# Financial Institutions Forecasting and Sensitivity Analysis for Decision Support Systems 

# Financial Institutions Forecasting and Sensitivity Analysis for Decision Support Systems 

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We hereby certify that this dissertation, submitted by Hevel Jean-Baptiste, satisfies the dissertation requirements for the degree of Doctor of Philosophy.

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#### Abstract

Financial institutions have to make sure that they have enough capital to operate in an adverse economic stress scenario. In PPNR (Pre-Provision Net Revenue Framework), there is provision for how businesses should be prepared for such a scenario. The CLASS (Capital and Loss Assessment under Stress Scenarios) model is a framework for stress testing. There are several issues (collinearity, variable selection, alternative model methodology) that can be resolved with the CLASS model.

In this research, we present a novel approach for PPNR econometrics analysis, or an alternative solution to the CLASS model. After replicating CLASS model, we focus on the systematic econometric study of seven key components of PPNR. We evaluate the parameter estimates of the econometric equations for some PPNR key components of United States financial companies and the 19 companies that were part of the initial CLASS and CCAR (Comprehensive Capital Analysis and Review 2012: Methodology and results for Stress Scenario) model projections. We report our findings based on our econometrics analysis study of the CLASS model. We present an improved alternative - the CLASS-X model - that can be used in a financial Decision Support System (DSS). CLASS-X is an eXtension of CLASS for the seven key PPNR components.


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## Chapter 1: Introduction

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Very often global financial institutions have used Capital Stress Testing as a supervisory and macroprudential tool (Acharya V. R., 2013). They also use a VaR (Value at Risk) model to measure risk of investments. The CLASS (Capital and Loss Assessment under Stress Scenarios) model was developed by Beverly Hirtle, Ann Kovner, James Vickery and Meru Bhanot at the Federal Reserve Bank of New York as a guideline for Annual Financial Capital Stress Testing. Central banks and bank supervisors have increasingly relied on capital stress testing and a supervisory and macroprudential tool. It is a way to anticipate the unknown. The recent financial crisis highlighted the importance of the amount and quality of bank capital in ensuring public confidence in individual financial institutions and in the financial system as a whole. That helps investors know where to invest their money safely. Stress tests have been used by central banks and supervisors to assess the resilience of individual banking companies to adverse macroeconomic and financial market conditions as a way of gauging additional capital needs at individual firms, and as means of assessing the overall capital adequacy of the banking system.

In the United States, the first formal bank supervisory stress tests - the Supervisory Capital Assessment Program (SCAP) - were performed during 2009, and stress tests have since been made permanent through the implementation of the stress test provisions of the Dodd-Frank Act (DoddFrank Act Stress Tests, or DFAST) and the introduction of the Comprehensive Capital Analysis and Review (CCAR) (Beverly Hirtle, February 2014). There are several foreign banks that develop similar solutions. European banking supervisors conducted stress tests of the largest European banking companies yearly as well ${ }^{1}$. We have seen a number of central banks construct systemwide stress test frameworks to assess the robustness of their banking systems to adverse macroeconomic environments ${ }^{2}$.

It is required by financial institutions that have assets that are greater than $\$ 50 \mathrm{Billion}$ to perform a Capital Plan early during the first quarter of every year to show how their companies are capitalized or plan to operate during several different macroeconomic and financial market

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scenarios (normal financial condition, adverse financial condition, and severe financial condition). The Capital and Loss Assessment under Stress Scenarios (CLASS) model is a framework for assessing the impact of macroeconomic conditions on the U.S. banking system. The CLASS model is a "top-down" model of the U.S. commercial banking industry that generates projections of commercial bank and bank holding company (BHC) income and capital under macroeconomic scenarios. These projections are based on regression models of components of bank income, expense and loan performance, combined with assumptions about provisioning, dividends, asset growth and other factors. These are the structure components of the CLASS model. While the CLASS model framework is very useful for financial institutions to perform their financial stress tests, it has areas that need to be improved. Several of these areas were outlined by the authors.

In this paper, we focus on Systematic Econometric study of PPNR (Pre-Provision Net Revenue) to present CLASS-X as an alternative solution to the CLASS model after replicating CLASS model.

### 1.1 The PPNR/CLASS Model - Problem

There are several areas that can be improved in the CLASS model for stress tests of PreProvision Net Revenue. The authors mentioned some of these future researches that can be done in the model. 1) Collinearity Issues: According to the authors they do not estimate the joint Matrix. They estimate each equation separately, rather than as a system. Exploring these confidence intervals and the correlation of the variables and equations represents an avenue for future work. 2) Cross-sectional Issues to Macroeconomic conditions need to be investigated. When we were testing the CLASS model, we discovered several indicators that explain the issues related to strong correlation within model variables.

First, we performed the replication of the seven key components of PPNR. Next, we evaluated the parameter estimates of the econometric equations of United States financial companies and the companies (19) ${ }^{3}$ that were part of CLASS (Comprehensive Capital Analysis and Review 2012: Methodology and results for Stress Scenario) model projections. We discovered strong correlation within the variables, and have found the quality of the model deteriorates when we subdivided the data (data for the 19 companies).

### 1.2 The Current Solution/Methods and Their Limitations

The current solution about the strong correlation in the CLASS model is to caution the users when using this model with a sub data set (i.e., some selected companies instead of all the companies together). Another phrase is to use that model at your own risk. While this model can be used with aggregate data (i.e., all the US financial companies) it has limitation with sub data sets. It is important to mention that the CLASS model uses the OLS Ordinary Least Square method, multilinear regression procedure.

### 1.3 Our Proposed Solutions

The solutions that we present to improve the PPNR/The CLASS model are novel. We present CLASS-X as an alternative solution (CLASS eXtended Solutions for Pre-Provision Net

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Revenue stress test). CLASS-X has three specifications. We can present them as CLASS-X1, X2 and X3. Each one of the specifications used different techniques, methods approach or procedure.

For CLASS-X Model 1, we propose a longitudinal procedure with the Ordinary Least Square (OLS) method. This model will be using the same method as class CLASS, but with a different procedure. Because of the nature of the data, a longitudinal procedure will fit the model better than the CLASS model. For CLASS-X Model 2, we propose a multilinear regression procedure with the Ordinary Least Square (OLS) method. This model will be using the same method and procedure as the CLASS model, but with a different variable selection. We reduced strong correlation by the following techniques - stepwise, forward selection, backward selection, and AIC model selection. We think AIC helps to identify the best model for the data. This model (CLASS-X2) will give a better result in forecasting than the CLASS model. For CLASS-X Model 3, we propose a VARMAX model with a Maximum Likelihood Estimate (MLE) method to fit the data. This model will be using a different method and different procedure than the CLASS model. Again, because of the nature of the data (time series), VARMAX ${ }^{4}$ Bayesian Vector Error Correction Model (BVECM) ${ }^{5}$ will fit the model better than the CLASS model. For the two CLASS-X (X1 and X2) models that use OLS methods, the MSE (Minimum Square Error) of these models are less than with the CLASS model. That means these models will forecast better. For the CLASS-X Model 3 that uses the MLE method, the AIC (Akaike Information Criterion) value is less than with the CLASS model. In comparing models with the same methodology, like OLS, a model with lower RMSE is better. We also use AIC as another indicator for model quality or accuracy.

CLASS-X is our research contribution. It is documented in the subsequent chapters, and Appendix C to G have the models' summary, or CLASS-X results. The more accurate a model is, the better the forecast and its sensitivity analysis are. For example, the PPNR is used extensively in capital planning (i.e., how much money a financial company needs to operate on a specific timeperiod (a year, nine quarters and so on)) with some other models (e.g., ALLL (Allowance for Loan and Lease Losses), PD (Probability of Default), LGD (Loss Given Default), EAD (Exposure at Default), and others). The ALLL formula is: ALLL= PD*LGD*EAD. If the result of any one of these models (PD*LGD*EAD) is incorrect, it will pose a risk to a company. If the value of ALLL is too high, the company will hold more cash in reserve than it should need to. Therefore, there is a loss of income. The company could generate some income for a large sum of cash that it holds for anticipation of loss. However, if the value for ALLL is too low, there is a risk that the company could have problems paying its obligation. In an adverse financial situation, that could cause damage to financial reputation or a buy-out by other companies. We witnessed several cases like that during the US financial crisis.

Banks have to make sure that they have enough capital to operate in an adverse economic stress scenario. In the PPNR (Pre-Provision Net Revenue) framework, there is provision for how businesses should be prepared for an adverse economic stress scenario.

We will use these data to perform our econometrics analysis for BHC financial institutions. We will perform the following tasks: a) replicate the regressions of the PPNR/CLASS model, b) segment the data for the 19 CCAR stress test companies and re-run the regressions for the 19

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companies, $c$ ) segment the data for an individual company, $d$ ) repeat steps $a$ and $b$ with SAS proc panel data, e) perform model analysis (i.e., variables selection, multi collinearity and other techniques) to study how to improve the CLASS model. We will perform these operations with our CLASS-X model as well.

### 1.3.1 Definition of Key PPNR Components

The seven key components are defined below. The generic definitions are normal definition of the terms and the technical definitions are related to FR 9-YC financial report (Reserve, Sample).

Net Interest Margin: a measure of the difference between the interest income generated by banks or other financial institutions and the amount of interest paid out to their lenders (for example, deposits), relative to the amount of their (interest-earning) assets. Net Interest Margin is a result of (Net interest Income/Interest Earning Assets).

