**<BANK NAME>**

**<YYYY-QQ> <PORTFOLIO> PPNR**

**MODEL MONITORING REPORT**

**Version** <Version No.>

**Released on**: <Date>

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# EXECUTIVE SUMMARY

## Performance Status

**OVERALL RATING**: Caution (Illustrative)

<Model Owner Comments>

**SUMMARY OF RESULTS**:

Overall Results for each Section. Please refer to individual sections for more details

|  |  |
| --- | --- |
| ASSESSMENT | RATING |
| Data Quality | Pass |
| Linear Regression Robustness Testing | Pass |
| Forecast Accuracy | Pass |
| Back Testing | Fail |
| Sensitivity | Fail |

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

# MODEL BACKGROUND

## Model Use Details

The Debit Card Revenue model will be used for bank-wide stress tests and help with forecast capital requirements for the CCAR process. Specifically, it forecasts Debit Card fee revenue, one component of non- interest income in the forecasting of pre-provision net revenue (PPNR). As part of CCAR stress testing, PPNR is forecast under all scenarios (baseline, adverse, severely adverse, etc.) in order to assess the Bank Holding Company’s capital adequacy.

## Model Functional Form

Debit Card fee income revenue consists of three major components:

* Business Interchange revenue: Combination of macro-economic sensitive component (# of transaction per card) and recent history based assumptions (number of cards).
* Consumer Interchange revenue: Combination of macro-economic sensitive component (# of transaction per card) and recent history based assumptions (number of cards).
* Other Fee Revenue: Gift Card, Smart Access Fee, Prepaid Card Fee and any other fees.

Debit Card interchange revenue

=

1. Repeat and aggregate calculation for personal and business accounts

Empirical Assumption

Model

Judgmental Assumption

Debit other Fee revenue

= Debit interchange revenue \* Expected % share of interchange revenue

Expected % share

Debit interchange revenue

Gift Card and prepaid interchange revenue and fees

= Debit interchange revenue \* Expected % share of interchange revenue

Expected % share

Debit interchange revenue

Smart Access revenue

= Debit interchange revenue \* Expected % share of interchange revenue

Expected % share

Debit interchange revenue

Debit Card Model has 2 statistical models namely

* **Business transaction per card Amount**

|  |  |
| --- | --- |
| Business Transaction per card Growth Rate | Coefficients |
| Intercept | 0.012635123 |
| Personal Consumption Expenditure QoQ growth 1Q Lag | -0.150109679 |
| Seasonal Factor Q1 | -0.010823723 |
| Seasonal Factor Q2 | 0.001215004 |

* **Consumer Transaction Per card Amount**

|  |  |
| --- | --- |
| Consumer Transaction per card Growth Rate | Coefficients |
| Intercept | 0.010829653 |
| Personal Consumption Expenditure QoQ growth 2Q Lag | 0.049524516 |
| Seasonal Factor Q1 | 7.59393E-05 |
| Seasonal Factor Q2 | 0.002000566 |
| Seasonal Factor Q4 | 0.001729714 |

ASSUMPTIONS / NON MODEL INPUTS

**Model Assumptions and their Classifications**

|  |  |  |
| --- | --- | --- |
| Assumptions | Classification | Forecasted Since |
| Number of Business DDA Account | Judgmental | CCAR15 |
| Business Debit Card Penetration rate | Empirical | CCAR15 |
| Business Debit Card Activity Rate | Empirical | CCAR15 |
| Number of Consumer DDA Account | Judgmental | CCAR15 |
| Consumer Debit Card Penetration rate | Empirical | CCAR15 |
| Consumer Debit Card Activity rate | Empirical | CCAR15 |
| Interchange Fee rate | Judgmental | CCAR15 |
| Other Fee Revenue as % of Interchange Revenue | Empirical | CCAR15 |
| GC and prepaid Card Fee as % of interchange revenue | Empirical | CCAR15 |
| SmartAccess fee as % of interchange revenue | Empirical | CCAR15 |

