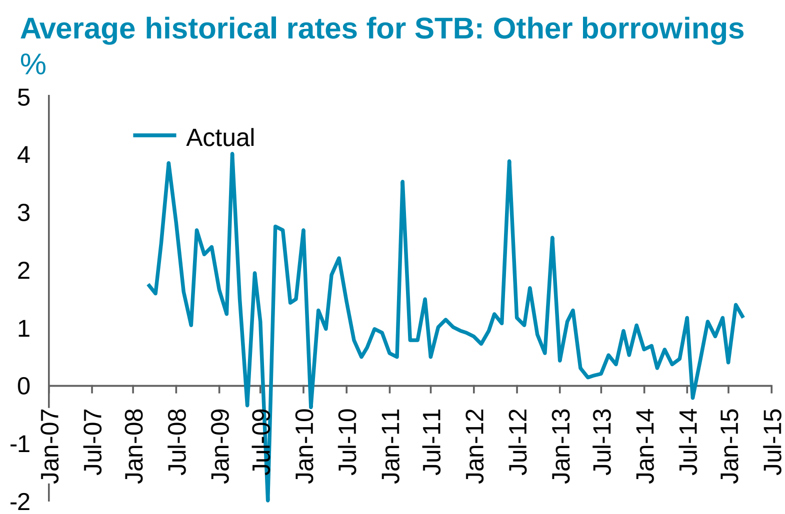
11.18.4. Approach limitations

The choice to issue commercial paper is strongly impacted by management decisions. The qualitative framework follows the BNY Mellon Working Group's assumption that that the Company will not issue commercial paper during the 9-quarter period. Change to this decision will impact future balances, which may diverge from the original run-off assumptions.

11.19. Short-term borrowings: Other borrowings

11.19.1. Historical data

Figure 495: Average historical rates for Short-term borrowings: Other borrowings



Historical rates have been very volatile in this segment, in part due to the miscellaneous nature of the balances in the segment.

11.19.2. General data issues

A few negative data rates were observed for Short-term borrowings: Other borrowings. Because the number of these negative points was small, no adjustments were made to the data. Additionally, the qualitative framework ultimately selected mitigates the impact of these few uncharacteristic data points.

11.19.3. Summary of approach

A model was originally hypothesized to model rates using the LIBOR 1-month and overnight repo rate. The approach was discussed and approved by the Working Group. However, the resulting model did not produce strong results. Given that a statistical model could not be found, as well as the miscellaneous nature of this category and inability to sub-segment, a qualitative framework was employed.

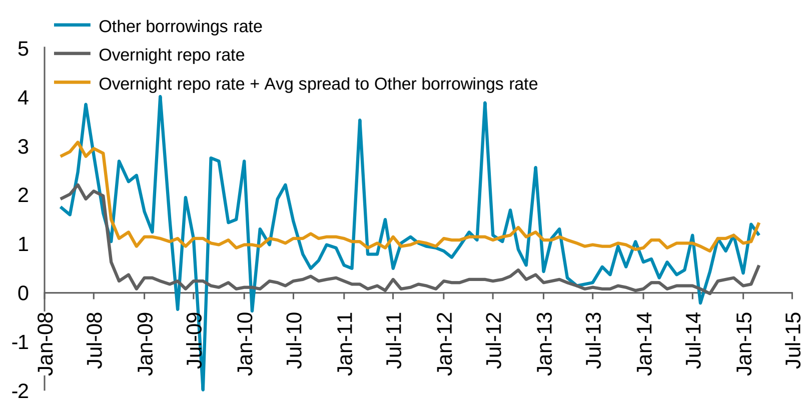
Following the failed modeling attempt, a qualitative method was developed instead whereby the forecasted Other Borrowings Rate was reflected as the overnight repo rate plus the average spread of the entire historical data series so that it captured a part of the higher rate environment. The remainder of this section describes the approach and rationale for each of:

1. The use of the overnight repo rate
2. Calculation of the spread above the overnight repo rate

The overnight repo rate was chosen as the benchmark rate because it most closely mimics the very short-term nature of the borrowings. Line of business feedback confirmed that these borrowings were typically short-term in nature and indicated the use of the overnight repo rate was appropriate. Given the nature of this segment, as well as changes over time, it was not possible to further decompose rates in this segment to evaluate behavior at a sub-segment level.

The spread component of this qualitative framework is intended to capture the premium paid for these short-term borrowings. This spread was computed to be 87bps (computed as the monthly average spread of the Other Borrowing Rates over the overnight repo rate from January 2008-March 2015). As the time series below indicates, and confirmed by business feedback, these rates can be volatile over time for a number of idiosyncratic reasons. As such, the use of an average was selected to avoid over- or under-emphasizing any single data point. Macroeconomic sensitivity is introduced to this approach through any differences in the overnight repo rate forecast across scenarios.

Figure 496: Historic rates for STB: Other Borrowed Funds Approach



11.19.4. Approach limitations

The overnight repo rate plus average 7-year spread methodology results in only an approximate rate. In actuality, the rates for STB: Other borrowings have been very volatile, and not all borrowings in this segment are directly linked to the overnight repo rate. If the composition of the portfolio changes significantly, there could be greater forecast error if underlying rates or spreads change.

11.20. Long-term debt

11.20.1. Historical data

Historical issuances and yields are presented below, by issuance. The data was used to understand the debt issuances outstanding, as well as the types and terms of new debt likely to be issued based on past issuance patterns. Additionally, the historical yields of issued debt were compared against the yields from from Moody's Analytics (further described in Section 11.20.3) to assess whether the selected Moody's forecast was a reasonable proxy for BNY Mellon future debt issuances.

Figure 497: Historical long-term debt issuances January 2009 to February 2015

Issue Date Mellon Issuance	Maturity	Amount $(millions)	Description	Coupon	Swaps
				2009 Issuance	
3/31/09	6/29/2012	$603	SENIOR NOTES-3-Year TLGP(Floater)	L(3)+16bps.	NA
5/12/09	5/15/2014	$1,000	SENIOR NOTES-5-Year	4.30% T+225	L(1)+179.25 bps.
5/12/09	5/15/2019	$500	SENIOR NOTES-10-Year	5.45% T+230	L(1)+216.75 bps.
11/6/09	1/15/2015	$750	SENIOR NOTES-5 1/4-Year	3.10% T+83	L(3)+37 bps.
11/6/09	1/15/2020	$500	SENIOR NOTES-10 1/4-Year	4.60% T+112	L(3)+91 bps.
	Total	$3,353			
				2010 Issuance	
6/11/10	6/18/2015	$650	SENIOR NOTES-5-Year	2.95% T+95	L(3)+59.85 bps.
12/2/10	12/9/2013	$100	SENIOR NOTES-3-Year (Floater)	L(3)+27bps.	NA
12/2/10	1/15/2016	$600	SENIOR NOTES-5-Year 1 mo.	2.50% T+83	L(3)+50.25 bps.
	Total	$1,350			
				2011 Issuance	
1/25/11	1/31/2014	$350	SENIOR NOTES-3-Year (Floater)	L(3)+28bps.	NA
1/25/11	1/31/2014	$350	SENIOR NOTES-3-Year (Fixed)	1.50% T+55	L(3)+27.3 bps.
1/25/11	2/1/2021	$500	SENIOR NOTES-10-Year	4.15% T+85	L(3)+75.09 bps.
7/21/11	7/28/2014	$600	SENIOR NOTES-3-Year (Floater)	L(3)+27bps.	N/A
7/21/11	7/28/2016	$1,000	SENIOR NOTES-5-Year (Fixed)	2.305 T+78	L(3)+44.15 bps.
9/16/11	9/23/2021	$1,000	SENIOR NOTES-10-Year (Fixed)	3.55% T+148	L(3)+126.6 bps.
11/17/11	11/24/2014	$250	SENIOR NOTES-3-Year (Floater)	L(3)+85bps.	NA
11/17/11	11/24/2014	$500	SENIOR NOTES-3-Year	1.70% T+135	L(3)+80.5(84) bps.
11/17/11	1/17/2017	$500	SENIOR NOTES-5-Year	2.40% T+158	L(3)+103.48(107) bps.
	Total	$5,050	2011 Total		

				2012 Issuance	
2/13/12	2/20/2015	$750	SENIOR NOTES-3-Year	1.20% T+85	L(3)+54.4 bps.
	9/23/2021	$500	SENIOR NOTES-10-Year-Reopening**	3.141% T+115	L(3)+110.25 bps.
5/10/12	6/20/2017	$500.1	SENIOR NOTES-5-Year -Remarketeing	1.969% T+100	L(3)+83.125 bps.
9/12/12	PerpNC5	$582.5	Fixed for Life Perpetual Preferred Stock NC5	5.200%	NA
10/25/12	10/23/2015	$600	SENIOR NOTES-3-Year	0.70% T+33	L(3)+23 bps.
10/25/12	10/23/2015	$400	SENIOR NOTES-3-Year (Floater)	L(3)+23 bps.	NA
10/25/12	1/25/2018	$500	SENIOR NOTES-5-Year	1.30% T+55	L(3)+38 bps.
		$3,333			
				2013 Issuance	
3/4/13	3/4/2016	$300	SENIOR NOTES-3-Year	0.70% T+38	L(3)+23 bps.
3/4/13	3/4/2016	$300	SENIOR NOTES-3-Year (Floater)	L(3)+23 bps.	NA
3/4/13	3/6/2018	$600	SENIOR NOTES-5-Year	1.35% T+60	L(3)+38 bps.
3/4/13	3/6/2018	$300	SENIOR NOTES-5-Year (Floater)	L(3)+44 bps.	NA
5/10/13	PerpNC10	$500	Fixed / Float Perpetual Preferred Stock	4.50%	L(3)+246 bps.
7/25/13	8/1/2018	$600	SENIOR NOTES-5-Year	2.10% T+75	L(3)+54.55 bps.
7/25/13	8/1/2018	$500	SENIOR NOTES-5-Year (Floater)	L(3)+56 bps.	NA
8/2/13	8/9/2018	$100	SENIOR NOTES-5-Year (Floater)	L(3)+50 bps.	NA
11/13/13	1/15/2019	$800	SENIOR NOTES-5.2-Year	2.10% T+73	L(3)+54.8 bps.
11/13/13	11/18/2025	$400	SENIOR NOTES-12-Year	3.95% T+125	L(3)+84.4 bps.
		$4,400			
				2014 Issuance	
1/28/14	3/4/2019	$500	SENIOR NOTES-5.08-Year	2.20% T+67	L(3)+50.4 bps.
1/28/14	2/4/2024	$750	SENIOR NOTES-10-Year	3.65% T+95	L(3)+80.5 bps.
2/6/14	2/12/2019	$200	SENIOR NOTES-5-Year (Floater)	L(3)+50 bps.	NA
5/2/14	5/15/2019	$750	SENIOR NOTES-5.02-Year	2.20% T+57	L(3)+47 bps.
5/2/14	5/15/2024	$500	SENIOR NOTES-10.02-Year	3.40% T+82	L(3)+68.8 bps.
9/4/14	9/11/2019	$1,150	SENIOR NOTES-5-Year	2.30% T+60	L(3)+46.19
9/4/14	9/11/2024	$500	SENIOR NOTES-10-Year	3.25% T+85	L(3)+71.55
9/4/14	9/11/2019	$350	SENIOR NOTES-5-Year (Floater)	L(3)+48 bps	NA
		$4,350			

				2015 Issuance	
Issue Date	Maturity	Amount $(millions)	Description	Coupon	Swaps
2/19/15	2/24/2020	$1,250	SENIOR NOTES-5-Year	2.15% T+62	L(3)+41.7 bps.
2/19/15	2/24/2025	$750	SENIOR NOTES-10-Year	3.00% T+92	L(3)+75.35 bps.
		$2,000			
4/23/15	PerpNC5	$1,000	Fixed / Float Perpetual Preferred Stock	4.95%	L(3)+342 bps.
5/22/15	5/22/2018	$500	SENIOR NOTES-3-Year	1.60 T+60%	L(3)+37.575 bps.
5/22/15	5/22/2018	$300	SENIOR NOTES-3-Year (Floater)	L(3)+38 bps	

11.20.2. General data issues

Historical rates for each BNY Mellon issuance that matures after March 2015 were provided by the business. No issues were found in the data provided.