Noninterest Nontrading Income Ratio: noninterest income is bank and creditor income derived primarily from fees, including deposit and transaction fees, insufficient funds (NSF) fees, annual fees, monthly account service charges, inactivity fees, check and deposit slip fees, and so on. Institutions charge fees that provide non-interest income as a way of generating revenue and ensuring liquidity (Kapadia S. M., 2012) in the event of increased default rates. Credit card issuers also charge penalty fees, including late fees and over-the-limit fees. While trading income is the income generated on trades, Noninterest Nontrading Income Ratio is derived from (Noninterest Income - Trading Income) divided by (Total Assets).

Return on Trading Assets: ROA gives an idea as to how efficient management is at using its assets to generate earnings. Calculated by dividing a company's annual earnings by its total assets, ROA is displayed as a percentage. Sometimes this is referred to as "return on investment."

Return on Net Assets (RONA) is a measure of financial performance calculated as net income divided by fixed assets and net working capital. RONA can be used to discern how well a company is performing versus others in its industry. It reveals if a company and its management are deploying assets in economically valuable ways or if the company is performing poorly versus its peers. Return on Trading Assets is the result of (Trading Income/Trading Assets).

Compensation Noninterest Expense Ratio: Noninterest expenses can include employee salaries and benefits, equipment and property leases, taxes, loan loss provisions, and professional service fees. Compensation Noninterest Expense Ratio is the result of (Compensation Expense divided by Total Assets).

Fixed Asset Noninterest Expense Ratio: assets that are purchased for long-term use and are not likely to be converted quickly into cash, such as land, buildings, and equipment. Fixed Asset Noninterest Expense Ratio is the result of (Fixed Asset Expense) divided by (Total Assets).

Other Noninterest Expense Ratio: Any other Noninterest Expense Ratio. Other Noninterest Expense Ratio is the result of ((Amortization Impair plus Goodwill Impair plus Other Noninterest Expense) divided by Total Assets).

Return on AFS Securities: Return on Available-for-Sale (AFS) portfolios. Return on AFS Securities is the result of (Realized Net Gains on AFS Securities divided by Total Available for Sale Securities).

The macroeconomic variables are as follows: Annualized Real GDP growth (\%), term spread (10 year minus 3 months pct. pt), 3 Month Treasury Yield (\%), quarterly change in 10 year Treasury yield (pct. pt), stock market returns (quarterly, \%), quarterly change in BBB bond spread (pct. pt), quarterly change in BBB spread if change is positive (else zero), quarterly change in BBB

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spread if change is positive x Risky AFS Ratio, annualized change in unemployment (\%), home price growth (\%, year-over-year), home price growth if growth is negative (else zero), commercial property price growth (\%, year-over-year), and Commercial Property Price Growth if negative (else zero).

The control variables are as follows: time trend annual and firm balance sheet controls. The details of the model specification can be seen in Appendix B of the document. The firm balance sheets are as follows: balance sheet ratios (as \% of Interest Ear Percentage Residential RE loans is the proportion of residential real estate loans. Percentage Commercial Loans is the proportion of commercial real estate loans. Percentage Commercial Industrial Loans is the proportion of C \& I loans. Percentage Credit Card Loans is the proportion of credit card loans. Percentage Trading Assets is the proportion of trading assets. Percentage Firm Assets are the firm assets as \% of industry.

We tested these variables with several different equations before we decided to use three different types of models (Multilinear, Panel Data and others) to fit our data. We used two sets of equations to fit our model. In the first set of equations, we used multilinear regression and in the second set of equations we used Data Panel regression and others. We will use the following tools for data management and model regressions: Excel, SAS tool, and STATA.

First, we will replicate the 22 equations of the CLASS model and perform an econometric analysis. Second, we look at ways (e.g., minimize strong correlation, improve variables selection and others) to improve the CLASS model. Third, we present our CLASS- $\mathrm{X}^{6}$ model which is an alternative solution to the CLASS model.

It is important to mention that specifications for the CLASS model can be seen in Figure 5, and specifications for the CLASS-X model can be seen in Table 17. Here are the equations (equations for the key components of PPNR) that we came up with to do our study.

Equations Set 1 - Here, we will estimate these 7 equations for the companies. The dependent variables of these equations are: 1) Net Interest Margin, 2) Noninterest, nontrade income ratio, 3) Return on Trading Assets, 4) Comp. Noninterest Expense Ratio, 5) Fixed Asset Noninterest Expense Ratio - Fixed Asset Noninterest Expense Ratio, 6) Other Noninterest Expense Ratio Other Noninterest Expense Ratio, and 7) Return on AFS Securities - Return on Asset for Sale Securities.

The model specification in Appendix B provides detailed information about all the elements (i.e., dependent and independent variables) of the model.

Below is the general form of the equation:

$$
P P N R-K C_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\beta_{2 c} B_{2 c t}+\beta_{3 c} T_{3 c t}+\varepsilon_{c t}
$$

Equation 1: CLASS-X Equation for Model 1 and Model 2
The PPNR key component equation is: Constant or Intercept + Vector of the Macroeconomic values + Vector of the Balance sheet values ratio + Vector of the Time Control +

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Error term. CLASS-X specification provides details about this model. The detailed specifications of this model can be seen in Appendix F of the document.

The regression forms of these equations are as follows. We have the same format for each one of the other six PPNR components.

$$
\begin{aligned}
& \text { 1. Net Interest } \text { Margin }_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+ \\
& \beta_{1 c} T_{1 c . . .}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}
\end{aligned}
$$

Equation 2: CLASS and CLASS-X Model Equation details ${ }^{7}$
The CLASS model has 22 Equations. We replicated the regressions to study how the model is made. As we study the regressions, we will make our CLASS-X model an alternative solution to the CLASS model.

Equations Set 2 - Next, we planned to estimate the CLASS and CLASS-X models of the above 7 equations by pooling data for all the 19 initial CCAR stress test companies. We will use SAS panel data regression for the consolidated data.

We will use some of the same input variables to perform regressions for the following PPNR components as well: Net Interest Margin, Noninterest Nontrading Income Ratio, Return on Trading Asset, Compensation Non-Interest Expense Ratio, Fixed Asset Noninterest Expense Ratio, Other Noninterest Expense Ratio, and Return on AFS Securities.

We will perform the following analysis (Scenarios Analysis, Sensitivity Analysis and other) and analyze the differences in key parameters of each component for macroeconomic variables and key PPNR components: Pre-Provision Revenue, (1) Net Interest Margin, (2) Nonet. Nontrade. Income Ratio, (3) Return on Trading Assets, (4) Compensation Noninterest Expense Ratio, (5) Fixed Asset Noninterest Expense Ratio, (6) Other Noninterest Expense Ratio, and (7) Return on AFS Securities. More details will be provided later about these key PPNR components.

This dissertation will produce a set of CLASS-X models (i,e., X is an alternative to the CLASS model), sets of equations ( $7 \times 19$ equations for PPNR key components and 7 equations for the consolidated data for the 19 companies. It is important to mention that we will use several Feeder models (PPNR component models) to feed the equations. We will test the projected net income and regulatory capital. In conclusion, we will document our findings and provide guidelines about how to use the PPNR\CLASS-X model. We will also provide future research that can be done in this field (econometrics analysis of PPNR).

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### 1.4 The General Form of the Regression Equation

The general form of the regression equation is given in the section above. Appendix D Figure 17 has the specifications of the CLASS-X model. We will replicate the PPNR components and securities specifications by following these steps:

Step 1 - We will use multilinear regression to estimate PPNR components. We will segment the data for the 19 CCAR companies and we will use multilinear regression to estimate PPNR components for the 19 companies. Step 2 - We will use the same data in Step 1 and use proc panel regression to repeat the same thing that we did in Step 1. Step 3 - We will segment the data and perform analysis in an individual company instead of all the companies together.

We will fit this model for all the companies and each one of the 19 companies that were in this research (the CLASS model or PPNR/CCAR). Below is the flow model diagram:


Figure 1: Model diagram for Eq. 1, eq. 2 and Eq. 3

### 1.5 Reason for this Research

The main reason we conducted this research was to find a way to improve the PPNR/CLASS model. We will integrate major components of PPNR in multiple types of regression to help us analyze the best way to perform econometrics analysis for key PPNR components and scenario analysis together. The seven key PPNR components are as follows: Net Interest Margin, Noninterest Nontrading Income Ratio, Trading Income Ratio, Compensation Expense Ratio, Fixed Asset Expense Ratio, All Other Expense Ratio, and Return on Asset for Sale. We will document our findings and suggest other research that can be done in this field (i.e., econometrics analysis of key PPNR components).

### 1.6 Problem Statement

There are several areas that need to be improved in the PPNR/CLASS model. Collinearity - Strong correlation within some of the variables is problematic when we subdivide the data.

Variables Selection - Some of the variables selected are not statistically significant.
Model Methodology - Other methodology could produce a more accurate model.
These three problems could create a defect for forecasting or prediction with the CLASS model. Making financial decisions on incorrect or less accurate data could have negative consequences. For our alternative solutions, we will consolidate data from the quarterly FR Y9C financial report created by financial institutions to analyze the underlined data. We will use the CLASS model data to replicate the seven key PPNR components. We will use data from the CLASS model to fit our CLASS-X specifications. We will perform regressions for PPNR key components with CLASS-X. We will also show the difference in the results between the CLASS and CLASS-X models for PPNR key components. Therefore, researchers, risk management practitioners, or others can see why they should use CLASS-X for scenarios analysis and sensitivity analysis in decisions Support.

