**<BANK NAME>**

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

**MODEL MONITORING REPORT**

**Version** <Version No.>

**Released on**: <Date>

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# EXECUTIVE SUMMARY

## Model Background

<To be filled later>

## Performance Status

<To be filled later>

## Model Monitoring – Conclusion and Limitations

<To be filled later>

# OUTCOME OF MODEL MONITORING

## Recent Performance

<To be filled later>

## Component Performance

<To be filled later>

## Segment Performance Report Card

<To be filled later>

# MODEL BACKGROUND

## Model Use Details

<To be filled later>

## Model Functional Form

<To be filled later>

## Model Components

<To be filled later>

# 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 |  |

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**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 |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

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Consumer:-

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

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**CONCLUSION AND RECOMMENDATIONS**:

<Model Owner Comments>

# BACK-TESTING

# SENSITIVITY ANALYSIS

# BENCHMARKING