11.20.3. Summary of approach

To align to the balance forecast approach for this segment, rates are forecast for two different components of the overall segment:

1. Debt outstanding
2. New issuances

Rates for debt outstanding can be modeled using QRM, which contains all rates, balances, and maturities of debt outstanding and can therefore forecast the run-off of these balances. This method aligns with the qualitative framework of forecasting the rates of run-off portfolios such as HELOCs and Other mortgages.

To forecast new issuance rates, the Moody's forecast of average yields for AA-rated 5-year bonds will be used as a proxy for the yield on BNY Mellon long-term debt, in line with the average S&P rating of the Bank across its subsidiaries presented in the business overview of long-term debt balances. For conservative purposes, the S&P rating will be used as the S&P rating is the lowest average rating across the various rating agencies. This rate would apply to all new issuances at any time point. The 5-year yield is appropriate as most of the outstanding historical issuances have tenors of 5 years.

In scenarios where BNYM's credit rating is downgraded, for example idiosyncratic BHC scenario, the corresponding bond yield of similarly rated debt forecasted by Moody's will be used. For example, if the average S&P credit rating downgrades to A, the average corporate A-rated yields will be utilized to determine the yield on BNY Mellon's long-term debt. The bond yields forecasted by Moody's are a composite yield, so capture the continuous range of potential ratings for the bank. For example, the A-rated 5-year bond is a composite yield based on debt rated A+, A, and A-. Therefore, the A-rated 5-year yield will be appropriate if BNYM is downgraded to any rating from an A+ to A-. However, if the bank is downgraded to an average rating below A-, the BBB-rated yield will be used.

11.20.4. Model limitations

The forecasted rates of new issuances rely on Moody's forecast of bond yields, which carries with it the same modelling risk as any statistically based modeled forecast, namely that the forecast of yields is subject to modeling error.

12. Net interest income Segments

12.1. Overview

Section 3.1.3 discusses the balance sheet segmentation, which includes deposits, loans, other balance sheet items and the investment portfolio. Two segments, however, are not included in these 4 categories, as their models directly impact net interest income (NII). The tables below show the segmentation, along with the type of forecasting method used to forecast balances for each segment.

Table 442 NII Items

#	NII Segments	Description	Dec '15 interest income ($ mm)	Balance forecasting method
1	Loan Fees	Loan Fees that are accounted for in net interest income (NII)	2.91	Qualitative
2	Interest Income and Expense from Specials (Pershing)	Specials are hard-to-borrow securities, in which Pershing earns an above market rate on the securities	7.45	Qualitative

Both of these segments required a qualitative framework. Such qualitative frameworkes will require business input and management review to ensure balance and rate forecasts are consistent with expectation and intuition under different scenarios.

The qualitative frameworkes can be categorized as shown in the table below.

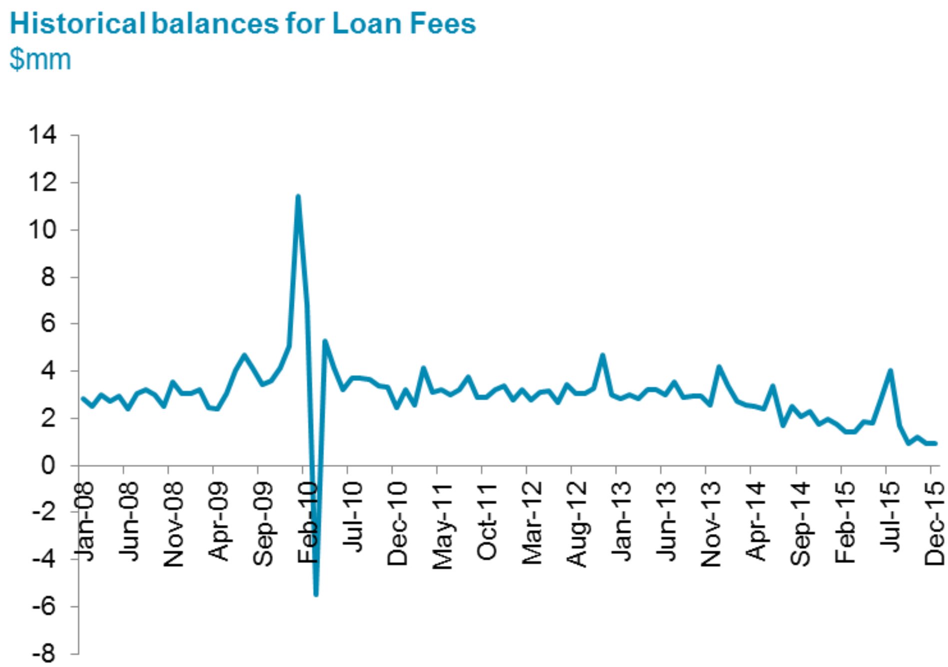
Table 443 Description of qualitative frameworkes

#	Category	Description	Segments covered
1	**Management driven (non-growth)**	Changes in balances heavily influenced by management decision Balances do not follow simple growth trend Qualitative framework may rely on statistical model to produce starting point for forecasts, or use data-driven assumptions	Specials (Pershing)
2	**Direct quantitative relationship with other segments**	Balances can be calculated using other segments' balances, either mathematically or with a simplified model	Loan Fees

12.2. Loan Fees

12.2.1. Historical data

Figure 498 Historical balances for Loan Fees



The modeling team received information on the loan fee types (as classified by BNY Mellon) that are included in the Loan Fees entering NII. In summary, loan fees that fall under NII consist of the following line items:

- Ticking Fees (accrual and up front): These fees are paid on syndicated deals during the period of time when the lender obtains the credit approval until the date the credit agreement is signed. This is in addition to any commitment fees.
- Non-Revolving Facility Term Loan Facility fees: These fees accrue when Non-Revolving/Term Loan facilities have the first draw. Further, for converted term loans, the remaining fees of the related revolving facility (should only represent the remaining unamortized amount).

12.2.2. General data issues

The quality of historical data for Loan Fees is not sufficient to produce a valid statistical model. The historical Loan Fees have been affected by accounting changes as Loan Fee classification has been revised during the period for which data could be obtained. These reclassifications do not reflect client preferences, line of business or segment performance and are therefore expected not to be related to macroeconomic variables or loan balances in a systematic manner. For instance, several General Ledger loan fee line items were reclassified to NII in

2013 whereas prior they were not. As such, the historical data of Loan Fees comprises of different components throughout the historical data period.

Despite this reclassification, the modeling team attempted to find a statistical relationship with various loan segments. However, attempts failed to produce a valid statistical model on this data as well.

12.2.3. Summary of approach

Two models (CRE and Commercial Total Commitments) were chosen as a basis to forecast Loan Fees. Total Commitments amounts (as opposed to drawn amount or unfunded commitments) were chosen as Loan Fees apply to drawn amounts as well as unfunded commitments. The specific loan segments (Commercial and CRE loans) were chosen because they are primarily comprised of the Credit Services line of business. Credit Services comprises (89.24%) of all loan fees, while fourteen other lines of business comprise the remainder.

<u>Description of qualitative framework</u>

The Loan Fees are forecasted as 0.003% of the sum of the forecasted Commercial Loans Total Commitment and CRE Loans Total Commitment amounts, equal to:

$$Forecast_{t\ in\ forecasting\ period} = (Commercial\ Loans\ Total\ Commitments + CRE\ Loans\ Total\ Commitments)_{t\ in\ forecasting\ period} * ((Loan\ Fees_{Dec\ 2015}) / (Commercial\ Loans\ Total\ Commitments + CRE\ Loans\ Total\ Commitments)_{Dec\ 2015})$$

<u>Basis for adoption</u>

As mentioned above, in 2013 BNY Mellon changed the accounting rules that determine what portion of total loan fees are attributable to NII versus fee revenue. To determine which loan segments to use as a basis for the Loan Fee forecast, data prior to 2013 is therefore disregarded. To construct the approach, two questions needed to be answered:

1. Which loan segments are related to Loan Fees and can be used to forecast Loan Fees?
2. Once loan segment(s) with a relationship to Loan Fees are identified, what data (specifically time period) do we use to base projections on?

1. <u>Loan segments that contribute to Loan Fees</u>

In order to determine how each line of business contributed to the Loan Fees, the modeling team reviewed Loan Fee data from 2013 to 2015. This period was chosen to exclude the period during which the accounting re-classifications took place and Loan Fees can be expected to be defined consistently during that time.

From 2013 to 2015, the data reveals that Loan Fees from Credit Services account for 89.24% of all loan fees on an average basis. No other line of business was determined to contribute materially to Loan Fees. There are fourteen other lines of business that contributed smaller amounts to Loan Fees, but most contributed less than 1% on an average basis. Wealth Management had the second highest contribution, with 8%, but this is skewed by a spike in late 2015, which is seen as unusual and not in line with the historical data.

As such, the modeling team chose to base the forecast on the sum of total commitments in the Commercial Loans and Commercial Real Estate Loans segments. Credit Services are accountable for the largest proportion of each of these segments (78.3 percent of funded Commercial loans and 88.16 percent of funded CRE loans, March 2015 spot balances) and the two segments together account for 98.2 percent of funded Credit Services loans (March 2015 spot balances).

2. Given the segment(s), identify appropriate time period to base projections going forward

The approach for forecasting is based on an average rate of Loan Fees to total commitment amounts of the Commercial loan and CRE loan segments. The rate is calculated on the latest spot balances in the historical period. The calculation uses the last spot instead of a historical average or growth because no significant correlation can be found between movements in loan balances and Loan Fees. For example, loan balances for Credit Services increase from 2013 to 2015, while Loan Fees for the same line of business decrease over the same period. Thus a calculation based in growth or change over time is less conservative than last spot balances.

This average rate is then applied to the total commitments forecast for the two aforementioned loan segments. The application of the average rate yields the Loan Fee forecast.

12.3. Specials income and expense

12.3.1. Business overview

Securities are either "general collateral" (GC) or "hard-to-borrow" (HTB) securities.