### 1.7 Thesis - Abstract

The thesis of this work is summarized as follows: Alternative solutions to the PPNR/CLASS model key components with the CLASS-X model for more accuracy, better forecasting and sensitivity analysis for DSS (Decision Support Systems).

We will review the literature for the components of the PPNR\The CLASS model and CCAR. We will test each key component individually for each financial institution of the 19 BHC (Bank Holding Companies) that were part of the PPNR study. We will examine the adequacy of the model by performing an analysis of the residuals of the fitted model. The test includes the outliers test, influence statistics, leverage statistics, test for nonlinearity, and test for normality. We will document findings to help us prepare the data better for multivariate regression and others. The models that we will create are based on PPNR aggregate data (data received from the FR Y9C report). But, the method can be applied to different types of businesses, institutions, countries, or worldwide. We will perform several types of multivariate regressions and use the results of these regressions to document how this framework (CLASS or CLASS-X) can be used within financial institutions.

## Chapter 1: Introduction

### 1.8 Dissertation Roadmap

In this work, we use FR Y-9C ${ }^{8}$ data for our data analysis to try to understand the underlining data structure of the CLASS model. Next, we analyze PPNR/The CLASS model data. Finally, we use CLASS data to make sure that we compare the results of our study with the CLASS model in a more constructive way. Therefore, the data used in CLASS-X are the same data used by the CLASS model. The major contributions of this work include the following:

1. Understanding model risk management - model rationalization in the financial industry
2. Model risk management systems - back-end, middleware, front-end and analytics
3. Meta meta-analytics for risk forecast using big data meta-regression in the financial industry

This work is organized as follows:
Chapter 1: Introduction of our research study
Chapter 2: Review the works related to PPNR (Pre-Provision Net Revenue)
Chapter 3: Replicate the regressions of the CLASS model and segment the data
Chapter 4: Present CLASS-X specifications and forecast
Chapter 5: Perform model evaluation and methodology review
Chapter 6: Provide guidelines for model implementation
Chapter 7: Present conclusion, research findings summary and future researches
Appendix A: Provide high-level analysis of the CLASS model
Appendix B: Present replication of the CLASS model regression results with proc reg
Appendix C: Present the CLASS model regression results with proc panel
Appendix D: Present CLASS-X specifications (our main contribution)
Appendix E: Present forecast for the seven key PPNR components
Appendix F: Document sensitivity results for assets growth, provisioning and dividends
Appendix G: Document CLASS and CLASS-X regression results when we segment the data Appendix H: Analysis of several different types of models

[^5]
## Chapter 2: Literature Review

### 2.1 The Capital and Loss Assessment under Stress Scenarios (CLASS) Model

The CLASS model is a top-down capital stress testing framework that projects the effect of different macroeconomic scenarios on U.S. banking firms. The model is based on simple economic models estimated using public data and assumptions about loan loss provisioning, taxes, asset growth, and other factors. They use this framework to calculate a projected industry capital gap relative to a target ratio at different points in time under a common stressful macroeconomic scenario (Guerrieri, 2012). This estimated capital gap began rising four years before the financial crisis and peaked at the end of 2008. The gap has fallen and is now significantly below precrisis levels. In the cross-section, firms projected the most sensitive to macroeconomic conditions have higher capital ratios, consistent with a 'precautionary' view of bank capital (Beverly Hirtle, February 2014) (Berger A. a., 2013).

Rather than simply expensing credit losses when they are finally realized (e.g. when the property securing a delinquent mortgage is sold at a foreclosure auction), BHCs (Bank Holding Companies) and banks reserve against future probable credit losses on their loan portfolio, in accordance with supervisory rules and generally accepted accounting principles. Accounting for loan and lease losses involves three closely related measures. 1) Net charge-offs (NCOs): NCOs are the credit losses realized by the firm in the current accounting period, net of any recoveries (that is, net of any payments received on loans previously viewed as uncollectible); 2) allowance for loan (Office of the Comptroller of the Currency, 2006) and lease losses (ALLL): the reserve held by the firm against "estimated credit losses," that is, losses that have not yet occurred but are "likely to be realized" in the future. The ALLL is recorded as a contra-asset on the firm's balance sheet; 3) provision expense for loan and lease losses: the expense incurred in the current accounting period in order to set aside additional reserves against future loan losses.

Note that ALLL is a stock, while NCOs and provision expenses are flows. The ALLL represents the existing stock of reserves. The realization of NCOs reduces the ALLL over time, while provision expenses incurred by the firm increase the ALLL. Thus, there is a mathematical identity between the three accounting variables for a given firm.

$$
A L L L_{t}=A L L L_{t-1}+\text { Provision for loan and lease } \text { losses }_{t}-\text { net chargeoffs }{ }_{t}
$$

NCOs do not directly affect net income, but have an important indirect effect on the income statement, since (as seen in the above equation) higher NCOs must be offset by a higher provision expense in order to keep the level of loan loss reserves at a given target level (Beverly Hirtle, February 2014). Here, the Federal Reserve wanted to know the reserve held by financial institutions. This stress test (Bookstaber, 2013) was very critical.

### 2.2 Comprehensive Capital Analysis and Review 2012

The Federal Reserve expects large, complex BHCs to hold sufficient capital in order to maintain access to funding (Eisenbach, 2014), to continue to serve as credit intermediaries, to meet their obligations to creditors and counterparties, and to continue operations, even under adverse economic conditions. The Comprehensive Capital Analysis and Review (CCAR) is a supervisory assessment by the Federal Reserve of the capital planning processes and capital adequacy of these large, complex bank holding companies (BHCs). The CCAR is the Federal Reserve's central mechanism for developing supervisory assessments of capital (Acharya V. R., 2012) adequacy at these firms.

Nineteen BHCs were required to participate in this year's CCAR (CCAR 2012). The BHCs that participated are Ally Financial Inc., American Express Company, Bank of America Corporation, The Bank of New York Mellon Corporation, BB\&T Corporation, Capital One Financial Corporation, Citigroup Inc., Fifth Third Bancorp, The Goldman Sachs Group, Inc., JPMorgan Chase \& Co., Keycorp, MetLife, Inc., Morgan Stanley, The PNC Financial Services Group, Inc., Regions Financial Corporation, State Street Corporation, SunTrust Banks, Inc., U.S. Bancorp, and Wells Fargo \& Company.

In early January, these BHCs submitted comprehensive capital plans to the Federal Reserve describing their strategies for managing their capital over a nine-quarter planning horizon. The purpose of requiring BHCs to develop and maintain these capital plans is to ensure that the institutions have robust, forward-looking capital planning processes that account for their unique risks, and that the institutions have sufficient capital to continue operations throughout times of economic and financial market stress. As part of its assessment of the plans, the Federal Reserve projected losses, revenues, expenses, and capital ratios (Berger A. R., 2008) for each of the 19 BHCs under a severely adverse macroeconomic scenario specified by the Federal Reserve. This paper describes this scenario, and provides an overview of the analytical framework and empirical methods used by the Federal Reserve to generate these stress scenario projections. (RESERVE, March 12, 2012).

Projecting Net Income and Regulatory Capital


This formula provides a summary of projected net income within CCAR framework.

### 2.2.1 Comprehensive Capital Analysis and Review 2012

These projections represent hypothetical estimates that involve an economic outcome that is more adverse than expected. These estimates are not forecasts of expected losses, revenues, or net income before taxes or capital ratios. The two minimum capital ratios presented below are for the period Q4 2011 through Q4 2013 and do not necessarily occur in the same quarter.

The Federal Reserve made changes to the following table on March 16, 2012, to correct computation errors for some loss rates and levels. The corrections do not impact other figures, including capital ratios.

|  | Projected Capital Ratios through Q4 2013 <br> Under the Hypothetical Supervisory Stress Scenario |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |


| Projected Losses, Revenue and Net Income before Taxes for Q4 2011 through Q4 2013 Under the Hypothetical Supervisory Stress Scenario |  |  |
| :---: | :---: | :---: |
|  | $\begin{aligned} & \text { Billions of } \\ & \text { Dollars } \\ & \hline \end{aligned}$ | Percent of Average Assets |
| Pre-Provision Net Revenue (2) | 294 | 2.5 |
| Other Revenue (3) less | 2 |  |
| Provisions | 324 |  |
| Realized Losses/Gains on Securities (AFS/HTM) | 31 |  |
| Trading and Counterparty Losses (4) | 116 |  |
| Other Losses/Gains [5) equals | 45 |  |
| Net Income before Taxes | -222 | -1.9 |

Projected Loan Losses by Type of Loans for Q4 2011 through Q4 2013 Under the Hypothetical Supervisory Stress Scenario

|  | Billions of <br> Dollars | Portfolio Loss <br> Rates (\%) |
| :--- | :---: | :---: |
| Loan Losses [6) |  |  |
| First Lien Mortgages, Domestic | 341 | 8.1 |
| Junior Liens and HELOCs, Domestic | 61 | 7.3 |
| Commercial and Industrial | 56 | 13.2 |
| Commercial Real Estate, Domestic | 67 | 8.2 |
| Credit Cards | 24 | 5.2 |
| Other Consumer | 92 | 17.2 |
| Other Loans | 26 | 5.9 |