# DATA QUALITY

**OBJECTIVE**: To check whether data quality for model is intact and similar to the development population

**OVERALL RATING**: Caution (Illustrative)

<Model Owner Comments>

**SUMMARY OF RESULTS**:

Dependent Variable Summary Statistics are provided in the section. Other Test with their rating is given in the below section

|  |  |
| --- | --- |
| TEST | RATING |
| Data Reconciliation | Pass |
| KS 2-Sample Distribution Test (Business) | Pass |
| KS 2-Sample Distribution Test (Consumer) | Fail |

<Model Owner Comments>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Data Reconciliation

**METHODOLOGY**: Focus Question: Is the model output value and modeling data consistent in the database?

When considering the health of the model in practice, high quality data is essential. The modeling equations used to transform the forecasted values of the business drivers into the line item forecast that the model outputs must hold continue to hold true for the data to be an accurate depiction of the business. Thus we must determine the certainty with which we know the model output actual. Often we will be able to determine the model output actual in several different ways. First, line of business (LOB) provides the Data Integration Group (DIG) a value from their data representing the business line item the model is predicting with its final output. Secondly, there is a General Ledger (GL), which also captures the line item. Both of these values should be very close as they all represent the same thing. Any deviations will lead us to realizing shortcomings in the model data and the model's representativeness in the larger ecosystem of the balance sheet.

**THRESHOLD**: Absolute Percentage Error (APE) <2% for recent 2 years data

**RATING**: Pass (Illustrative)

**RESULTS**:

|  |  |  |  |
| --- | --- | --- | --- |
| YYYY-Q | LOB | Essbase/GL | APE |
| 2017Q2 |  |  |  |
| 2017Q3 |  |  |  |
| 2017Q4 |  |  |  |
| 2018Q1 |  |  |  |
| 2018Q2 |  |  |  |
| 2018Q3 |  |  |  |
| 2018Q4 |  |  |  |
| 2019Q1 |  |  |  |

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**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Dependent Variable Distribution Test

**METHODOLOGY**: Focus Question: Is the new data consistent with distribution of development data?

The predictive power of linear regression models is based on the fundamental assumption that the dependent variable will continue to follow the same distribution in the forecasted time period as it did in the model development period. Hence, the out-of-sample period data should display approximately the same distributional characteristics as the development sample. Thus we can split the data into two periods, in-sample and out-of-sample, and test whether these two samples have the same distribution. We will do this using the 2-Sample Kolgomorov-Smirnoff (K-S) Test. The setup for the 2-Sample K-S test is based on the following hypotheses.

H0: The two samples are from the same distribution

H1: The two samples come from different distributions

Output is p-value of KS 2-sample Test

**THRESHOLD**: If p < 0.05 we will reject the hypothesis that the samples have the same distribution

**RATING**:

Business: Pass (Illustrative)

Consumer: Pass (Illustrative)

**RESULTS**:

|  |  |
| --- | --- |
| Segment | p-value |
| Business |  |
| Consumer |  |

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Dependent Variable Summary Statistics

**METHODOLOGY**: Focus Question: How much are the properties of the dependent variable changing in the out-of-sample period relative to the in-sample period?

The predictive power of linear regression models is based on the fundamental assumption that the dependent variable will continue to follow the same distribution in the forecasted time period as it did in the model development period. While we have the 2-Sample K-S test to determine whether these distributions are statistically different in the data available, it is often good to present the characteristics of the dependent variable and the development period and the out-of-sample period as it could provide relevant information to model performance. For example, this can provide a basis for determining and justifying compensating measures. The following summary statistics will be utilized and displayed for the full, in-sample, and out-of-sample series: mean, standard deviation, minimum, maximum, median.