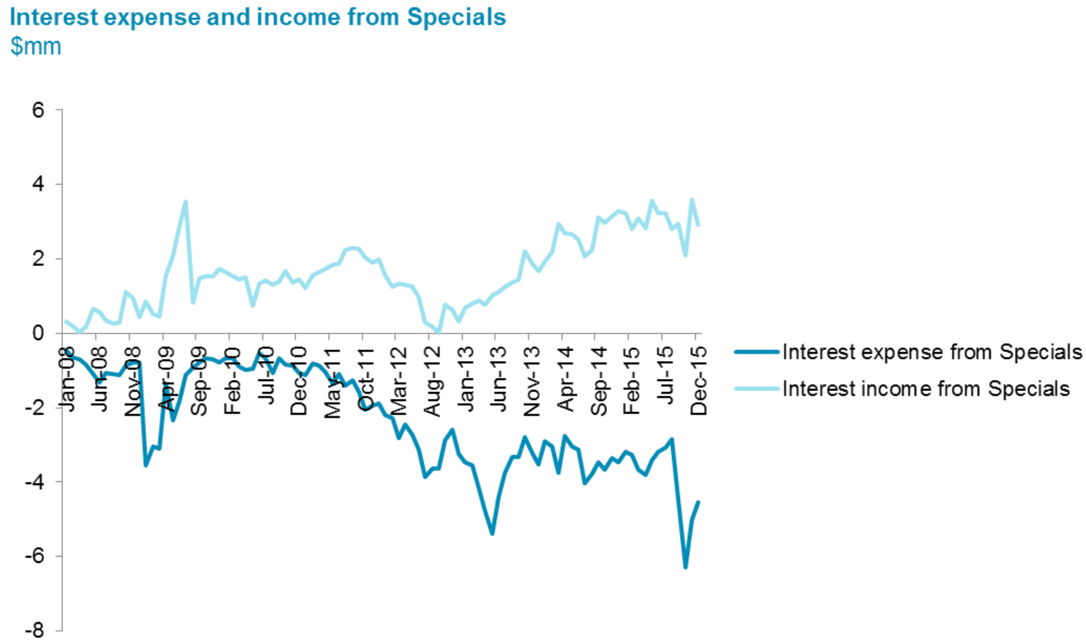
Specials are hard-to-borrow securities. Generally, when Pershing borrows GC securities in exchange for cash, Pershing would earn a market rate on the cash it lends to receive the securities. If securities were HTB, Pershing would earn a below market rate. When securities are in such demand that the lender of the security is asking Pershing to pay a premium for borrowing them, such securities are deemed "specials". Pershing would then mark up the rate (cost) and pass it on to the short seller (Pershing client). This would increase the interest income Pershing receives.

Conversely, if Pershing has access to such HTB /Specials securities in its portfolio (hypothecated by customers), the securities would be lent to the street to earn a rate (premium) on them. At times this can be negative interest expense for Pershing, which is actually income.

Market conditions determine the rate earned or paid on HTB/Specials. This could change daily, depending on the demand and supply for such securities. The income from specials can vary significantly and if blended into the GC stock borrow / loan rates (tied to overnight rates) could cause the overall stock borrow / lending rate to swing a lot (fluctuations cannot be explained by changes in the overnight market rates).

Specials (Pershing) is a highly market driven portfolio. Given the term, size and price of different underlying collateral types, the Specials (Pershing) could be affected by multiple factors and cannot be predicted using a consistent set of macroeconomic variables. Thus a qualitative framework was adopted to predict the interest income and expense generated from Specials (Pershing).

12.3.2. Historical data



12.3.3. General data issues

Historical balances and rates were not available for specials, and thus interest income is directly forecasted.

12.3.4. Summary of approach

The qualitative framework suggested for forecasting the interest income and expense in Specials is as follows:

$$\textit{Interest income for specials}_{t=1,\,\ldots,\,27} = (\textit{Interest income for specials}_{t=0} + \textit{Interest income for specials}_{t=-1} + \textit{Interest income for specials}_{t=-2}) \,/\, 3$$

$$\textit{Interest expense for specials}_{t=1,\,\ldots,\,27} = (\textit{Interest expense for specials}_{t=0} + \textit{Interest expense for specials}_{t=-1} + \textit{Interest expense for specials}_{t=-2}) \,/\, 3$$

with $t = 0$ being the last month in the historical data and $t = 1$ the first month of the forecasting period.

Thus, interest income from Specials is held at \$2.87mm per month and interest expense from Specials is held at -\$5.28mm per month, which correspond to the average income and expense between October 2015 and December 2015.

The basis of adoption for this approach is as follows:

- The last few months are most reflective of the recent environment determining interest income and expense from specials, both in terms of amount of demand for specials and BNY Mellon's ability to provide them. Given the lack of theoretical support for a qualitative framework, the simple qualitative framework suggested above provides a simple, transparent and repeatable process to forecast interest income and expense from specials.
- The materiality of the interest income and interest expense is low. In 2015, net interest expense from specials was $10.4 million ($36.3 million interest income and $46.7 million interest expense), which is 0.3 percent of BNY Mellon's NII of $3,026 million in 2015. Therefore, a simple approach is appropriate for forecasting interest income and expense from specials.

The IRR team had previously considered blending the interest income and expense from Specials into the Securities Borrowing and Reverse Repo (Pershing) rate, Section 11.8, and Short-term borrowings: Repos (Pershing), Section 11.17, as Specials simply have a repo rate below the GC repo rate. However, while reverse repo and repo rates are market prices that can be modeled with macroeconomic variables, the additional income and expense from a Special cannot be captured by a consistent set of macroeconomic variables and thus would dilute the predictive power of the statistical model for the segments.

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Appendix

Contents

1. Meetings list

Table 444: Details of Meetings Held

Meeting Category	Meeting Date	Attendees
General	05/28/15	Ahluwalia, Randhir; Smetaniouk, Taras; Mangion, James R; Summer, Cindy; Austin, Franklin
	05/29/15	Ahluwalia, Randhir; Summer, Cindy; Austin, Franklin
	06/01/15	Schwartzman, Sam M; Demaio, Joseph; Fink, James G; Mangion, James R; Ahluwalia, Randhir
		Ahluwalia, Randhir
	06/05/15	Mangion, James R; Ahluwalia, Randhir; Tucker, Robert N; Koch, Robert K; Connor, Matthew M
	06/18/15	Fu, Mengmeng
	06/19/15	Ahluwalia, Randhir; Mangion, James R
	06/22/15	Grinvald, Eliyahu; Marwah, Pallavi
		Summer, Cindy; Grinvald, Eliyahu; Marwah, Pallavi
	06/23/15	Nuttal, Andrew; Mangion, James R
	06/26/15	Summer, Cindy; Mangion, James R
	07/01/15	Ahluwalia, Randhir
	07/02/15	Ahluwalia, Randhir
	07/21/15	Summer, Cindy
	07/23/15	Buxton, Patrick
	07/28/15	Buxton, Patrick
	07/29/15	Ahluwalia, Randhir; Hart, Charles W
		Lee, Hwidong; Dworzanski, Paulette; Grinvald, Eliyahu; Ahluwalia, Randhir; Hart, Charles W
	07/30/15	Ahluwalia, Randhir; Mangion, James R; Smetaniouk, Taras; Summer, Cindy;
		Lopchinsky, Avi; Gilhooley, David; Ahluwalia, Randhir; Mittal, Akshat; Buxton, Patrick
	08/03/15	Ahluwalia, Randhir; Summer, Cindy; Smetaniouk, Taras; Mangion, James R; Gilhooley, David; Lopchinsky, Avi; Fu, Mengmeng; Thornton, Matthew A; Buxton, Patrick; Zhang, Wenhao; Mittal, Akshat; Hart, Charles W; Liu, Jun
		Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles W
	08/05/15	Ahluwalia, Randhir; Hart, Charles W; Mittal, Akshat; Summer, Cindy;
	08/06/15	Mittal, Akshat; Summer, Cindy; Ahluwalia, Randhir
	08/11/15	Ahluwalia, Randhir; Summer, Cindy; Mangion, James R; Mittal, Akshat; Hart, Charles W
	08/13/15	Hart, Charles W
	08/21/15	Thornton, Matthew A
	09/01/15	Flannery, Michael; Malanga, George P; Ahluwalia, Randhir; Mittal, Akshat
	09/02/15	Meiman, Tom; Ahluwalia, Randhir; Mittal,Mittal, Akshat; Hart, Charles W

Meeting Category	Meeting Date	Attendees
		Koch, Robert; Tucker, Robert; Ahluwalia, Randhir; Mittal,Mittal, Akshat; Hart, Charles W
	09/15/15	Summer, Cindy; Ahluwalia, Randhir
		Mittal, Akshat; Hart, Charles W; Ahluwalia, Randhir
Deposits	06/02/15	Fink, James G; Mangion, James R
	06/05/15	Demaio, Joseph
	06/08/15	Meiman, Tom; Ahluwalia, Randhir; Mangion, James R
		Ahluwalia, Randhir; Fink, James G; Mangion, James R
	06/22/15	Schwartzman, Sam M; Demaio, Joseph; Barber, Gerry; Ahluwalia, Randhir; Mangion, James R
	06/23/15	Fu, Mengmeng; Napolitano, Dominic; Foglia, Carol
	06/24/15	Tucker, Robert N; Koch, Robert K; Ahluwalia, Randhir; Mangion, James R; Connor, Matthew M
		Ahluwalia, Randhir; Mangion, James R; Wirth, John; Alexis, Stephen
	06/29/15	Schwartzman, Sam M; Demaio, Joseph; Barber, Gerry; Ahluwalia, Randhir; Mangion, James R
		Ahluwalia, Randhir; Mangion, James R; Meiman, Tom
	07/01/15	Thornton, Matthew A; Mangion, James R; Doshi, Nimit
	07/08/15	Austin, Franklin
		Fink, James G
		Borawski, Gary; Kennedy, Kim; Doshi, Nimit
	07/14/15	Ahluwalia, Randhir; Mangion, James R; Wirth, John; Alexis, Stephen
	07/16/15	Ahluwalia, Randhir; Mangion, James R; Wirth, John; Alexis, Stephen
	09/01/15	Schultz, Karl; Ahluwalia, Randhir; Mittal,Mittal, Akshat; Hart, Charles W
		Schwartzman, Sam M; Demaio, Joseph; Barber, Gerry; Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles
		Ferraioli, Donald; Gordon, Kurt; Hart, Charles; Mittal, Akshat ; Ahluwalia, Randhir; Schultz.Karl; Ellison, Robert M
	09/02/15	Meiman, Tom; Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles
		Koch, Robert; Tucker, Robert; Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles
	09/03/15	Wirth, John; Alexis, Stephen; Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles
	09/08/15	Schwartzman, Sam M; Demaio, Joseph; Barber, Gerry; Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles
	09/15/15	Goldberg, Karen; Morik, John; Wirth, John; Alexis, Stephen; Ahluwalia, Randhir; Mittal, Akshat; Hart, Charles; Fink, James G
Loans	06/01/15	Marwah, Pallavi; Ahluwalia, Randhir; Mangion, James R; Summer, Cindy
	06/03/15	Velkov, Stiliyan; Fink, James G; Ahluwalia, Randhir
		Marwah, Pallavi; Summer, Cindy
	06/08/15	Drexler, Alan P; Filip, Adrian; Radocaj, Robert; Summer, Cindy; Mangion, James R; Dougherty, Edward J; Rogers, Mark T
	06/10/15	Su, Hang
		Ahluwalia, Randhir; Reedy, Ronald; Caffrey, Thomas; Atwater, Douglas K; Johnson, Louella; Marwah, Pallavi