### 2.2.2 Comprehensive Capital Analysis and Review 2012

Estimates of Minimum Tier 1 Common Ratios, Q4 2011 through Q4 2013.
The minimum stressed ratios (\%) are the lowest quarterly ratios from Q4 2011 to Q4 2013 in the supervisory stress scenario. The left column shows minimum ratios assuming no capital actions after Q1 2012. The right column shows minimum ratios with all proposed capital actions through Q4 2013. Minimum ratios may occur in different quarters across the BHCs, and in different quarters for each BHC across the two columns.

| Bank Holding Company | Minimum stressed ratios <br> assuming no capital actions <br> after Q1 2012 (1) | Minimum stressed ratios <br> with all proposed capital <br> actions through Q4 2013 |
| :--- | :---: | :---: |
|  | 2.5 |  |
| Ally Financial Inc. | 12.4 | 2.5 |
| American Express Company | 5.7 | 10.8 |
| Bank of America Corporation | 13.3 | 5.9 |
| The Bank of New York Mellon Corporation | 7.3 | 13.0 |
| BB\&T Corporation | 7.2 | 6.4 |
| Capital One Financial Corporation | 5.9 | 7.8 |
| Citigroup Inc. | 7.7 | 4.9 |
| Fifth Third Bancorp | 5.8 | 6.3 |
| The Goldman Sachs Group, Inc. | 6.3 | 5.7 |
| JPMorgan Chase \& Co. | 6.3 | 5.4 |
| Keycorp | 5.4 | 5.3 |
| MetLife, Inc. | 5.4 | 5.1 |
| Morgan Stanley | 6.6 | 5.4 |
| The PNC Financial Services Group, Inc. | 5.7 | 5.9 |
| Regions Financial Corporation | 15.1 | 6.6 |
| State Street Corporation | 5.5 | 12.5 |
| SunTrust Banks, Inc. | 7.7 | 4.8 |
| U.S. Bancorp | 6.6 | 5.4 |
| Wells Fargo \& Company | 6.0 |  |

Assumes planned capital actions through Q1 2012, but no material capital issuances March 31, 2012.

Notes: Capital actions include common dividends (Acharya V. I., 2009), common share repurchases, and common share issuance.
Source: Federal Reserve estimates in the Supervisory Stress scenario (RESERVE, March 12, 2012).

Below are some related works to the VaR (Value at Risk) model.

### 2.3 Value at Risk - The New Benchmark for Managing Financial Risk

The author summarizes the definition of Value at Risk and briefly provides a history of Value at Risk. Value at Risk traces its roots to the infamous financial disasters of the early 1990s. Further, he describes VaR as a method of assessing risk that uses standard statistical techniques used routinely in other fields. Loosely, VaR summarizes the worst loss over a target horizon that will not exceed with a given level of confidence. Based on firm scientific foundations, VaR provides users with a summary measure of Market Risk (Jorion, 2007) .

### 2.4 Market Risk Analysis - Value at Risk

Here the author presents a Value at Risk as a loss that, we are fairly sure, will not be exceeded if the current portfolio is held over some period of time. We shall assume that VaR is measured at the portfolio level, without considering the mapping of portfolios to their risk factors. Later, the
author outlines the different elements of the Value at Risk model and provides great details of Value at Risk (Alexander, 2008).

### 2.5 A VaR Approach to Measuring Equity Trading Risk Exposure in Emerging Stock Markets

Here the author presents his research as an attempt to fill a gap in the equity trading risk management literature, particularly from the perspective of emerging and illiquid financial markets, such as in the context of the Moroccan stock market. This paper provides real-world risk management techniques and strategies that can be applied to equity trading/investment portfolios in emerging markets. In this work, we divulge a proactive approach for the measurement/management of risk exposure for financial trading portfolios that contain illiquid equity securities. This approach is based on the renowned concept of Value at Risk (VaR) along with the creation of a software tool utilizing a matrix-algebra technique. The recommended, feasible analytical/quantitative techniques and procedures can be utilized in almost all-emerging economies, if they are tailored to match-up with each market's initial level of complexity. In order to exemplify the appropriate use of VaR and stress-testing techniques, real-world examples and attainable reports of risk management are presented for the Casablanca Stock Exchange (CSE). To this end, some case studies are accomplished with the intent of creating a realistic framework of equity trading risk measurement and control reports (Janabi, 2007).

### 2.6 Regulatory Evaluation of Value at Risk Models

The author presents a great summary of regulatory evaluation of Value at Risk models. Beginning in 1998, U.S. commercial banks may determine their regulatory capital requirements for financial market risk exposure using VaR models; i.e., models of the time-varying distributions of portfolio returns. Currently, regulators have three hypothesis-testing methods available for evaluating the accuracy of VaR models: the binomial method, the interval forecast method, and the distribution forecast method. These methods use hypothesis tests to examine whether the VaR forecasts in question exhibit properties characteristic of accurate VaR forecasts. However, given the low power often exhibited by these tests, these methods may often misclassify forecasts from inaccurate models as accurate. A new evaluation method that uses loss functions based on probability forecasts, is proposed. Simulation results indicate that this method is capable of differentiating between accurate and inaccurate forecasts from alternative VaR models (Lopez, 1998/1999).

### 2.7 Variance Reduction Technique for Calculating Value at Risk in Fixed Income Portfolios

Financial institutions and regulators increasingly use Value at Risk (VaR) as a standard measure for market risk. Thus, a growing amount of innovative VaR methodologies are being developed by researchers in order to improve the performance of traditional techniques. A variance-covariance approach for fixed income portfolios requires an estimate of the variancecovariance matrix of the interest rates that determine its value. We propose an innovative methodology to simplify the calculation of this matrix. Specifically, we assume the underlying interest rate parameterization found in the model proposed by Nelson and Siegel (1987) to estimate the yield curve. Here, the author shows the VaR calculating methodology provides a more accurate measure of risk compared to other parametric methods (Benito, June 2010).

### 2.8 The Use of Value at Risk by Institutional Risk by Institutional Investors

Here, the author outlines that Value at Risk (VaR) models have been accepted by banking regulators as tools for setting capital requirements for market risk exposure. Three statistical methodologies for evaluating the accuracy of such models have been examined, specifically, evaluation based on the binomial distribution, interval forecast evaluation as proposed by Christoffersen (1995), and distribution forecast evaluation as proposed by Crnkovic and Drachman (1995). These methodologies test whether the VaR forecasts in question exhibit properties characteristic of accurate VaR forecasts. However, the statistical tests used often have low power against alternative models. A new evaluation methodology, based on the probability forecasting framework discussed by Lopez (1995), is proposed. This methodology gauges the accuracy of VaR models using forecast evaluation techniques. It is argued that this methodology provides users, such as regulatory agencies, with greater flexibility to tailor the evaluations to their particular interests by defining the appropriate loss function. Simulation results indicate that this methodology is clearly capable of differentiating among accurate and alternative VaR models (Simons, December 2000).

### 2.9 An Overview of Value at Risk

Here, the author presents a review of Value at Risk, or VaR, and describes some of the basic issues involved in measuring the market risk of a financial firm's book and the list of positions in various instruments that expose the firm to financial risk. While there are many sources of financial risk, they concentrate here on market risk, meaning the risk of unexpected changes in prices or rates. Credit risk should be viewed as one component of market risk. They nevertheless focus narrowly here on the market risk associated with changes in the prices or rates of underlying traded instruments over short-time horizons. This article is designed to give a fairly broad and accessible overview of VaR (Pan, January 21, 1997).

### 2.10 Scenarios Analysis and Sensitivity Analysis

In this paper, the author outlines the difference between scenarios analysis and sensitivity analysis. Scenario analysis is a what-if analysis in which a model's output is calculated for a number of scenarios. It is more complex than sensitivity analysis because, in scenario analysis, all inputs are changed towards one extreme, while in sensitivity analysis only one input is changed while keeping the other constant.

Sensitivity analysis is an analysis that finds out how sensitive an output is to any change in an input while keeping other inputs constant (Jan, p. Site Information).

### 2.11 Different Modeling Techniques

We reviewed the literature on the different models that we can use to model the data for PPNR. We looked at linear and non-linear models. In SAS, we looked at - panel data models, proc regression, a semiparametric model, rank-based statistical models, SM-VAR, or Markov Swishing Variance Autoregression, and others, to make sure that we have a better accuracy model for our research.

Matthieu presents several methods for non-linear regressions. First, he presents the MonteCarlo experiment to explore the finite-sample properties of estimates of vector autoregressive models subject to switches in regimes governed by a hidden Markov chain. Second, he presents the use of Bayesian impulse responses for a Markov-switching vector autoregression model. Third, he proposed a method of testing restrictions for ganger non-causality in mean, variance, and distribution in the framework of Markov-switching VAR models. The analysis may be applied to
financial and macroeconomic time series with changes of parameter values over time and heteroscedasticity (Droumaguet, December 2012).