**RESULTS**:

Business:-

|  |  |  |  |
| --- | --- | --- | --- |
| Statistics | In-Sample | Out-Sample | Full Sample |
| Mean |  |  |  |
| Median |  |  |  |
| Minimum |  |  |  |
| Maximum |  |  |  |
| Standard Deviation |  |  |  |

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Consumer:-

|  |  |  |  |
| --- | --- | --- | --- |
| Statistics | In-Sample | Out-Sample | Full Sample |
| Mean |  |  |  |
| Median |  |  |  |
| Minimum |  |  |  |
| Maximum |  |  |  |
| Standard Deviation |  |  |  |

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**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

# LINEAR REGRESSION ROBUSTNESS TESTING

**OBJECTIVE**: To check whether model qualifies all the assumptions of linear regression on Out-of-sample data

**OVERALL RATING**:

Business: Caution (Illustrative)

Consumer: Caution (Illustrative)

<Model Owner Comments>

**SUMMARY OF RESULTS**:

Test with their rating is given in the below section for Business Segment

|  |  |
| --- | --- |
| TEST | RATING |
| Outlier Testing | Pass |
| Dependent Variable Normality Test | Fail |
| Multicollinearity Test | Pass |
| Parameter Validity Test | Pass |

<Model Owner Comments>

Test with their rating is given in the below section for Consumer Segment

|  |  |
| --- | --- |
| TEST | RATING |
| Outlier Testing | Pass |
| Dependent Variable Normality Test | Fail |
| Multicollinearity Test | Pass |
| Parameter Validity Test | Pass |

<Model Owner Comments>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Outlier Testing

**METHODOLOGY**

**Focus Question**: Are there outliers in the current data series?

Outlier detection is an important aspect of model monitoring because outliers in the data collected since development may provide evidence of a shift in the data or an idiosyncratic event that has affected the business since the model was calibrated. To determine the possibility of an outlier in our data series we will examine the Cook's distance, which is designed to find highly influential points in a regression.

Let's assume our regression output, , can then be described by , .Let *j(i)* be the predicted value for the j-th observation when the regression is performed with observation *i* removed: Using this concept, we can define Cook's distance for observation *i* simply as the sum of all the changes in the regression model when it is removed from our sample.

*Di=∑nj=1 (j - j(i))2/ps2*

**THRESHOLD**: <Dynamic (Fetched from table>

**RATING**:

Business: Pass (Illustrative)

Consumer: Pass (Illustrative)

**RESULTS**:

Business:-

Top 5 Cook’d observations

|  |  |
| --- | --- |
| YYYY-Q | COOK’S Distance |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

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Business:-

Top 5 Cook’d observations

|  |  |
| --- | --- |
| YYYY-Q | COOK’S Distance |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

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**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Dependent Variable Normality Test

**METHODOLOGY**:

**Focus Question**: Is the dependent variable still normally distributed?

Normality of the dependent variable is a fundamental assumption of linear regression. Thus, to perform a re-estimation of the regression found in the model, it is necessary that the dependent variable continue to be normally distributed in the out-of-sample period. The Shapiro-Wilk test will be used to test the null hypothesis that the variable is normally distributed. Output is P-value for the Shapiro-Wilk Test

**THRESHOLD**: p-value>=0.05

If the p-value is <0.05, then we can reject the null hypothesis and conclude at a 95% confidence level that the dependent variable is not normally distributed

**RATING**:

Business: Fail (Illustrative)

Consumer: Fail (Illustrative)

**RESULTS**:

|  |  |
| --- | --- |
| Segment | p-value |
| Business |  |
| Consumer |  |

<add q-q plots from dashboard>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Multicollinearity Test

**METHODOLOGY**:

**Focus Question:** Would multicollinearity be present if the model was recalibrated using current data?

To determine the effects of multicollinearity in the hypothetical recalibration of the model, we will examine variance inflation factors (VIF).

The term *1/(1-R2j)* is the variance inflation factor. So the variance in our parameters is based on the RMSE of the model, the size of the sample, the variability of the associated variable, and the VIF. Thus outside of the aforementioned items, the VIF reflects all other factors that influence the uncertainty in the coefficient estimates. If we have orthogonality with all other regression variables, our VIF will equal 1. If the VIF is greater than one, it is not orthogonal and some multicollinearity is present.