Meeting Category	Meeting Date	Attendees
		Filip, Adrian; Radocaj, Robert; Ahluwalia, Randhir; Mangion, James R
	06/15/15	Mangion, James R; Summer, Cindy; Marwah, Pallavi
		Mangion, James R; Summer, Cindy
	06/16/15	Filip, Adrian; Stromoski, Scott
	06/30/15	Summer, Cindy
	07/01/15	Filip, Adrian; Stromoski, Scott; Drexler, Alan P; Radocaj, Robert
	07/08/15	Grinvald, Eliyahu; Lee, Hwidong; Filip, Adrian; Stromoski, Scott; Drexler, Alan P; Summer, Cindy
	07/14/15	Filip, Adrian; Stromoski, Scott; Lee, Hwidong; Drexler, Alan P; Summer, Cindy; Grinvald, Eliyahu
	07/15/15	Grinvald, Eliyahu
		Lee, Hwidong; Summer, Cindy; Mangion, James R; Filip, Adrian; Drexler, Alan P; Grinvald, Eliyahu
	07/16/15	Summer, Cindy
	07/29/15	Lee, Hwidong; Grinvald, Eliyahu; Dworzanski, Paulette; Ahluwalia, Randhir; Hart, Charles W
	08/05/15	Drexler, Alan P; Filip, Adrian; Radocaj, Robert; Summer, Cindy
	08/06/15	Connor, Matthew M; Koch, Robert K; Mittal, Akshat; Tucker, Robert N; Ahluwalia, Randhir
	08/20/15	Hart, Charles W; Ahluwalia, Randhir; Dougherty, Edward J; Zito, Michael; Rogers, Mark T; Chu, Kin; Schroeder, Michael
	08/27/15	Clark, David; Malanga, George P; Mittal, Akshat; Ahluwalia, Randhir
	08/28/15	Summer, Cindy; Ahluwalia, Randhir
	08/31/15	Grinvald, Eliyahu
	09/01/15	Mittal, Akshat; Elm, Kim D; Ahluwalia, Randhir; Hart, Charles W
	09/04/15	Mittal, Akshat; Rogers, Mark T; Hart, Charles W; Ahluwalia, Randhir; Malanga, George P; Galati, Maria; Burns, Peggy
	09/09/15	Mittal, Akshat; Hart, Charles W; Ahluwalia, Randhir; Dougherty, Edward J; Malanga, George P; Rogers, Mark T; Galati, Maria; Burns, Peggy; Francis, Marcia
		Tucker, Robert N
	09/10/15	Marwah, Pallavi; Fink, James G; Mangion, James R; Ahluwalia, Randhir
	09/11/15	Summer, Cindy; Marwah, Pallavi
	09/14/15	Mittal, Akshat; Rawal, Manoj; Ahluwalia, Randhir; Hart, Charles W
	09/15/15	Drexler, Alan P; Tippet, Bryan Baxter; Schroeder, Michael; Zhang, Jun; Zheng, Xiangyin; Ma, Weiman
	09/16/15	Hart, Charles W; Rawal, Manoj; Ahluwalia, Randhir
Model Validation	07/20/15	Ahluwalia, Randhir; Mangion, James R; Fu, Mengmeng; Austin, Franklin; Zhang, Wenhao
		Mangion, James R; Ahluwalia, Randhir; Fu, Mengmeng; Austin, Franklin; Zhang, Wenhao
	07/29/15	Fu, Mengmeng; Liu, Jun; Zhang, Wenhao; Smetaniouk, Taras; Mittal, Akshat
	08/03/15	Fu, Mengmeng; Jin, Wen; Zhang, Wenhao
Pershing	06/04/15	Rawal, Manoj; Summer, Cindy; Ahluwalia, Randhir; Mangion, James R

Meeting Category	Meeting Date	Attendees
	06/22/15	Ahluwalia, Randhir; Mangion, James R; Rawal, Manoj; Sciabbarrasi, Rich
		Summer, Cindy; Ahluwalia, Randhir; Mangion, James R; Rawal, Manoj; Sciabbarrasi, Rich
	06/30/15	Franco, Diana
		Madaio, Michael; Conahan, James S; Bousri, Raymond; Rawal, Manoj
Repos	08/17/15	Tippet, Bryan Baxter; Kohad, Amit; Quarles, Shea; Zheng, Xiangyin; Fu, Mengmeng; Ma, Weiman
Systems	08/17/15	Summer, Cindy; Mangion, James R; Mittal, Akshat; Hart, Charles W; Ahluwalia, Randhir
Overdrafts	09/01/15	Hart, Charles W; Flannery, Michael; Malanga, George P; Ahluwalia, Randhir; Mittal, Akshat
Risk	07/24/15	Austin, Franklin; Drexler, Alan P
	08/18/15	Gegick, Gary
	08/25/15	Hysenbegasi, Katie; Radocaj, Robert; Lamar, David T; Austin, Franklin; Ahluwalia, Randhir; Drexler, Alan P; Taylor, Rebecca; Tippet, Bryan Baxter; Karmarkar, Neel; Fu, Mengmeng; Kohad, Amit; Samara, Artan
	09/01/15	Hart, Charles W; Lamar, David T; Drexler, Alan P; Ahluwalia, Randhir; Mittal, Akshat; Knoll, Ryan
		Lamar, David T; Drexler, Alan P; Ahluwalia, Randhir; Mittal, Akshat; Knoll, Ryan
Investment Portfolio	06/08/15	Mittal, Akshat; Smetaniouk, Taras; Ahluwalia, Randhir
	06/15/15	Mittal, Akshat; Smetaniouk, Taras; Mangion, James R
	06/17/15	Mittal, Akshat; Smetaniouk, Taras; Mangion, James R
	06/25/15	Freidenrich, Scott; Austin, Franklin; Mangion, James R; Smetaniouk, Taras; Mittal, Akshat; Swintek, J Mark; Freidenrich, Scott; Austin, Franklin; Mangion, James R; Smetaniouk, Taras; Mittal, Akshat; Swintek, J Mark
	07/16/15	Budd, Stephen; Swintek, Mark; Austin, Franklin; Freidenrich, Scott
	07/27/15	Ahluwalia, Randhir; Mangion, James R; Smetaniouk, Taras; Summer, Cindy
	08/28/15	Hart, Charles W; Mittal, Akshat
Placements	07/01/15	Drexler, Alan P; Mangion, James R
Central Bank Deposits	08/07/15	Ellison, Robert M; Gesuele, Vincent; Ahluwalia, Randhir; Mittal, Akshat
	08/20/15	Feazell, Joel; Ahluwalia, Randhir; Hart, Charles W
Reverse Mortgages	08/07/15	Mittal, Akshat; Ahluwalia, Randhir; Wilkinson, Timothy Sean
Iron Hound	08/07/15	Mittal, Akshat; Passaro, George V; Ahluwalia, Randhir; Bansal, Malay
Securities Financing	08/20/15	Bockian, Jeffrey A; Zito, Michael; Schroeder, Michael; Ahluwalia, Randhir; Hart, Charles W
Short term borrowings	08/19/15	Bockian, Jeffrey A; Schultz, Karl R; Ahluwalia, Randhir; Hart, Charles W
	08/26/15	Ferraioli, Donald; Mittal, Akshat; Ahluwalia, Randhir
Trading Assets/Liabilities	08/26/15	Mcfadden, Michael; Hart, Charles W; Ahluwalia, Randhir; Meredith-Carpeni, Regina; Fisher, EG; Curran, Michael; Samela, William; McAuliffe, James; Strumeyer, Gary; Donovan, Timothy; Costa, Fernando A

2. Independent variable stationarity test results

Table 445: Stationarity results with constant for zero growth variables on levels of applicable independent variables

Variable Name	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Explanation
Inflation	**0.018**	<0.01	0.326	**YES**	
EU inflation	**0.169**	0.022	0.067	**NO**	
EU Real GDP	**<0.01**	0.185	0.618	**YES**	
UK Real GDP	**0.089**	0.332	0.109	**YES**	
Nom Disposable Income	**0.064**	<0.01	0.786	**YES**	
Nominal GDP growth	**0.294**	0.012	0.217	**YES**	Visual assessment not consistent with ADF, visual assessment supported by economic theory
Real Disposable Income	**0.14**	<0.01	0.534	**YES**	Visual assessment not consistent with ADF, visual assessment supported by economic theory
Real GDP growth	**0.185**	0.087	0.085	**YES**	Visual assessment not consistent with ADF, visual assessment supported by economic theory
Unemp rate	**0.232**	0.637	0.068	**NO**	
UK inflation	**0.663**	0.126	0.082	**NO**	
Baa to Treasury Spread	**0.171**	0.295	0.237	**NO**	
Bond and Income Mut Fund Cash Flow	**0.249**	0.25	0.172	**NO**	
Baa Corporate Yield	**0.815**	0.836	<0.01	**NO**	
BNYM - Peer Group Debt Yield Spread	**0.222**	0.21	0.051	**NO**	
BNYM - Peer Group Debt Yield Ratio	**0.326**	0.358	0.086	**NO**	
EONIA	**0.168**	0.613	<0.01	**NO**	
10Y EUR Swap	**0.96**	0.956	<0.01	**NO**	
3M EUR Swap	**0.332**	0.724	<0.01	**NO**	
5Y EUR Swap	**0.737**	0.868	<0.01	**NO**	
Federal Funds Rate	**<0.01**	<0.01	<0.01	**NO**	Visual assessment not consistent with ADF and PP, visual assessment consistent with general findings in literature

Variable Name	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Explanation
Germany 10yr bond	**0.933**	0.939	<0.01	**NO**	
1 week LIBOR 1 week OIS spread	**0.3**	<0.01	<0.01	**NO**	
Money market fund Cash Flow	**0.082**	0.097	0.105	**NO**	Visual assessment not consistent with ADF
Mortgage Rate	**0.419**	0.567	<0.01	**NO**	
Ovrnt LIBOR	**0.044**	0.423	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment consistent with general findings in literature
Ovrnt LIBOR-1wk OIS spread	**0.366**	0.51	0.026	**NO**	
Ovrnt Repo Rate	**0.095**	<0.01	<0.01	**NO**	Visual assessment not consistent with ADF and PP, visual assessment consistent with general findings in literature
Prime rate	**<0.01**	<0.01	<0.01	**NO**	Visual assessment not consistent with ADF and PP, visual assessment consistent with general findings in literature
SONIA	**0.058**	0.392	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment consistent with general findings in literature
Stock Mut Fund Cash Flow	**0.112**	0.048	0.292	**NO**	
10Y Treasury	**0.254**	0.473	<0.01	**NO**	
1M Treasury rate	**<0.01**	<0.01	<0.01	**NO**	Visual assessment not consistent with ADF and PP, visual assessment consistent with general findings in literature
1Y Treasury	**0.127**	<0.01	<0.01	**NO**	
20Y Treasury	**0.619**	0.777	<0.01	**NO**	
2Y Treasury	**0.381**	<0.01	<0.01	**NO**	
30Y Treasury	**0.579**	0.752	<0.01	**NO**	
3M Treasury	**<0.01**	<0.01	<0.01	**NO**	Visual assessment not consistent with ADF and PP, visual assessment consistent with general findings in literature
3Y Treasury	**0.356**	0.032	<0.01	**NO**	
5Y Treasury	**0.014**	0.13	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment

Variable Name	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Explanation
					consistent with economic theory
7Y Treasury	**0.078**	0.264	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment consistent with general findings in literature
1M-3M Treasury Spread	**0.448**	<0.01	0.368	**YES**	Visual assessment not consistent with ADF
3M to 10Y T Spread	**0.18**	0.036	0.125	**YES**	Visual assessment not consistent with ADF
3M to 5Y T Spread	**0.072**	0.11	0.234	**YES**	
T spread with Fed Funds	**<0.01**	0.116	0.018	**NO**	Visual assessment not consistent with ADF
10Y UK Swap	**0.754**	0.732	<0.01	**NO**	
3M UK Swap	**0.232**	0.51	<0.01	**NO**	
5Y UK Swap	**0.305**	0.613	<0.01	**NO**	
10Y US Swap	**0.371**	0.322	<0.01	**NO**	
3M US Swap	**0.134**	0.086	<0.01	**NO**	
5Y US Swap	**0.035**	0.246	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment consistent with general findings in literature
1 Month EUR LIBOR	**0.359**	0.664	<0.01	**NO**	
3 Month EUR LIBOR	**0.231**	0.705	<0.01	**NO**	
1 Month GBP LIBOR	**0.092**	0.455	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment consistent with general findings in literature
3 Month GBP LIBOR	**0.237**	0.49	<0.01	**NO**	
6 Month USD LIBOR	**<0.01**	0.084	<0.01	**NO**	Visual assessment not consistent with ADF and PP, visual assessment consistent with general findings in literature
ECB Marginal Lending Rate	**0.374**	0.788	<0.01	**NO**	
BoE Clearng Base Rate	**0.044**	0.487	<0.01	**NO**	Visual assessment not consistent with ADF, visual assessment consistent with general findings in literature