Many longitudinal studies are designed to investigate changes over time in a characteristic which is measured repeatedly for each study participant. Models for the analysis of longitudinal data must recognize the relationship between serial observations on the same unit. Multivariate models with a general covariance structure are often difficult to apply to highly unbalanced data, whereas two-stage random-effects models can be used easily. In two-stage models, the probability distributions for the response vectors of different individuals belong to a single family, but some random-effects parameters vary across individuals, with a distribution specified at the second stage. A general family of models is discussed, which includes both, growth models and repeatedmeasures models, as special cases. A unified approach to fitting these models, based on a combination of empirical Bayes and maximum likelihood estimation of model parameters and using the EM algorithm, is discussed (Ware, Dec., 1982).

This paper provides a review of linear panel data models with slope heterogeneity, introduces various types of random coefficients models, and suggests a common framework for dealing with them. It considers the fundamental issues of statistical inference of a random coefficients formulation using both the sampling and Bayesian approaches. The paper also provides a review of heterogeneous dynamic panels, testing for homogeneity under weak exogeneity, simultaneous equation random coefficient models, and the more recent developments in the area of cross-sectional dependence in panel data models (Pesaram, August 2004) .

A critical question that banking supervisors are trying to answer is what is the amount of capital or liquidity resources required by an institution in order to support the risks taken in the course of business. The financial crises of the last several years have revealed that traditional approaches, such as inadequate regulatory capital ratios, give rise to supervisory stress testing as a primary tool. Critical input into this process are macroeconomic scenarios that are provided by the prudential supervisors to institutions for exercises such as the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) program. Additionally, supervisors are requiring that banks develop their own macroeconomic scenarios. A common approach is to combine management judgment with a statistical model, such as a Vector Autoregression (VAR), to exploit the dependency structure between both, macroeconomic drivers, as well between modeling segments. However, it is well-known that linear models such as VAR are unable to explain the phenomenon of fat-tailed distributions that deviate from normality, an empirical fact that has been well documented in the empirical finance literature. We propose a challenger approach, widely used in the academic literature, but not commonly employed in practice - the Markov Switching VAR (MS-VAR) model. We empirically test these models using Federal Reserve Y-9 filing and macroeconomic data gathered and released by the regulators for CCAR purposes, respectively. We find the MS-VAR model to be more conservative than the VAR model, and also exhibits greater accuracy in model testing, as the latter model can better capture extreme events observed in history (Michael Jacobs, November 1, 2016).

In statistics solutions sites, we have found several assumptions about linear regression, multiple linear regression, and other statistical advice. This advice is helpful for multicollinearity studies and model validations (StatisticsSolutions, p. site).

Here, the author outlines that vector autoregressions with Markov-switching parameters (MS-VARs) fit the data better than their constant-parameter predecessors do. He also mentioned that Bayesian inference for MS-VARs with existing algorithms remains challenging. He tried to show that Sequential Monte Carlo (SMC) estimators accurately estimate Bayesian MS-VAR
posteriors. Relative to multi-step, model-specific MCMC routines, SMC has the advantages of generality, parallelizability, and freedom from reliance on particular analytical relationships between prior and likelihood. He also showed how he used SMC's flexibility to demonstrate that the choice of prior drives the key empirical finding of Sims, Waggoner (Bognanni, 2014).

The researchers outlined that modeling was becoming popular nowadays, and there are several analyses used in research for modeling, one of them known as applied multiple linear regressions (MLR). They also mentioned that to obtain a bootstrap, robust and fuzzy multiple linear regression, an experienced researcher should be aware of the correct method of statistical analysis in order to get a better, improved result. The main idea of bootstrapping is to approximate the entire sampling distribution of some estimator. To achieve this, we resample from our original sample. The author concentrated on combining and modeling using bootstrapping, robust, and fuzzy regression methodology. They also presented an algorithm for combining method given by SAS language (Wan Muhamad Amir W Ahmad, November 2016).

Here, the author presented how we can use Proc MIXED to fit many common types of multilevel models. The author presented a general strategy for working with multilevel data in SAS; for substituting in to arrive at a single equation; and by writing a single equation that specifies the multiple sources of variation creating data sets at several levels. He also mentioned that multilevel models can be expressed in at least three different ways by writing separate equations at multiple levels (Singer, Winter, 1998).

In this paper, the author provides a brief, theoretical overview of methods available to analyze time series cross-sectional (panel) data provided. An empirical example is given to compare different techniques, and demonstrate the PANEL procedure's capabilities (Erdman, 2007). Dynamic panel methods are discussed and compared to other techniques. Finally, the PANEL procedure is compared to other SAS procedures, such as the MIXED procedure and the TSCSREG procedure.

We looked at the TSCSREG (Time Series Cross Section Regression) procedure, which analyzes a class of linear econometric models that commonly arise when time series and crosssectional data are combined. The TSCSREG procedure deals with panel data sets that consist of time series observations on each of several cross-sectional units.

The performance of any estimation procedure for the model regression parameters depends on the statistical characteristics of the error components in the model. The TSCSREG procedure estimates the regression parameters in the preceding model under several common error structures. The error structures and the corresponding methods the TSCSREG procedure uses to analyze them are one and two-way fixed and random effects models. If the specification is dependent only on the cross section to which the observation belongs, such a model is referred to as a model with one-way effects. A specification that depends on both the cross section and the time series to which the observation belongs is called a model with two-way effects. Apart from the possible one-way or two-way nature of the effect, the other dimension of difference between the possible specifications is the nature of the cross sectional or time series effect. The models are referred to as fixed effects models if the effects are nonrandom, and as random effects models otherwise.

The Parks method is used to estimate this model (first-order autoregressive model with contemporaneous correlation). This model assumes a first order autoregressive error structure with contemporaneous correlation between cross sections. The covariance matrix is estimated by a twostage procedure leading to the estimation of model regression parameters by GLS. The Da Silva method is used to estimate this model (mixed variance-component moving average error process).

The Da Silva method estimates the regression parameters using a two-step GLS-type estimator (SAS The TSCSREG Procedure - Chapter 20, 1999, p. SAS).

Here, the author introduced specifying multilevel models using PROC MIXED. After a brief introduction to the field of multilevel modeling, users were provided with concrete examples of how PROC MIXED can be used to estimate (a) two-level organizational models, (b) two-level growth models, and (c) three-level organizational models. Both, random intercept and random intercept and slope models, were illustrated. The author also showed examples using different realworld data sources, including the publicly available Early Childhood Longitudinal StudyKindergarten cohort data. For each example, different research questions were examined through both, narrative explanations and examples of the PROC MIXED code, and corresponding output (Bethany A. Bell, 2013).

The author presented how mediation modeling is quite prevalent in a number of disciplines to answer questions about how or why one variable exerts its influence on another variable. He mentioned that mediation can be assessed in the context of several types of study designs, and the use of cross sectional data and a single-mediator model tend to be the most commonly reported features in empirical tests of mediation. There are several limitations associated with assessing mediation with cross-sectional data, perhaps the most significant being that mediated effect estimates are biased in the case of true longitudinal mediation. For this, and several other reasons, there has been a greater emphasis on the development of longitudinal mediation models.

Before exploring models for assessing longitudinal mediation, it may be helpful to summarize issues with respect to basic mediation modeling. Numerous articles estimating and testing mediated effects, especially in the psychology literature, have been published in a variety of substantive areas, most typically employing a cross-sectional design with $\mathrm{X}, \mathrm{M}$, and Y measured simultaneously, usually as continuous variables. In addition to these content applications, a number of methodological and statistical issues with respect to mediation have been explored. Many of these issues have been investigated with Monte Carlo simulation methods (Paxton, Curran, Bollen, Kirby, \& Chen, 2001; Fan \& Fan, 2005; Bandalos, 2006) while others have been investigated analytically (e.g., Maxwell \& Cole, 2007), (Bentley, 2011).

Here, the author presented MSVAR (Markov-SwitchingVector Autoregressions) as a package designed for the econometric modelling of univariate and multiple time series subject to shifts in regime. It provides the statistical tools for the maximum likelihood estimation (EM algorithm) and model evaluation of Markov-Switching Vector Autoregressions as discussed in Krolzig (1997). A variety of model specifications regarding the number of regimes, regimedependence versus invariance of parameters, etc. provides the necessary flexibility for empirical research, and will be of use to econometricians intending to construct and use models of dynamic, non-linear, non-stationary, or cointegrated systems. While this model can be used to model PPNR key components more accurately than the CLASS model, according to a researcher, we have not found substantial evidence to support that claim (KROLZIG, December 15, 1998).

### 2.12 PPNR Preliminary Works

We have gathered data from several sources (FRED for Macroeconomics and Federal Reserve for PPNR Pre-Provision Net Revenue). The Federal Reserve data come quarterly while the FRED Macroeconomics data come monthly. The details work can be seen in Appendix A of this document.

The following are the steps that we took to consolidate the data:


Figure 1: Data Consolidation steps

### 2.12.1 List of Things We Looked at for the Estimated Equations

We looked at several statistics indicators to assess the data and the model. At a high level, we looked at parameter estimates tables; analysis of variance tables (including R-square and adjusted R-square); standard error of the coefficients, p-values; tables showing the number of observations and the dependent variable; scatter plots of the dependent (response) variable vs. each independent variable; line plots of the dependent variable and each independent variable; scatter plots of predicted vs. actual; and regression results (actual, predicted, residuals, studentized residuals, Rstudent, press, Cooks D, standard error of residual, hat diagonal, DFBETAS, and confidence intervals for mean and individual predictions). For plots, we looked at: scatter plot of predicted values vs. residuals; scatter plot of Rstudent by predicted values; Cooks D plot; plot of press residuals; DFFITS plot; DFBETAS plot; Q-Q plot of residuals; histogram of residuals; and outlier and leverage diagnostics plot. For collinearity, we looked at elements for collinearity diagnostics (eigenvalues, condition index, proportion of variance of each coefficient associated with eigenvalues, partial regression residual plot, heteroscedasticity, and auto correlation of errors). We also assessed the impact of each independent variable on the dependent variable. We
looked at how a unit changed in one explanatory variable and estimated the effect on the explanatory variable.