**THRESHOLD**: VIF<10

**RATING**:

Business: Pass (Illustrative)

Consumer: Pass (Illustrative)

**RESULTS**:

Business:-

|  |  |  |
| --- | --- | --- |
| Independent Variable | VIF | Pass/Fail |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

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Consumer:-

|  |  |  |
| --- | --- | --- |
| Independent Variable | VIF | Pass/Fail |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

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**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Parameter Validity Test

**METHODOLOGY**:

Focus Question: If the model were recalibrated, would the new parameters be outside the 95% confidence interval for parameters of the old regression?

When considering the health of the model, we must consider the robustness of the form of the model. If the effects that the model is built on are changing constantly in the evolving environment, it will lose predictive power. One way to measure this is to create a new regression with all of the presently available data and then compare this equation to the one created at model development If the model form is sound, the parameter estimates should not change significantly with the additional out-of-sample added to the regression sample. During regression, a 95% confidence interval is produced on each parameter. Thus if we were to run a recalibration where the new parameter is no longer within this confidence interval, there is evidence that the model form is not robust for prediction in the current environment.

**THRESHOLD**: Recallibrated Parameter estimates should lie between L95 and U95 confidence interval

**RATING**:

Business: Pass (Illustrative)

Consumer: Pass (Illustrative)

**RESULTS**:

Business:-

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Independent Variable | Estimate (Development) | L95 | U95 | Estimate (Recalibrated) | Pass/Fail |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

<Paste the chart from Dashboard>

Consumer:-

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Independent Variable | Estimate (Development) | L95 | U95 | Estimate (Recalibrated) | Pass/Fail |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

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**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

# Forecast Accuracy

## Recent Performance

**OBJECTIVE**: To check whether model forecast is closer to the actual revenue

**THRESHOLD**:

|  |  |
| --- | --- |
| Threshold | RATING |
| MAPE <= 5% | Pass |
| 5% < MAPE <= 10% | Caution |
| MAPE > 10% | Fail |

**RATING**:

Pass (Illustrative)

**RESULTS**:

<Paste CCAR17 Graph from Dashboard>

<Paste MAPE for 9Q CCAR17 forecast>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

# BACK-TESTING

**OBJECTIVE**: To check how the model would have done ex-post. It checks out how the model would have played out using the historical data.

**OVERALL RATING**:

Caution (Illustrative)

<Model Owner Comments>

**SUMMARY OF RESULTS**:

Test with their rating is given in the below section for Business Segment

|  |  |
| --- | --- |
| TEST | RATING |
| Regression Back Testing (Business) | Pass |
| Regression Back Testing (Consumer) | Fail |
| Dynamic Back Testing | Pass |

<Model Owner Comments>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Regression Back Testing

**METHODOLOGY**

Focus Question: What is the model output impact of the regression error?

The purpose of a static backtest is to quantity the error in the model as it predicts on a one quarter ahead basis. Thus we will consider what the output would be for the model one quarter at time, and then aggregate the errors together to compile more meaningful statistics such as RMSE or MAPE.

To present lust the dollar value error and not the relative error would be a naive approach as we are interested in the model performance. The relative metric is the most useful for capturing this element. We calculate Ratio of OOS RMSE/IS RMSE

**THRESHOLD**:

|  |  |
| --- | --- |
| Threshold | RATING |
| Ratio <= 1 | Pass |
| 1 < Ratio <= 1.5 | Caution |
| Ratio > 1.5 | Fail |

**RATING**:

Business: Pass (Illustrative)

Consumer: Pass (Illustrative)

**RESULTS**:

Business:-

<Paste the chart from Dashboard>

<Paste the RMSE value from Dashboard>

Business:-

<Paste the chart from Dashboard>

<Paste the RMSE value from Dashboard>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Dynamic Backtesting

**METHODOLOGY**:

Focus Question: What is the 9Q model output impact of the error caused by using forecast values of regression outputs and empirical assumptions?"