Table 446: Stationarity results with trend for growth variables on levels of applicable independent variables

Variable Name	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
ABS Issuance	**>0.10**	<0.01	<0.01	**NO**	
BNYM AUC	**>0.10**	0.669	0.015	**NO**	
Com Real Estate Price Index	**>0.10**	0.995	<0.01	**NO**	
Corp Debt Outstanding	**>0.10**	0.999	<0.01	**NO**	
DJI	**>0.10**	0.886	<0.01	**NO**	
Debt Share of Asset Financing	**>0.10**	0.947	<0.01	**NO**	
Eurekahedge NA FoF Index	**>0.10**	0.881	<0.01	**NO**	
Eurekahedge NA HF Index	**>0.10**	0.512	0.106	**NO**	
EUR M1	**>0.10**	1	0.067	**NO**	
EUR M2	**>0.10**	0.059	0.013	**NO**	
EUR M3	**>0.10**	0.066	0.027	**NO**	
EU Outstanding debt (ex gov)	**>0.10**	0.922	<0.01	**NO**	
EU Gross debt issuances (ex gov)	**>0.10**	<0.01	0.154	**NO**	
Euro Stoxx Price Index	**>0.10**	0.939	<0.01	**NO**	
Euro Stoxx Volatility Index	**>0.10**	0.038	0.067	**NO**	
Nominal Exports	**>0.10**	0.305	0.078	**NO**	
FTSE 100 Price Index	**>0.10**	0.61	<0.01	**NO**	
FTSE 100 Volatility Index	**>0.10**	0.019	0.124	**NO**	
FTSE All Price Index	**>0.10**	0.635	<0.01	**NO**	
Fed balance sheet	**>0.10**	0.509	0.092	**NO**	
HFRX NA Index	**>0.10**	0.671	<0.01	**NO**	
HPI	**>0.10**	0.958	<0.01	**NO**	
Industrial Production	**>0.10**	0.923	<0.01	**NO**	
KBW Bank Index	**>0.10**	0.601	<0.01	**NO**	
MSCI WORLD Index	**>0.10**	0.808	<0.01	**NO**	
Market Vol	**<0.10**	0.047	0.14	**NO**	Visual assessment not consistent with ADF or PP
Nominal Imports	**>0.10**	0.86	0.052	**NO**	
Real estate loans	**>0.10**	0.613	0.016	**NO**	

Variable Name	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Real Imports	**>0.10**	0.837	0.01	**NO**	
S&P Euro Sov Bond Index	**>0.10**	0.72	0.021	**NO**	
S&P Vol (30D MAVG)	**>0.10**	0.112	0.251	**NO**	
10 Year US T-Note Volatility Index	**>0.10**	0.069	0.071	**NO**	
Total Bond Issuance (ex MBS, gov)	**>0.10**	<0.01	<0.01	**NO**	
Total Bond Issuance (ex MBS, treasuries)	**>0.10**	<0.01	0.215	**NO**	
UK M0	**>0.10**	0.606	0.026	**NO**	
UK M4	**>0.10**	0.747	<0.01	**NO**	
UK debt (ex MBS)	**>0.10**	<0.01	0.143	**NO**	
UK debt (ex MBS, gov)	**>0.10**	<0.01	0.137	**NO**	
USD/EUR	**>0.10**	0.68	0.722	**NO**	
Weighted Avg USD FX rate	**>0.10**	0.96	0.029	**NO**	
USD/GBP	**>0.10**	0.699	<0.01	**NO**	
US M1	**>0.10**	0.331	<0.01	**NO**	

Table 447: Stationarity results with constant on variable first differences of applicable independent variables