We pulled the data for the 19 companies from the whole dataset and performed a regression to get the results for the sub-dataset.

| $\#$ | Company | Data Use in <br> document |
| :--- | :--- | :--- |
| 1 | Ally Financial Inc. | Y |
| 2 | American Express Company | Y |
| 3 | Bank of America Corporation | Y |
| 4 | The Bank of New York Mellon Corporation | Y |
| 5 | BB\&T Corporation | Y |
| 6 | Capital One Financial Corporation | Y |
| 7 | Citigroup Inc. | Y |
| 8 | Fifth Third Bancorp | Y |
| 9 | The Goldman Sachs Group, Inc. | Y |
| 10 | JPMorgan Chase \& Co. | Y |
| 11 | Keycorp | Y |
| 12 | MetLife, Inc. | Y |
| 13 | Morgan Stanley | Y |
| 14 | The PNC Financial Services Group, Inc. | Y |
| 15 | Regions Financial Corporation | Y |
| 16 | State Street Corporation | Y |
| 17 | SunTrust Banks, Inc. | Y |
| 18 | U.S. Bancorp | Y |
| 19 | Wells Fargo \& Company | Y |
|  | Data Summary of the 19 Banks | Y |

Table 1: The list of the 19 companies that were part of the initial PPNR/CLASS model.
We analyzed the data that we consolidated and the data that was consolidated by the CLASS model team from the Federal Reserve, and decided to use the Federal Reserve's consolidated data. These data will help us replicate the regressions in the CLASS model and come up with the specification for CLASS-X. It will also help us compare the CLASS model and CLASS-X model better because they use similar dataset.

## Chapter 3: The CLASS Model Replication and Data Segmentation

### 3.1 Purpose of the CLASS Model Replication and Data Segmentation

Before we started working on the presentation of our alternative econometrics analysis for PPNR key components, we thought it would be reasonable to replicate the regressions of the PPNR/CLASS model. We looked at how we could replicate the PPNR components by looking at how we could replicate PPNR specification. Appendix B has the results of that specification. It is the blue print for the CLASS model.

The purpose of this exercise was to try to understand the equations in the PPNR specification and the results of the regressions. That could therefore help us anticipate any impacts that could occur in any of the seven key components of PPNR of a company. We could also anticipate impacts the independent variables can have in a financial system of a region, a country, or worldwide. With that knowledge, we could anticipate the actions that needed to be taken to mitigate any risks and prevent financial disasters more accurately.

We simplified our regressions as follows and focused on the seven key PPNR components. These are the dependent variables: (1) Net Interest Margin, 2) NonInterest Nontrading Income Ratio, 3) Return on Trading Asset, 4) Compensation Non-Interest Expense Ratio, 5) Fixed Asset NonInt Expense Ratio, 6) Other NonInt Expense Ratio, and 7) Return on AFS Assets for Sale Securities). The independent variables are the macroeconomic variables, the balances sheet ratios (as \% of interest earning assets), and the time series controls. The specification of the CLASS model can be seen in Figure 5 of this document.

### 3.2 Definition of Key Components of PPNR Variables

The following are the technical definitions of key components of PPNR variables:
Net Interest Margin $=($ Net interest Income/Interest Earning Assets)
Noninterest Nontrading Income Ratio $=(($ NonInterest Income - Trading Income $) /$ Total assets $)$
Return on Trading Assets $=$ (Trading Income/Trading Assets)
Compensation Noninterest Expense Ratio $=($ Compensation Expense/Total Assets)
Fixed Asset Noninterest Expense Ratio $=($ Fixed Asset Expense/Total Assets)
Other Noninterest Expense Ratio $=(($ Amortization Impair. + Goodwill Impair + Other Noninterest Expense)/Total assets)
Return on AFS Securities $=($ Realized Net Gains on AFS Securities/Total Available for Sale Securities)

### 3.2.1 Net Interest Margin

Net Interest Margin (NIM) is a measure of the difference between the interest income generated by banks or other financial institutions and the amount of interest paid out to their lenders (for example, deposits), relative to the amount of their (interest-earning) assets.

### 3.2.2 Noninterest Nontrading Income Ratio

Noninterest income is bank and creditor income derived primarily from fees, including deposit and transaction fees, insufficient funds (NSF) fees, annual fees, monthly account service charges, inactivity fees, check and deposit slip fees, and so on. Institutions charge fees that provide non-interest income as a way of generating revenue and ensuring liquidity in the event of increased default rates. Credit card issuers also charge penalty fees, including late fees and over-the-limit fees, while trading income is the income generated on trades.

### 3.2.3 Return on Trading Assets

ROA gives an idea as to how efficient management is at using its assets to generate earnings. Calculated by dividing a company's annual earnings by its total assets, ROA is displayed as a percentage. Sometimes this is referred to as "return on investment."
Return on Net Assets (RONA) is a measure of financial performance calculated as net income divided by fixed assets and net working capital. RONA can be used to discern how well a company is performing versus others in its industry. It reveals if a company and its management are deploying assets in economically valuable ways or if the company is performing poorly versus its peers.

### 3.2.4 Compensation Noninterest Expense Ratio

Noninterest expense-fixed operating costs that a financial institution must incur, such as anticipated heavy debt provisions. Noninterest expenses can include employee salaries and benefits, equipment and property leases, taxes, loan loss provisions and professional service fees.

### 3.2.5 Fixed Asset Noninterest Expense Ratio

Assets that are purchased for long-term use and are not likely to be converted quickly into cash, such as land, buildings, and equipment.

### 3.2.6 Other Noninterest Expense Ratio

Any other noninterest expense ratio. That is one of the Key components of PPNR.

### 3.2.7 Return on AFS Securities

We performed regressions for all the companies (200 largest US companies plus one), the 19 original CCAR stress test companies, and some individual companies with SAS proc regression. Then, we repeated the same thing with SAS proc panel regression for all the companies and the 19 sub-companies.

### 3.2 Replication of PPNR Components and Securities Specification

As we mentioned before, Figure 5 has the CLASS model specification. It has the summary of the different vector elements that made up this model and the key PPNR components or the dependent variables (Net Interest Margin, Noninterest Nontrading Income Ratio, Return on Trading Assets, Compensation NonInt. Expense Ratio, Fixed Asset Noninterest Expense Ratio, Other Noninterest Expense Ratio, and Return on AFS Securities). For independent variables, it
has the net charge specifications (First Lien Residential, Junior Lien Residential, HELOC, construction multifamily, nonfarm nonresidential, credit card, other consumer, commercial and industrial, leases, other real estate, depository institutions, agriculture, foreign governments and other loans). It also has the macroeconomic variables (annualized real GDP growth (\%); term spread (10 year minus 3 months, pct. pt); 3-month treasury yield (\%); quarterly change in 10-year treasury yield (pct. pt); stock market returns (quarterly, \%); quarterly change in BBB bond spread (pct. pt); quarterly change in BBB spread if change is positive (else zero); quarterly change in BBB spread if change is positive x risky AFS ratio; annualized change in unemployment (\%); home price growth ( $\%$, year-over-year); home price growth if growth is negative (else zero); commercial property price growth (\%, year-over-year); commercial property price growth if negative (else zero), time trend (annual); and firm balance sheet controls). Below is the PPNR specification for the CLASS model. The statistical results of the regressions of the CLASS models can be seen in Appendix B Table 10.


Figure 2: The CLASS model specifications
We replicated the regressions of the CLASS model to analyze the model specifications. The results of our PPNR key components in our replication are the same as what was reported in the CLASS model research paper. That helped us validate that our replication was correct. Therefore, we could use the PPNR equations to continue our research. However, we found that some of the explanatory variables in the CLASS model are strongly correlated. In our findings, we documented our statistically significant variables and correlation findings as follows. We documented variables statistically significant as: $* * * \mathrm{p}<0.01 * * \mathrm{p}<0.05 * \mathrm{p}<0.1$ and Correlation -

High $=>.9$, Medium $<.9$ or $>.5$, Low $=<.5$. You will see these values (legends) throughout this document.

Appendix C of the document has the CLASS model specification results and our research findings. The regression results that we found after replicating PPNR specifications are almost the same as the results that are reported in the CLASS model research paper. Therefore, we could conclude that we had a good start. While we had a good start with the regression results for all the companies (largest $200+1$ that aggregated data for the rest of the companies), we wanted to know how the PPNR/The CLASS model specifications would hold when we segmented the data for the 19 companies that were part of the original CCAR test.

Knowing that the CLASS model has a top-down structure (Kapinos, 2015), we looked at the statistical results of the same equations when we segmented the data for the 19 original CCAR stress test companies. This test would give us an idea about the quality of this model (i.e., will the quality of this model improve or diminish).