The purpose of a dynamic backtest is to quantify the error in the model as it predicts over a nine quarter period of time. We choose to use eight quarters here because while results are typically reported in terms of the nine quarter forecast, using eight quarters reduces the impact of seasonality in the errors and will give more meaningful average error results. Thus we will consider what the output would be for the model for eight quarters. For the purposes of this backtest, let's consider the model defined by

f (D,EA,JA,S) = Model Output

Where D is the business driver that is being modeled by the macroeconomic regression used in the model and we denote D as the output of the regression, EA is the set of empirical LOB assumptions. JA is the set of Judgmental LOB assumptions that complete the model form and S Is the spot value for the dependent variable.

f(D’,EA’,JA,S) — f(D,EA,JA,S) = Error

(f(D’,EA’,JA,S) — f(D,EA,JA,S))/f(D,EA,JA,S)=Relative Error

Where ‘ values correspond to values derived using forecasting methodology.

**THRESHOLD**:

APE<5%

**RATING**:

Fail

**RESULTS**:

<add plots from dashboard>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

# SENSITIVITY ANALYSIS

**OBJECTIVE**: To check how sensitive the model is to its various inputs/components

**OVERALL RATING**:

Caution (Illustrative)

<Model Owner Comments>

**SUMMARY OF RESULTS**:

Test with their rating is given in the below section

|  |  |
| --- | --- |
| TEST | RATING |
| Spot Sensitivity (Business) | Pass |
| Spot Sensitivity (Consumer) | Fail |
| Component Sensitivity | Pass |

<Model Owner Comments>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Spot Sensitvity

**METHODOLOGY**

Focus Question: What is the model output sensitivity to the spot rate?

To build a model based on a stationary business driver, many models dependent variables are transformed based on differencing or a % growth rate. Thus the model is exposed to risk based on an idiosyncratic spot rate. The impact of the potentially unrepresentative spot value can be quantified by its impact on the metrics describing the nature of the 9-quarter forecast. In order to bound the potential impact of an idiosyncratic spot value, we will consider the volatility of the dependent variable. Our sensitivity analysis is based around the modeling equations function, let's define it by what it is a function of using a black box perspective of the model we can generalize as follows-

f(M,B,A,S,O) = Model Output

Where M is the macroeconomics variables used in the model, B the parameter vector, A is the set of LOB assumptions that complete the model form, S is the spot value for the dependent variable, and O is a catch-all for amy other input to the model such as a spot rate. Now we consider what the model output forecast for the last stress test would look like if the spot was moved one standard deviation away, denoted S+ for upward movement and S- for downward movement. We can then quantify the impact of a one standard deviation shift in the spot, had it happened for the most recent stress test as follows-

f(M,B,A,S,O)— f(M,B,A,S+,O)= Spot+(Standard Deviation)\*(Model Output Impact)

f(M,B,A,S,O)— f(M,B,A,S-,O)= Spot-(Standard Deviation)\*(Model Output Impact)

Output is 9Q forecast for most recent stress test with original spot and also at +(standard Deviation). Plots of the original forecast vs modified forecasts with 8Q of history included.

**THRESHOLD**:

|  |  |
| --- | --- |
| Threshold | RATING |
| MOI <= 20% | Pass |
| 20% < MOI <= 50% | Caution |
| MOI > 50% | Fail |

**RATING**:

Business: Pass (Illustrative)

Consumer: Pass (Illustrative)

**RESULTS**:

Business:-

<Paste the chart from Dashboard>

<Paste the MOI value from Dashboard>

Business:-

<Paste the chart from Dashboard>

<Paste the MOI value from Dashboard>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

## Component Sensitivity

**METHODOLOGY**:

Focus Question: What is the model output sensitivity in the severely adverse scenario to each component of the model?

In PPNR modeling, there are many aspects of a LOB that come together to make up the line item being forecasted. Not all of these are considered key business drivers, thus not all are forecasted using regression models. Assumptions are used to predict these non-key elements of the model and must be monitored for the impact they have on the model output as well. We define a model component to be either a business driver that is forecasted via regression or an assumption that is forecasted by LOB. Once these components are defined, it is prudent to monitor how sensitive the model output is to a particular component. This is particular interest in the severely adverse scenario

**THRESHOLD**:

APE<5%

**RATING**:

Fail

**RESULTS**:

<add plots from dashboard>

**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>