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
ABS Issuance	First difference - MoM	<0.01	<0.01	**0.104**	**YES**	
ABS Issuance	First difference - QoQ	<0.01	<0.01	**0.023**	**NO**	
ABS Issuance	First difference - YoY	0.051	<0.01	**0.015**	**NO**	
ABS Issuance	Percent change - MoM	0.129	<0.01	**0.376**	**YES**	
ABS Issuance	Percent change - QoQ	0.217	<0.01	**0.621**	**YES**	
ABS Issuance	Percent change - YoY	0.073	<0.01	**0.55**	**YES**	
BNYM AUC	First difference - MoM	0.032	0.032	**0.329**	**YES**	
BNYM AUC	First difference - QoQ	0.387	0.05	**0.327**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
BNYM AUC	First difference - YoY	0.015	0.496	**0.081**	**NO**	
BNYM AUC	Percent change - MoM	0.02	0.026	**0.527**	**YES**	
BNYM AUC	Percent change - QoQ	0.238	0.046	**0.517**	**YES**	
BNYM AUC	Percent change - YoY	0.023	0.461	**0.17**	**YES**	
Baa to Treasury Spread	First difference - MoM	0.033	<0.01	**0.475**	**YES**	
Baa to Treasury Spread	First difference - QoQ	0.013	0.021	**0.434**	**YES**	
Baa to Treasury Spread	First difference - YoY	<0.01	0.41	**0.178**	**YES**	
Bond and Income Mut Fund Cash Flow	First difference - MoM	0.019	<0.01	**0.914**	**YES**	
Bond and Income Mut Fund Cash Flow	First difference - QoQ	0.077	<0.01	**0.899**	**YES**	
Bond and Income Mut Fund Cash Flow	First difference - YoY	<0.01	0.237	**0.596**	**YES**	
Inflation	First difference - MoM	<0.01	<0.01	**0.98**	**YES**	
Inflation	First difference - QoQ	<0.01	<0.01	**0.985**	**YES**	
Inflation	First difference - YoY	0.018	0.011	**0.753**	**YES**	
Com Real Estate Price Index	First difference - MoM	0.481	0.057	**0.059**	**NO**	
Com Real Estate Price Index	First difference - QoQ	0.653	0.137	**0.046**	**NO**	
Com Real Estate Price Index	First difference - YoY	0.392	0.752	**<0.01**	**NO**	
Com Real Estate Price Index	Percent change - MoM	0.342	0.044	**0.076**	**YES**	Visual assessment not consistent with KPSS
Com Real Estate Price Index	Percent change - QoQ	0.442	0.112	**0.061**	**NO**	
Com Real Estate Price Index	Percent change - YoY	0.712	0.725	**<0.01**	**NO**	
Baa Corporate Yield	First difference - MoM	0.047	<0.01	**0.515**	**YES**	
Baa Corporate Yield	First difference - QoQ	0.082	<0.01	**0.497**	**YES**	
Baa Corporate Yield	First difference - YoY	0.016	0.387	**0.322**	**NO**	Visual assessment not consistent with KPSS
Corp Debt Outstanding	First difference - MoM	0.463	0.29	**0.082**	**NO**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Corp Debt Outstanding	First difference - QoQ	0.346	0.408	**0.078**	**NO**	
Corp Debt Outstanding	First difference - YoY	0.515	0.662	**0.036**	**NO**	
Corp Debt Outstanding	Percent change - MoM	0.349	0.251	**0.119**	**YES**	
Corp Debt Outstanding	Percent change - QoQ	0.266	0.336	**0.113**	**YES**	
Corp Debt Outstanding	Percent change - YoY	0.216	0.497	**0.052**	**NO**	
DJI	First difference - MoM	0.493	0.015	**0.075**	**NO**	
DJI	First difference - QoQ	0.471	0.04	**0.06**	**NO**	
DJI	First difference - YoY	0.024	0.621	**<0.01**	**NO**	
DJI	Percent change - MoM	0.187	0.019	**0.192**	**YES**	
DJI	Percent change - QoQ	0.323	0.042	**0.174**	**YES**	
DJI	Percent change - YoY	0.041	0.453	**0.021**	**NO**	
BNYM - Peer Group Debt Yield Spread	First difference - MoM	0.075	<0.01	**0.42**	**YES**	
BNYM - Peer Group Debt Yield Spread	First difference - QoQ	0.073	<0.01	**0.24**	**YES**	
BNYM - Peer Group Debt Yield Spread	First difference - YoY	0.018	0.105	**0.032**	**NO**	
BNYM - Peer Group Debt Yield Ratio	First difference - MoM	<0.01	<0.01	**0.341**	**YES**	
BNYM - Peer Group Debt Yield Ratio	First difference - QoQ	<0.01	<0.01	**0.232**	**YES**	
BNYM - Peer Group Debt Yield Ratio	First difference - YoY	0.589	0.186	**0.012**	**NO**	
Debt Share of Asset Financing	First difference - MoM	0.359	<0.01	**0.068**	**NO**	
Debt Share of Asset Financing	First difference - QoQ	0.317	0.032	**0.053**	**NO**	
Debt Share of Asset Financing	First difference - YoY	0.228	0.699	**0.012**	**NO**	
Debt Share of Asset Financing	Percent change - MoM	0.381	<0.01	**0.063**	**NO**	
Debt Share of Asset Financing	Percent change - QoQ	0.118	0.032	**0.048**	**NO**	
Debt Share of	Percent change -	0.295	0.701	**0.011**	**NO**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Asset Financing	YoY					
Eurekahedge NA FoF Index	First difference - MoM	0.02	<0.01	**0.321**	**YES**	
Eurekahedge NA FoF Index	First difference - QoQ	0.06	0.014	**0.29**	**YES**	
Eurekahedge NA FoF Index	First difference - YoY	0.124	0.452	**0.043**	**NO**	
Eurekahedge NA FoF Index	Percent change - MoM	0.015	<0.01	**0.439**	**YES**	
Eurekahedge NA FoF Index	Percent change - QoQ	0.02	0.014	**0.404**	**YES**	
Eurekahedge NA FoF Index	Percent change - YoY	0.103	0.421	**0.073**	**NO**	
Eurekahedge NA HF Index	First difference - MoM	<0.01	<0.01	**0.685**	**YES**	
Eurekahedge NA HF Index	First difference - QoQ	0.02	<0.01	**0.692**	**YES**	
Eurekahedge NA HF Index	First difference - YoY	0.096	0.347	**0.253**	**YES**	
Eurekahedge NA HF Index	Percent change - MoM	<0.01	<0.01	**0.87**	**YES**	
Eurekahedge NA HF Index	Percent change - QoQ	<0.01	<0.01	**0.865**	**YES**	
Eurekahedge NA HF Index	Percent change - YoY	0.069	0.334	**0.555**	**YES**	
EONIA	First difference - MoM	0.102	<0.01	**0.393**	**YES**	
EONIA	First difference - QoQ	0.212	0.01	**0.375**	**YES**	
EONIA	First difference - YoY	0.036	0.48	**0.115**	**YES**	
10Y EUR Swap	First difference - MoM	<0.01	<0.01	**0.544**	**YES**	
10Y EUR Swap	First difference - QoQ	<0.01	<0.01	**0.658**	**YES**	
10Y EUR Swap	First difference - YoY	<0.01	0.244	**0.808**	**YES**	
3M EUR Swap	First difference - MoM	0.153	<0.01	**0.57**	**YES**	
3M EUR Swap	First difference - QoQ	0.061	0.043	**0.564**	**YES**	
3M EUR Swap	First difference - YoY	0.197	0.558	**0.217**	**NO**	Visual assessment not consistent with KPSS
5Y EUR Swap	First difference - MoM	<0.01	<0.01	**0.902**	**YES**	
5Y EUR Swap	First difference - QoQ	<0.01	<0.01	**0.92**	**YES**	
5Y EUR Swap	First difference - YoY	0.013	0.294	**0.601**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
EUR M1	First difference - MoM	0.638	<0.01	**0.056**	**NO**	
EUR M1	First difference - QoQ	0.374	0.441	**0.077**	**NO**	
EUR M1	First difference - YoY	0.134	0.942	**0.192**	**NO**	Visual assessment not consistent with KPSS
EUR M1	Percent change - MoM	0.358	<0.01	**0.194**	**YES**	
EUR M1	Percent change - QoQ	0.128	0.136	**0.295**	**YES**	
EUR M1	Percent change - YoY	0.029	0.8	**0.471**	**YES**	
EUR M2	First difference - MoM	0.231	<0.01	**0.05**	**NO**	
EUR M2	First difference - QoQ	0.208	0.12	**0.068**	**NO**	
EUR M2	First difference - YoY	0.029	0.29	**0.047**	**NO**	
EUR M2	Percent change - MoM	0.102	<0.01	**0.016**	**NO**	
EUR M2	Percent change - QoQ	0.162	0.112	**0.026**	**NO**	
EUR M2	Percent change - YoY	0.012	0.065	**0.022**	**NO**	
EUR M3	First difference - MoM	0.041	<0.01	**0.06**	**NO**	
EUR M3	First difference - QoQ	0.198	0.098	**0.087**	**NO**	
EUR M3	First difference - YoY	0.232	0.225	**0.082**	**NO**	
EUR M3	Percent change - MoM	0.04	<0.01	**0.036**	**NO**	
EUR M3	Percent change - QoQ	0.189	0.083	**0.06**	**NO**	
EUR M3	Percent change - YoY	0.154	0.066	**0.06**	**NO**	
EU Outstanding debt (ex gov)	First difference - MoM	<0.01	<0.01	**<0.01**	**YES**	Visual assessment not consistent with KPSS
EU Outstanding debt (ex gov)	First difference - QoQ	0.568	<0.01	**<0.01**	**NO**	
EU Outstanding debt (ex gov)	First difference - YoY	0.659	0.669	**<0.01**	**NO**	
EU Outstanding debt (ex gov)	Percent change - MoM	<0.01	<0.01	**<0.01**	**NO**	
EU Outstanding debt (ex gov)	Percent change - QoQ	0.587	<0.01	**<0.01**	**NO**	
EU Outstanding debt (ex gov)	Percent change - YoY	0.635	0.644	**<0.01**	**NO**	
EU Gross debt	First difference -	<0.01	<0.01	**0.796**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
issuances (ex gov)	MoM					
EU Gross debt issuances (ex gov)	First difference - QoQ	<0.01	<0.01	**0.837**	**YES**	
EU Gross debt issuances (ex gov)	First difference - YoY	0.027	0.017	**0.519**	**YES**	
EU Gross debt issuances (ex gov)	Percent change - MoM	<0.01	<0.01	**0.772**	**YES**	
EU Gross debt issuances (ex gov)	Percent change - QoQ	<0.01	<0.01	**0.623**	**YES**	
EU Gross debt issuances (ex gov)	Percent change - YoY	0.02	0.028	**0.116**	**YES**	
Euro Stoxx Price Index	First difference - MoM	<0.01	<0.01	**0.046**	**NO**	
Euro Stoxx Price Index	First difference - QoQ	0.051	<0.01	**0.057**	**NO**	
Euro Stoxx Price Index	First difference - YoY	0.445	0.563	**0.011**	**NO**	
Euro Stoxx Price Index	Percent change - MoM	0.01	<0.01	**0.122**	**YES**	
Euro Stoxx Price Index	Percent change - QoQ	0.032	<0.01	**0.106**	**YES**	
Euro Stoxx Price Index	Percent change - YoY	0.473	0.394	**0.019**	**NO**	
Euro Stoxx Volatility Index	First difference - MoM	<0.01	<0.01	**0.673**	**YES**	
Euro Stoxx Volatility Index	First difference - QoQ	0.013	<0.01	**0.74**	**YES**	
Euro Stoxx Volatility Index	First difference - YoY	<0.01	0.023	**0.261**	**YES**	
Euro Stoxx Volatility Index	Percent change - MoM	<0.01	<0.01	**0.379**	**YES**	
Euro Stoxx Volatility Index	Percent change - QoQ	0.012	<0.01	**0.455**	**YES**	
Euro Stoxx Volatility Index	Percent change - YoY	0.011	<0.01	**0.08**	**NO**	
EU inflation	First difference - MoM	<0.01	<0.01	**0.994**	**YES**	
EU inflation	First difference - QoQ	<0.01	<0.01	**0.881**	**YES**	
EU inflation	First difference - YoY	<0.01	0.026	**0.506**	**YES**	
Nominal Exports	First difference - MoM	0.44	<0.01	**0.897**	**YES**	
Nominal Exports	First difference - QoQ	0.013	<0.01	**0.581**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Nominal Exports	First difference - YoY	0.185	0.573	**0.514**	**NO**	Visual assessment not consistent with KPSS
Nominal Exports	Percent change - MoM	0.331	<0.01	**0.569**	**YES**	
Nominal Exports	Percent change - QoQ	0.028	<0.01	**0.558**	**YES**	
Nominal Exports	Percent change - YoY	0.182	0.524	**0.504**	**NO**	Visual assessment not consistent with KPSS
FTSE 100 Price Index	First difference - MoM	0.037	<0.01	**0.319**	**YES**	
FTSE 100 Price Index	First difference - QoQ	0.102	<0.01	**0.199**	**YES**	
FTSE 100 Price Index	First difference - YoY	0.391	0.383	**0.051**	**NO**	
FTSE 100 Price Index	Percent change - MoM	0.029	<0.01	**0.383**	**YES**	
FTSE 100 Price Index	Percent change - QoQ	0.083	<0.01	**0.304**	**YES**	
FTSE 100 Price Index	Percent change - YoY	0.363	0.325	**0.108**	**NO**	Visual assessment not consistent with KPSS
FTSE 100 Volatility Index	First difference - MoM	<0.01	<0.01	**0.491**	**YES**	
FTSE 100 Volatility Index	First difference - QoQ	0.016	<0.01	**0.689**	**YES**	
FTSE 100 Volatility Index	First difference - YoY	<0.01	0.014	**0.299**	**YES**	
FTSE 100 Volatility Index	Percent change - MoM	<0.01	<0.01	**0.295**	**YES**	
FTSE 100 Volatility Index	Percent change - QoQ	<0.01	<0.01	**0.419**	**YES**	
FTSE 100 Volatility Index	Percent change - YoY	<0.01	<0.01	**0.072**	**NO**	
FTSE All Price Index	First difference - MoM	0.04	<0.01	**0.236**	**YES**	
FTSE All Price Index	First difference - QoQ	0.12	<0.01	**0.152**	**YES**	
FTSE All Price Index	First difference - YoY	0.43	0.413	**0.044**	**NO**	
FTSE All Price Index	Percent change - MoM	0.03	<0.01	**0.328**	**YES**	
FTSE All Price Index	Percent change - QoQ	0.099	<0.01	**0.286**	**YES**	
FTSE All Price Index	Percent change - YoY	0.402	0.352	**0.1**	**NO**	
Fed balance sheet	First difference - MoM	0.032	<0.01	**0.832**	**YES**	
Fed balance sheet	First difference - QoQ	<0.01	<0.01	**0.794**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Fed balance sheet	First difference - YoY	0.096	0.252	**0.46**	**YES**	
Fed balance sheet	Percent change - MoM	0.076	<0.01	**0.553**	**YES**	
Fed balance sheet	Percent change - QoQ	0.096	<0.01	**0.418**	**YES**	
Fed balance sheet	Percent change - YoY	0.082	0.211	**0.105**	**YES**	
Federal Funds Rate	First difference - MoM	0.028	0.02	**0.015**	**YES**	Visual assessment not consistent with KPSS
Federal Funds Rate	First difference - QoQ	<0.01	0.066	**0.012**	**YES**	Visual assessment not consistent with KPSS
Federal Funds Rate	First difference - YoY	<0.01	0.678	**<0.01**	**NO**	
EU Real GDP	First difference - MoM	0.013	<0.01	**0.572**	**YES**	
EU Real GDP	First difference - QoQ	0.044	<0.01	**0.567**	**YES**	
EU Real GDP	First difference - YoY	<0.01	0.331	**0.429**	**YES**	
UK Real GDP	First difference - MoM	0.016	<0.01	**0.714**	**YES**	
UK Real GDP	First difference - QoQ	0.072	<0.01	**0.735**	**YES**	
UK Real GDP	First difference - YoY	<0.01	0.511	**0.414**	**YES**	
Germany 10yr bond	First difference - MoM	<0.01	<0.01	**0.676**	**YES**	
Germany 10yr bond	First difference - QoQ	0.022	<0.01	**0.73**	**YES**	
Germany 10yr bond	First difference - YoY	<0.01	0.179	**0.826**	**YES**	
HFRX NA Index	First difference - MoM	<0.01	<0.01	**0.619**	**YES**	
HFRX NA Index	First difference - QoQ	0.133	<0.01	**0.581**	**YES**	
HFRX NA Index	First difference - YoY	0.246	0.391	**0.092**	**NO**	
HFRX NA Index	Percent change - MoM	<0.01	<0.01	**0.652**	**YES**	
HFRX NA Index	Percent change - QoQ	0.107	<0.01	**0.572**	**YES**	
HFRX NA Index	Percent change - YoY	0.245	0.355	**0.094**	**NO**	
HPI	First difference - MoM	0.722	0.501	**<0.01**	**NO**	
HPI	First difference - QoQ	0.609	0.615	**<0.01**	**NO**	
HPI	First difference -	0.423	0.832	**<0.01**	**NO**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
	YoY					
HPI	Percent change - MoM	0.716	0.472	**<0.01**	**YES**	Allowed on exception basis, due to short development data period housing crisis has overly large impact in test period
HPI	Percent change - QoQ	0.614	0.599	**<0.01**	**NO**	
HPI	Percent change - YoY	0.345	0.843	**<0.01**	**NO**	
Industrial Production	First difference - MoM	0.105	0.36	**0.063**	**NO**	
Industrial Production	First difference - QoQ	0.499	0.475	**0.051**	**NO**	
Industrial Production	First difference - YoY	0.022	0.775	**0.014**	**NO**	
Industrial Production	Percent change - MoM	0.096	0.356	**0.076**	**NO**	
Industrial Production	Percent change - QoQ	0.497	0.463	**0.062**	**NO**	
Industrial Production	Percent change - YoY	0.032	0.767	**0.018**	**NO**	
KBW Bank Index	First difference - MoM	0.41	<0.01	**0.011**	**NO**	
KBW Bank Index	First difference - QoQ	0.135	<0.01	**0.019**	**NO**	
KBW Bank Index	First difference - YoY	<0.01	0.46	**<0.01**	**NO**	
KBW Bank Index	Percent change - MoM	0.19	<0.01	**0.135**	**YES**	
KBW Bank Index	Percent change - QoQ	0.061	<0.01	**0.129**	**YES**	
KBW Bank Index	Percent change - YoY	0.018	0.239	**0.024**	**NO**	
1 week LIBOR 1 week OIS spread	First difference - MoM	0.015	<0.01	**0.656**	**YES**	
1 week LIBOR 1 week OIS spread	First difference - QoQ	0.034	<0.01	**0.819**	**YES**	
1 week LIBOR 1 week OIS spread	First difference - YoY	<0.01	<0.01	**0.527**	**YES**	
MSCI WORLD Index	First difference - MoM	0.025	<0.01	**0.157**	**YES**	
MSCI WORLD Index	First difference - QoQ	0.162	<0.01	**0.162**	**YES**	
MSCI WORLD Index	First difference - YoY	0.55	0.469	**0.019**	**NO**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
MSCI WORLD Index	Percent change - MoM	0.084	<0.01	**0.271**	**YES**	
MSCI WORLD Index	Percent change - QoQ	0.053	<0.01	**0.314**	**YES**	
MSCI WORLD Index	Percent change - YoY	0.214	0.338	**0.05**	**NO**	
Market Vol	First difference - MoM	<0.01	<0.01	**0.903**	**YES**	
Market Vol	First difference - QoQ	<0.01	<0.01	**0.795**	**YES**	
Market Vol	First difference - YoY	<0.01	0.027	**0.354**	**YES**	
Market Vol	Percent change - MoM	<0.01	<0.01	**0.842**	**YES**	
Market Vol	Percent change - QoQ	<0.01	<0.01	**0.464**	**YES**	
Market Vol	Percent change - YoY	0.013	0.011	**0.083**	**NO**	
Money market fund Cash Flow	First difference - MoM	0.051	<0.01	**0.918**	**YES**	
Money market fund Cash Flow	First difference - QoQ	0.038	<0.01	**0.873**	**YES**	
Money market fund Cash Flow	First difference - YoY	0.107	0.025	**0.136**	**YES**	
Mortgage Rate	First difference - MoM	0.037	<0.01	**0.601**	**YES**	
Mortgage Rate	First difference - QoQ	0.124	<0.01	**0.7**	**YES**	
Mortgage Rate	First difference - YoY	0.025	0.25	**0.085**	**NO**	
Nom Disposable Income	First difference - MoM	<0.01	<0.01	**0.998**	**YES**	
Nom Disposable Income	First difference - QoQ	<0.01	<0.01	**0.997**	**YES**	
Nom Disposable Income	First difference - YoY	<0.01	<0.01	**0.723**	**YES**	
Nominal GDP growth	First difference - MoM	<0.01	<0.01	**0.989**	**YES**	
Nominal GDP growth	First difference - QoQ	0.034	<0.01	**0.915**	**YES**	
Nominal GDP growth	First difference - YoY	<0.01	0.017	**0.564**	**YES**	
Nominal Imports	First difference - MoM	0.104	0.101	**0.787**	**NO**	Visual assessment not consistent with KPSS
Nominal Imports	First difference - QoQ	0.034	0.186	**0.759**	**YES**	
Nominal Imports	First difference - YoY	<0.01	0.564	**0.43**	**YES**	
Nominal Imports	Percent change - MoM	0.098	0.127	**0.8**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Nominal Imports	Percent change - QoQ	0.179	0.207	**0.774**	**NO**	Visual assessment not consistent with KPSS
Nominal Imports	Percent change - YoY	0.064	0.567	**0.499**	**YES**	
Ovrnt LIBOR	First difference - MoM	0.23	<0.01	**0.182**	**YES**	
Ovrnt LIBOR	First difference - QoQ	0.451	0.028	**0.175**	**YES**	
Ovrnt LIBOR	First difference - YoY	0.209	0.616	**0.025**	**NO**	
Ovrnt LIBOR-1wk OIS spread	First difference - MoM	<0.01	<0.01	**0.52**	**YES**	
Ovrnt LIBOR-1wk OIS spread	First difference - QoQ	<0.01	0.011	**0.509**	**YES**	
Ovrnt LIBOR-1wk OIS spread	First difference - YoY	0.167	0.215	**0.528**	**NO**	Visual assessment not consistent with KPSS
Ovrnt Repo Rate	First difference - MoM	0.047	<0.01	**0.02**	**YES**	Visual assessment not consistent with KPSS
Ovrnt Repo Rate	First difference - QoQ	0.064	<0.01	**0.015**	**YES**	Visual assessment not consistent with KPSS
Ovrnt Repo Rate	First difference - YoY	0.033	0.225	**<0.01**	**NO**	
Prime rate	First difference - MoM	0.025	0.09	**0.017**	**YES**	Visual assessment not consistent with KPSS
Prime rate	First difference - QoQ	<0.01	0.158	**0.013**	**NO**	
Prime rate	First difference - YoY	<0.01	0.701	**<0.01**	**NO**	
Real estate loans	First difference - MoM	0.352	<0.01	**0.139**	**YES**	
Real estate loans	First difference - QoQ	0.723	0.023	**0.132**	**YES**	
Real estate loans	First difference - YoY	0.172	0.542	**0.095**	**NO**	
Real estate loans	Percent change - MoM	0.339	<0.01	**0.151**	**YES**	
Real estate loans	Percent change - QoQ	0.479	0.025	**0.125**	**YES**	
Real estate loans	Percent change - YoY	0.193	0.505	**0.088**	**NO**	
Real Disposable Income	First difference - MoM	<0.01	<0.01	**1**	**YES**	
Real Disposable Income	First difference - QoQ	0.019	<0.01	**1**	**YES**	
Real Disposable Income	First difference - YoY	0.035	<0.01	**0.972**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Real GDP growth	First difference - MoM	<0.01	<0.01	**0.93**	**YES**	
Real GDP growth	First difference - QoQ	0.088	<0.01	**0.923**	**YES**	
Real GDP growth	First difference - YoY	<0.01	0.13	**0.551**	**YES**	
Real Imports	First difference - MoM	0.042	0.094	**0.189**	**YES**	
Real Imports	First difference - QoQ	0.331	0.178	**0.176**	**NO**	Visual assessment not consistent with KPSS
Real Imports	First difference - YoY	0.256	0.709	**0.095**	**NO**	
Real Imports	Percent change - MoM	0.037	0.106	**0.243**	**YES**	
Real Imports	Percent change - QoQ	0.358	0.182	**0.232**	**NO**	Visual assessment not consistent with KPSS
Real Imports	Percent change - YoY	0.026	0.684	**0.14**	**YES**	
SONIA	First difference - MoM	0.261	<0.01	**0.187**	**YES**	
SONIA	First difference - QoQ	0.401	0.027	**0.177**	**YES**	
SONIA	First difference - YoY	0.234	0.613	**0.024**	**NO**	
S&P Euro Sov Bond Index	First difference - MoM	<0.01	<0.01	**0.317**	**YES**	
S&P Euro Sov Bond Index	First difference - QoQ	0.019	<0.01	**0.316**	**YES**	
S&P Euro Sov Bond Index	First difference - YoY	0.487	0.422	**0.278**	**NO**	Visual assessment not consistent with KPSS
S&P Euro Sov Bond Index	Percent change - MoM	<0.01	<0.01	**0.024**	**NO**	
S&P Euro Sov Bond Index	Percent change - QoQ	0.456	0.029	**0.026**	**NO**	
S&P Euro Sov Bond Index	Percent change - YoY	0.849	0.836	**0.065**	**NO**	
S&P Vol (30D MAVG)	First difference - MoM	0.012	<0.01	**0.901**	**YES**	
S&P Vol (30D MAVG)	First difference - QoQ	0.032	<0.01	**0.857**	**YES**	
S&P Vol (30D MAVG)	First difference - YoY	<0.01	0.078	**0.445**	**YES**	
S&P Vol (30D MAVG)	Percent change - MoM	<0.01	<0.01	**0.67**	**YES**	
S&P Vol (30D MAVG)	Percent change - QoQ	0.075	<0.01	**0.467**	**YES**	
S&P Vol (30D MAVG)	Percent change - YoY	<0.01	0.029	**0.077**	**NO**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Stock Mut Fund Cash Flow	First difference - MoM	<0.01	<0.01	**0.818**	**YES**	
Stock Mut Fund Cash Flow	First difference - QoQ	0.048	<0.01	**0.824**	**YES**	
Stock Mut Fund Cash Flow	First difference - YoY	0.018	0.066	**0.477**	**YES**	
10 Year US T-Note Volatility Index	First difference - MoM	0.012	<0.01	**0.615**	**YES**	
10 Year US T-Note Volatility Index	First difference - QoQ	0.031	<0.01	**0.458**	**YES**	
10 Year US T-Note Volatility Index	First difference - YoY	<0.01	0.032	**0.208**	**YES**	
10 Year US T-Note Volatility Index	Percent change - MoM	<0.01	<0.01	**0.592**	**YES**	
10 Year US T-Note Volatility Index	Percent change - QoQ	<0.01	<0.01	**0.377**	**YES**	
10 Year US T-Note Volatility Index	Percent change - YoY	<0.01	0.014	**0.085**	**NO**	
Total Bond Issuance (ex MBS, gov)	First difference - MoM	<0.01	<0.01	**0.094**	**NO**	
Total Bond Issuance (ex MBS, gov)	First difference - QoQ	<0.01	<0.01	**0.235**	**YES**	
Total Bond Issuance (ex MBS, gov)	First difference - YoY	0.05	<0.01	**0.011**	**NO**	
Total Bond Issuance (ex MBS, gov)	Percent change - MoM	<0.01	<0.01	**0.856**	**YES**	
Total Bond Issuance (ex MBS, gov)	Percent change - QoQ	<0.01	<0.01	**0.935**	**YES**	
Total Bond Issuance (ex MBS, gov)	Percent change - YoY	<0.01	<0.01	**0.239**	**YES**	
Total Bond Issuance (ex MBS, treasuries)	First difference - MoM	<0.01	<0.01	**0.242**	**YES**	
Total Bond Issuance (ex MBS, treasuries)	First difference - QoQ	<0.01	<0.01	**0.697**	**YES**	
Total Bond Issuance (ex MBS, treasuries)	First difference - YoY	0.055	<0.01	**0.233**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Total Bond Issuance (ex MBS, treasuries)	Percent change - MoM	<0.01	<0.01	**0.796**	**YES**	
Total Bond Issuance (ex MBS, treasuries)	Percent change - QoQ	0.06	<0.01	**0.947**	**YES**	
Total Bond Issuance (ex MBS, treasuries)	Percent change - YoY	<0.01	<0.01	**0.68**	**YES**	
10Y Treasury	First difference - MoM	0.017	<0.01	**0.74**	**YES**	
10Y Treasury	First difference - QoQ	0.214	0.017	**0.647**	**YES**	
10Y Treasury	First difference - YoY	0.046	0.46	**0.14**	**YES**	
1M Treasury rate	First difference - MoM	0.012	<0.01	**<0.01**	**NO**	
1M Treasury rate	First difference - QoQ	<0.01	0.011	**<0.01**	**NO**	
1M Treasury rate	First difference - YoY	<0.01	0.268	**<0.01**	**NO**	
1Y Treasury	First difference - MoM	0.039	0.023	**0.014**	**YES**	Visual assessment not consistent with KPSS
1Y Treasury	First difference - QoQ	0.011	0.049	**0.01**	**YES**	Visual assessment not consistent with KPSS
1Y Treasury	First difference - YoY	0.045	0.084	**<0.01**	**NO**	
20Y Treasury	First difference - MoM	0.014	0.01	**0.908**	**YES**	
20Y Treasury	First difference - QoQ	0.168	0.023	**0.884**	**YES**	
20Y Treasury	First difference - YoY	0.032	0.594	**0.51**	**YES**	
2Y Treasury	First difference - MoM	<0.01	<0.01	**0.031**	**YES**	Visual assessment not consistent with KPSS
2Y Treasury	First difference - QoQ	0.156	0.019	**0.019**	**YES**	Visual assessment not consistent with KPSS
2Y Treasury	First difference - YoY	0.057	0.051	**<0.01**	**NO**	
30Y Treasury	First difference - MoM	<0.01	0.01	**0.9**	**YES**	
30Y Treasury	First difference - QoQ	0.078	0.022	**0.877**	**YES**	
30Y Treasury	First difference - YoY	0.016	0.563	**0.647**	**YES**	
3M Treasury	First difference - MoM	<0.01	0.027	**<0.01**	**YES**	Visual assessment not consistent with