### 3.3 PPNR Specification for the 19 CCAR Stress Test Companies

We performed the regression for seven key components for the whole portfolio of the 19 companies that were part of the initial CCAR/PPNR stress test. We used the companies' financial data, meaning the data provided by financial institutions when filling out FR Y-9C report. That is the same data used by the PPNR/CLASS model. We found that the CLASS model deteriorates when we segment the data. The RMSE values increase while the R-squared values decrease. The number of correlation variables increases and the number of significant statistic variables diminishes. We also found that the CLASS model explanatory variables have a stronger correlation.

These findings are a good indication that the CLASS model can't be used as-is for the stress test for a subgroup of companies without adjusting the model or addressing the elements that we found after segmenting the data. Table 11 in Appendix B has our findings. The discrepancies can be seen in Table 10 and 11 in Appendix B of this document.

### 3.4 PPNR Specification for Individual Company of the 19 CCAR Test Companies

Here, we segmented the data further and used the same PPNR specification to find out the results of the regressions for several individual companies. We found that the quality of the model deteriorates slightly (e.g. stronger correlation, bigger RMSE values, and others) as we segment the data further. We summarized our findings in Table 12, 13 and 14 in Appendix B of this document.

### 3.5.1 PPNR Specification with All the Companies with SAS Proc Panel

After replicating the PPNR/CLASS model and segmenting the data for the 19 original CCAR stress test companies, and segmenting the data for several individual companies, we wanted to use other statistical techniques to test the CLASS model. Here, we used a SAS proc panel to test the CLASS model specifications. We did not find any major differences in the results of the regression of the equations with SAS proc reg and proc panel. Table 15 in Appendix C has the results of the CLASS model specification with proc panel for all the HBC companies.

### 3.5.2 PPNR Specification with the 19 CCAR Test Companies with SAS Proc Panel

We used the same dataset that we used with SAS proc reg to repeat the equation with SAS proc panel to study any variance in the results between SAS proc regression and SAS proc panel regression for PPNR/CLASS key components. Table A has the summary results of the regressions for all the companies and Table B has the results for the 19 original CCAR/PPNR stress test companies. We found that the RME is slightly higher and the number of significant variables
became lower. This is a similar pattern as when we used SAS proc reg after segmenting the data for the 19 original CCAR/PPNR stress test companies. Again, the quality of the model deteriorated after segmenting the data. Appendix C and Table 16 have the results of our regressions. Table 16 in Appendix C has the results of the CLASS model specification with proc panel for all the HBC companies

### 3.6 Data Summary or Table Results:

Here, we arranged the data in a panel. We can say that the data is a balanced panel. By sorting the data by date, we could do our regressions by time period across all the companies. That arrangement allowed us to use proc panel for the general, or summary, regression.

### 3.6.1 Regression with Panel Data - Guidelines

Multiple regression with proc panel is powerful for controlling the effect of variables on which we have data. If data is not available, however, they cannot be included in the regression, and the OLS estimators of the regression coefficient could have omitted variables bias.

Here, we analyzed a method for controlling for some types of omitted variables without actually observing them. This method requires a type of data called panel data in which each observational unit, or entity, is observed at two or more time periods. By studying changes in the dependent variables over time, it is possible to eliminate the effect of omitted variables that differ across entities but are constant over time.

### 3.6.2 Notation of the Panel Data

Panel data consist of observations on the same n entities at two or more timeperiods T , as is illustrated in the data sample. If the dataset contains observations on the variables X and Y , then the data are denoted

$$
\left(X_{i t}, Y_{i t}\right), i=1 \ldots . ., n \text { and } t=1 \ldots . . T
$$

where the first subscript, I, refers to the entity being observed and the second subscript, t , refers to the date at which it is observed. Panel data, also called longitudinal data, refers to data for n , different entities, observed at T, different time periods. We performed the regressions for the key components of PPNR.

When describing cross-sectional data, it was useful to use a subscript to denote the entity; for example, Yi referred to the variable Y for the ith entity. When describing panel data, we needed some additional notation to keep track of both the entity and the timeperiod. We did so by using two subscripts rather than one: the first, I, refers to entity, and the second, t , refers to the timeperiod of the observations. Thus $Y_{i t}$ denotes the variable Y observed for the $i^{\text {th }}$ of n entities in the $t^{t h}$ of T periods.

Some additional terminology associated with panel data describes whether some observations are missing. A balanced panel has all its observations; that is, the variables are observed for each timeperiod. A panel that has some missing data for at least one timeperiod is called an unbalanced panel. For the 19 companies that we are studying, some companies have less data than the others. However, the data was balanced.

### 3.6.3 Fixed Effects Regression

Fixed effects is a method for controlling for omitted variables in panel data when omitted variables vary across entities but do not change over time. The fixed effects regression model has n different intercepts, one for each entity. These intercepts can be represented by a set of binary,
or indicator, variables. The binary variables absorb the influences of all omitted variables that differ from one entity to the next by $t$ and are constant over time.

### 3.6.4 Regression with Time Fixed Effects

Just as fixed effects for each entity can control for variables that are constant over time but differ across entities, so can time fixed effects control for variables that are constant across entities but evolve over time. Here, for the key components of PPNR, we can control data over time. For both entity and time fixed effects, if some omitted variables are constant over time but vary across the other variables, while others are constant across but vary over time, then it is appropriate to include both entity and time effects. The combined entity and time fixed effects regression model is

$$
Y_{i t}=\beta_{1} X_{i t}+\propto_{i}+\lambda_{t}+u_{i t}
$$

Equation 3: Panel Procedure Equation
where $\propto_{i}$ is the entity fixed effect and $\lambda_{t}$ is the time effect. The model can be represented using n1 entity binary indicators and T-1 time binary indicators along with an intercept:

$$
Y_{i t}=\beta_{0}+\beta_{1} X_{i t} \ldots \ldots \ldots \beta_{n} X_{i T}+u_{i t}
$$

The combined company name and time fixed effects regression eliminates omitted variables bias arising both from unobserved variables that are constant over time and from unobserved variables that are constant across other variables.

### 3.6.5 Regression Assumptions and Standard Error for Fixed Effects Regression

In panel data, the regression error can be correlated over time within an entity. Like heteroscedasticity, this correlation does not introduce bias in the fixed effects estimator, but it affects the variance of the fixed effects estimator, and there are effects on how one computes standard errors. The standard errors for fix effects regressions reported are so-called cluster standard error.

### 3.6.6 Parameter Estimates with Proc Panel

In this section, we presented our findings and the parameter estimates for the seven PPNR variables that we studied in this research. Here are the variables - 1. Net Interest Margin, 2. Noninterest Nontrading Income Ratio, 3. Return on Trading Assets, 4. Compensation Noninterest Expense Ratio, 5. Fixed Asset Noninterest Expense Ratio, 6. Other Noninterest Expense Ratio, and 7. Return on AFS Securities. These are the dependent variables on our proc panel regressions. The results of these regressions can be seen in Appendix C Table 15.

### 3.7 Random Coefficients

For random coefficients, we reviewed an example from a pharmaceutical stability data simulation performed by Obenchain (1990). The observed responses are replicates, expressed in percent of label claim, at various shelf ages, expressed in months. The desired mixed model involves three batches of product that differ randomly in intercept (initial potency) and slope (degradation rate). This type of model is also known as a hierarchical or multilevel model (Singer 1998; Sullivan, Dukes, and Losina 1999). In Appendix H Section 1, we used SAS to demonstrate this model.

In the DATA step, Monthc is created as a duplicate of Month in order to enable both a continuous and a classification version of the same variable. The variable Monthc is used in a subsequent analysis.

In the PROC MIXED statements, Batch is listed as the only classification variable. The fixed effect Month in the MODEL statement is not declared as a classification variable; thus, it models a linear trend in time. An intercept is included as a fixed effect by default, and the $S$ option requests that the fixed-effects parameter estimates be produced.

The two random effects are Int and Month, modeling random intercepts and slopes respectively. Note that Intercept and Month are used as both fixed and random effects. The TYPE=UN option in the RANDOM statement specifies an unstructured covariance matrix for the random intercept and slope effects. In mixed model notation, G is block diagonal with unstructured $2 \times 2$ blocks. Each block corresponds to a different level of Batch, which is SUBJECT= effect. The unstructured type provides a mechanism for estimating the correlation between the random coefficients. The $S$ option requests the production of the random-effects parameter estimates. It is also possible to fit a random coefficients model with error terms that follow a nested structure SAS Reference. We present one way to do this with an SAS sample in Appendix H of this document.

The variable Monthc is added to the CLASS and RANDOM statements, and it models the nested errors. Note that Month and Monthc are continuous and classification versions of the same variable. Also, the TYPE=UN option is dropped from the RANDOM statement, resulting in the default variance components model instead of correlated random coefficients. The results from this analysis are shown in Output Appendix H.

### 3.8 Conclusion and Summary - With Proc Reg and Proc Panel Regressions

As you can see in the tables in Appendix C and D, the results of these regressions with SAS proc reg and proc panel are not major. However, SAS proc panel provided slightly better results than proc reg. Now we know that the quality of the CLASS model deteriorates when we segment or subdivide the dataset. This finding is our contribution to PPNR research study. We call the proc panel regression model CLASS-X Model $1^{9}$.