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
						KPSS
3M Treasury	First difference - QoQ	<0.01	0.074	**<0.01**	**YES**	Visual assessment not consistent with KPSS
3M Treasury	First difference - YoY	<0.01	0.137	**<0.01**	**NO**	
3Y Treasury	First difference - MoM	0.022	<0.01	**0.063**	**YES**	Visual assessment not consistent with KPSS
3Y Treasury	First difference - QoQ	0.315	0.013	**0.038**	**NO**	
3Y Treasury	First difference - YoY	0.215	0.068	**<0.01**	**NO**	
5Y Treasury	First difference - MoM	0.088	<0.01	**0.195**	**YES**	
5Y Treasury	First difference - QoQ	0.367	0.015	**0.136**	**YES**	
5Y Treasury	First difference - YoY	0.174	0.213	**<0.01**	**NO**	
7Y Treasury	First difference - MoM	0.024	<0.01	**0.424**	**YES**	
7Y Treasury	First difference - QoQ	0.261	0.016	**0.332**	**YES**	
7Y Treasury	First difference - YoY	0.081	0.336	**0.041**	**NO**	
1M-3M Treasury Spread	First difference - MoM	0.314	<0.01	**1**	**YES**	
1M-3M Treasury Spread	First difference - QoQ	<0.01	<0.01	**0.565**	**YES**	
1M-3M Treasury Spread	First difference - YoY	0.033	<0.01	**0.088**	**NO**	
3M to 10Y T Spread	First difference - MoM	0.14	<0.01	**0.047**	**NO**	
3M to 10Y T Spread	First difference - QoQ	0.158	0.019	**0.045**	**NO**	
3M to 10Y T Spread	First difference - YoY	0.29	0.495	**0.025**	**NO**	
3M to 5Y T Spread	First difference - MoM	0.182	<0.01	**0.163**	**YES**	
3M to 5Y T Spread	First difference - QoQ	0.172	0.01	**0.162**	**YES**	
3M to 5Y T Spread	First difference - YoY	0.331	0.536	**0.067**	**NO**	
T spread with Fed Funds	First difference - MoM	0.021	<0.01	**0.963**	**YES**	
T spread with Fed Funds	First difference - QoQ	<0.01	<0.01	**0.814**	**YES**	
T spread with Fed Funds	First difference - YoY	<0.01	<0.01	**0.129**	**YES**	
Unemp rate	First difference -	0.409	<0.01	**<0.01**	**YES**	Visual assessment

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
	MoM					not consistent with KPSS
Unemp rate	First difference - QoQ	0.411	0.132	**<0.01**	**NO**	
Unemp rate	First difference - YoY	0.695	0.837	**<0.01**	**NO**	
10Y UK Swap	First difference - MoM	<0.01	<0.01	**0.851**	**YES**	
10Y UK Swap	First difference - QoQ	0.057	<0.01	**0.842**	**YES**	
10Y UK Swap	First difference - YoY	0.033	0.269	**0.155**	**YES**	
3M UK Swap	First difference - MoM	0.18	<0.01	**0.216**	**YES**	
3M UK Swap	First difference - QoQ	0.165	0.01	**0.215**	**YES**	
3M UK Swap	First difference - YoY	0.067	0.551	**0.041**	**NO**	
5Y UK Swap	First difference - MoM	0.012	<0.01	**0.636**	**YES**	
5Y UK Swap	First difference - QoQ	0.026	<0.01	**0.487**	**YES**	
5Y UK Swap	First difference - YoY	0.175	0.344	**0.023**	**NO**	
UK M0	First difference - MoM	<0.01	<0.01	**0.654**	**YES**	
UK M0	First difference - QoQ	0.037	<0.01	**0.724**	**YES**	
UK M0	First difference - YoY	0.388	0.384	**0.336**	**NO**	Visual assessment not consistent with KPSS
UK M0	Percent change - MoM	<0.01	<0.01	**0.125**	**YES**	
UK M0	Percent change - QoQ	0.065	<0.01	**0.125**	**YES**	
UK M0	Percent change - YoY	0.424	0.405	**0.015**	**NO**	
UK M4	First difference - MoM	<0.01	<0.01	**<0.01**	**NO**	
UK M4	First difference - QoQ	0.486	<0.01	**0.01**	**NO**	
UK M4	First difference - YoY	0.295	0.621	**<0.01**	**NO**	
UK M4	Percent change - MoM	<0.01	<0.01	**<0.01**	**NO**	
UK M4	Percent change - QoQ	0.499	0.011	**<0.01**	**NO**	
UK M4	Percent change - YoY	0.231	0.605	**<0.01**	**NO**	
UK debt (ex MBS)	First difference - MoM	0.022	<0.01	**0.678**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
UK debt (ex MBS)	First difference - QoQ	0.1	<0.01	**0.902**	**YES**	
UK debt (ex MBS)	First difference - YoY	0.015	<0.01	**0.427**	**YES**	
UK debt (ex MBS)	Percent change - MoM	0.531	<0.01	**0.241**	**YES**	
UK debt (ex MBS)	Percent change - QoQ	0.299	<0.01	**0.922**	**YES**	
UK debt (ex MBS)	Percent change - YoY	0.014	<0.01	**0.149**	**YES**	
UK debt (ex MBS, gov)	First difference - MoM	<0.01	<0.01	**0.869**	**YES**	
UK debt (ex MBS, gov)	First difference - QoQ	<0.01	<0.01	**0.763**	**YES**	
UK debt (ex MBS, gov)	First difference - YoY	<0.01	<0.01	**0.59**	**YES**	
UK debt (ex MBS, gov)	Percent change - MoM	<0.01	<0.01	**0.194**	**YES**	
UK debt (ex MBS, gov)	Percent change - QoQ	<0.01	<0.01	**0.274**	**YES**	
UK debt (ex MBS, gov)	Percent change - YoY	<0.01	<0.01	**0.453**	**YES**	
UK inflation	First difference - MoM	<0.01	<0.01	**0.947**	**YES**	
UK inflation	First difference - QoQ	<0.01	<0.01	**0.86**	**YES**	
UK inflation	First difference - YoY	0.028	0.094	**0.267**	**YES**	
USD/EUR	First difference - MoM	<0.01	0.041	**0.4**	**YES**	
USD/EUR	First difference - QoQ	0.033	0.102	**0.455**	**YES**	
USD/EUR	First difference - YoY	0.111	0.381	**0.749**	**NO**	Visual assessment not consistent with KPSS
USD/EUR	Percent change - MoM	<0.01	0.047	**0.333**	**YES**	
USD/EUR	Percent change - QoQ	0.044	0.127	**0.372**	**YES**	
USD/EUR	Percent change - YoY	0.236	0.378	**0.69**	**NO**	Visual assessment not consistent with KPSS
Weighted Avg USD FX rate	First difference - MoM	<0.01	0.026	**0.196**	**YES**	
Weighted Avg USD FX rate	First difference - QoQ	0.18	0.083	**0.202**	**YES**	
Weighted Avg USD FX rate	First difference - YoY	0.761	0.406	**0.258**	**NO**	Visual assessment not consistent with KPSS
Weighted Avg USD FX rate	Percent change - MoM	0.012	0.025	**0.216**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
Weighted Avg USD FX rate	Percent change - QoQ	0.023	0.072	**0.235**	**YES**	
Weighted Avg USD FX rate	Percent change - YoY	0.548	0.406	**0.299**	**NO**	Visual assessment not consistent with KPSS
USD/GBP	First difference - MoM	0.046	<0.01	**0.663**	**YES**	
USD/GBP	First difference - QoQ	0.012	0.014	**0.593**	**YES**	
USD/GBP	First difference - YoY	0.084	0.367	**0.06**	**NO**	
USD/GBP	Percent change - MoM	0.034	<0.01	**0.729**	**YES**	
USD/GBP	Percent change - QoQ	<0.01	0.011	**0.698**	**YES**	
USD/GBP	Percent change - YoY	0.1	0.311	**0.074**	**NO**	
10Y US Swap	First difference - MoM	<0.01	<0.01	**0.617**	**YES**	
10Y US Swap	First difference - QoQ	0.015	<0.01	**0.635**	**YES**	
10Y US Swap	First difference - YoY	0.028	0.124	**0.074**	**NO**	
3M US Swap	First difference - MoM	0.121	<0.01	**0.047**	**NO**	
3M US Swap	First difference - QoQ	0.339	<0.01	**0.03**	**NO**	
3M US Swap	First difference - YoY	0.546	0.325	**<0.01**	**NO**	
5Y US Swap	First difference - MoM	0.016	<0.01	**0.212**	**YES**	
5Y US Swap	First difference - QoQ	0.028	<0.01	**0.221**	**YES**	
5Y US Swap	First difference - YoY	0.272	0.105	**<0.01**	**NO**	
US M1	First difference - MoM	0.144	<0.01	**0.028**	**NO**	
US M1	First difference - QoQ	0.13	0.011	**0.028**	**NO**	
US M1	First difference - YoY	0.572	0.209	**<0.01**	**NO**	
US M1	Percent change - MoM	0.024	<0.01	**0.337**	**YES**	
US M1	Percent change - QoQ	0.04	<0.01	**0.367**	**YES**	
US M1	Percent change - YoY	0.127	0.158	**0.311**	**NO**	Visual assessment not consistent with KPSS
1 Month EUR LIBOR	First difference - MoM	0.108	<0.01	**0.527**	**YES**	

Variable Name	Transform	ADF Pr > Tau	PP Pr > Tau	KPSS Prob	Include in models?	Justification
1 Month EUR LIBOR	First difference - QoQ	0.052	0.025	**0.5**	**YES**	
1 Month EUR LIBOR	First difference - YoY	0.227	0.514	**0.174**	**YES**	
3 Month EUR LIBOR	First difference - MoM	0.159	<0.01	**0.596**	**YES**	
3 Month EUR LIBOR	First difference - QoQ	0.059	0.039	**0.561**	**YES**	
3 Month EUR LIBOR	First difference - YoY	0.195	0.544	**0.228**	**YES**	
1 Month GBP LIBOR	First difference - MoM	0.18	<0.01	**0.216**	**YES**	
1 Month GBP LIBOR	First difference - QoQ	0.336	<0.01	**0.216**	**YES**	
1 Month GBP LIBOR	First difference - YoY	0.252	0.483	**0.034**	**NO**	
3 Month GBP LIBOR	First difference - MoM	0.161	<0.01	**0.203**	**YES**	
3 Month GBP LIBOR	First difference - QoQ	0.214	<0.01	**0.22**	**YES**	
3 Month GBP LIBOR	First difference - YoY	0.357	0.55	**0.042**	**NO**	
6 Month USD LIBOR	First difference - MoM	0.238	<0.01	**0.047**	**YES**	Visual assessment not consistent with KPSS
6 Month USD LIBOR	First difference - QoQ	0.082	<0.01	**0.031**	**YES**	Visual assessment not consistent with KPSS
6 Month USD LIBOR	First difference - YoY	0.297	0.29	**<0.01**	**NO**	
ECB Marginal Lending Rate	First difference - MoM	0.034	<0.01	**0.619**	**YES**	
ECB Marginal Lending Rate	First difference - QoQ	0.066	<0.01	**0.625**	**YES**	
BoE Clearing Base Rate	First difference - MoM	0.2	<0.01	**0.235**	**YES**	
BoE Clearing Base Rate	First difference - QoQ	0.351	0.052	**0.186**	**YES**	

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