We can conclude by saying that more analysis is needed to study how to improve the regression of PPNR key specification components. In the subsequent chapters we will present more details on how we can improve the PPNR/CLASS model. Appendix B and C have the results of our regressions of CLASS model.

[^6]
## Chapter 4: CLASS-X Model Specifications

### 4.1 Overview

In this chapter, we present a new model (i.e., CLASS-X) that can be used as an alternative solution to the CLASS model for PPNR key components. We have seen several areas where the CLASS model can be improved. In this chapter, we provide an overview of CLASS-X specification and the details on how we constructed this model. Variable selection can be complex when you are dealing with a specification that is made up of several models. And, each model can share explanatory variables. In this exercise, we will look at all the possible ways to improve the PPNR/CLASS model with CLASS-X.

Very often, econometricians, statisticians, or researchers look at stepwise, forward, and other techniques to select variables for a model. Information criteria uses the covariance matrix and the number of parameters in a model to calculate a statistic that summarizes the information represented by the model by balancing a trade-off between a lack of fit term and a penalty term. Akaike Information Criterion (AIC) estimates a measure of the difference between a given model and the "true" model. The model with the smallest AIC among all competing models is deemed the best model. It is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection.

The Mean Absolute Percentage Error (MAPE) or Average Absolute Percentage Error (AAPE), also known as Mean Absolute Percentage Deviation (MAPD), is a measure of prediction accuracy of a forecasting method in statistics. In the CLASS-X specification we looked at all these techniques to come up with the best model for the PPNR/CLASS-X model.

### 4.2 Analysis of PPNR Variables Selection for Seven Key Components

The CLASS-X model is an alternative and extended solution for the CLASS model. We followed several steps to make sure that we came up with a great model that could be used as a different solution for the CLASS model regressions. We know that a model is never perfect. However, we can compare several models and decide which is the best one by using different statistical techniques. The following are the steps that we used in our variable model selection for the CLASS-X model:

Step 1 - We looked at the AIC (Akaike Information Criterion) for a model. It is important to mention that AIC is a measure of the relative quality of statistical models for a given set of data.

Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection.

Step 2 - We performed variable selection with the following standard statistical techniques: minimizing RMSE, forward selection, backward elimination, and stepwise regression.Step 3 - We compared the performance of AIC with the standard statistical techniques from Step 2 to select the true model. Step 4 - We selected the true model by selecting the model with a smaller AIC. Step 5 - We performed a collinearity test on the selected model and reduced or documented collinearity in the model. We looked at several collinearity indicators in the exercise. Briefly, we can mention these indicators as - inflation variance, eigenvector values, correlation values, condition index, and others. We wanted to make sure that the selected model met the basic three pillars of Federal Reserve SR 11-7 standards (model conceptual soundness, outcome analysis, and ongoing monitoring).

### 4.2.1 Statistic Techniques

Five common statistical techniques taught in most statistics courses to determine the best linear model are minimizing the RMSE, maximizing R2, forward selection, backward elimination, and stepwise regression. The RMSE is a function of the sum of squared errors (SSE), number of observations $n$, and the number of parameters p. This is shown in Eqn. (1).

Eqn. (1)

$$
R M S E=\sqrt{\frac{S S E}{n-p}}
$$

The coefficient of determination R2 is the percentage of the variability of the dependent variable that is explained by the variation of the independent variables. Therefore, the R 2 value ranges from 0 to 1 . R2 is a function of the total sum of squares (SST) and the SSE. This is shown in Eqn. (2).

Eqn. (2)

$$
\mathrm{R}-\text { Squared }=1+\frac{S S E}{S S T}
$$

The R2 is calculated for all possible subset models. Using this technique, the model with the largest R2 is declared the best linear model. However, this technique has several disadvantages. First, the R2 increases with each variable included in the model. Therefore, this approach encourages including all variables in the best model, although some variables may not significantly contribute to the model. This approach also contradicts the principal of parsimony that encourages as few parameters in a model as possible.

Forward selection begins with only the intercept term in the model. For each of the independent variables, the F statistic is calculated to determine each variable's contribution to the model. The variable with the smallest $p$-value below a specified $\alpha$ cutoff value (e.g., 0.10) indicating statistical significance is kept in the model. The model is rerun keeping this variable and recalculating F statistics on the remaining p-1 independent variables. This process continues until no remaining variables have F statistic p-values below the specified $\alpha$. Once a variable is in the model, it remains in the model.

Backward elimination begins by including all variables in the model and calculating F statistics for each variable. The variable with the largest $p$-value exceeding the specified $\alpha$ cutoff value is then removed from the model. This process continues until no remaining variables have $F$ statistic p-values above the specified $\alpha$. Once a variable is removed from the model, it cannot be added to the model again.

Stepwise regression is a modification of the forward selection technique in that variables already in the model do not necessarily stay there. As in the forward selection technique, variables are added one at a time, as long as the F statistic p -value is below the specified $\alpha$. After a variable is added, however, the stepwise technique evaluates all the variables already included in the model and removes any variable that has an insignificant $F$ statistic $p$-value exceeding the specified $\alpha$. Only after this check is made, and the identified variables have been removed, can another variable be added to the model. The stepwise process ends when none of the variables excluded from the model have a significant F statistic at the specified $\alpha$, and every variable included in the model is significant at the specified $\alpha$.

Information criteria is a measure of goodness of fit or uncertainty for the range of values of the data. In the context of multiple linear regression, information criteria measures the difference between a given model and the "true" underlying model. Akaike (1973) introduced the concept of information criteria as a tool for optimal model selection. Akaike's Information Criteria (AIC) is a function of the number of observations $n$, the SSE and the number of parameters p , as shown in Eqn. (3).

Eqn. (3)

$$
A I C=n \cdot \ln \left(\frac{S S E}{n}\right)+2 p
$$

The first term in Eqn. (3) is a measure of the model lack of fit while the second term is a penalty term for additional parameters in the model. Therefore, as the number of parameters p included in the model increases, the lack of fit term decreases while the penalty term increases. Conversely, as variables are dropped from the model, the lack of fit term increases while the penalty term decreases. The model with the smallest AIC is deemed the "best" model since it minimizes the difference from the given model to the "true" model.

Using the 5 steps that we outlined in section 4.1 of this document, we came up with a new model specification which we named CLASS-X (Capital and Loss Assessment under Stress Scenarios eXtended Alternative Regressions). This model is an alternative regression model to the CLASS model. It looks at a way to improve the CLASS model. Appendix D and Table 17 have CLASS-X model specifications.

Similarily to the CLASS model, CLASS-X is very simple to focus on seven PPNR key components. It analyses each variable with different techniques (stepwise, forward, backward, and others) to select the best variable for the model. Next, we looked at the collinearity within the selected variables to further refine the variables selected.

While we performed these steps, we kept SR11-7 as a guideline to help us build CLASSX. We made sure that the three pillars that are the standard (conceptual soundness, outcome analysis, and ongoing monitoring) are reflected in the model. From a conceptual soundness perspective, we wanted to make sure that CLASS-X was statically sound. From an outcome analysis perspective, we wanted to compare the CLASS-X model with the CLASS model and other specification techniques. From the ongoing monitoring side, we wanted to ensure that the
performance of CLASS-X could be measured as well as adjusted to improve the performance of this model when it deploys to production.

The following are the steps that we used to come up with the final CLASS-X specifications. The steps have several sub-steps as well.


Figure 3: PPNR/CLASS-X Specification steps
In the data consolidation step, we looked at the raw data from the FRY 9C report to analyze the data (macroeconomic variables, banks balance sheet, and market data). In the data analysis step, we tried to visualize the data and understand its structure. With the replication of the CLASS model regressions, we tried to replicate all the replications that made up the CLASS model. That helped us see how that model was made up. After these critical steps, we asked ourselves this question: Can we build a better (i.e., more statistically significant) model? We tried several variable selection mechanisms and came up with what we thought was the best model. We refined the model for multicollinearity and finalized the CLASS-X model.

With Figure 7, you can see the steps that we used to create CLASS-X specification. The CLASS-X model structure can be visualized by this figure below.


Figure 4: CLASS-X Structure

### 4.3 CLASS-X Model Development

As you can see in the CLASS-X model specifications in Appendix C, we selected the variables that have a darker mark next to them after following the five steps that we described in the section above. Table 18 in Appendix D has all the techniques (AIC, forward, backward, and others) that we used in our variable selection and model selection for our CLASS-X model.

We concluded that CLASS-X specification was the better model than CLASS after comparing its statistic parameter results with all the other techniques by the other models that are in Appendix D Table 18 of this document. The table below also presents a summary of the parameter estimates of CLASS-X and the other techniques for the variable selection.

\begin{tabular}{|c|c|c|c|c|c|c|c|c|}
\hline Legend \& \multicolumn{2}{|c|}{${ }^{* * *}$ p $<0.01{ }^{* *}$ p $<0.05{ }^{*} \mathrm{p}<0.1$} \& Correlation-High \& =>. 9 \& Medium \& <. 9 or $>.5$ \& Low \& $=<.5$ <br>
\hline \multicolumn{2}{|r|}{Net Interest Margin} \& $$
\begin{aligned}
& x \\
& \dot{\sim} \\
& \dot{3} \\
& \hline
\end{aligned}
$$ \& D

$\sum_{0}^{0}$

L \& [ \&  \& $$
\sum_{\propto<}^{u}
$$ \& \& <br>

\hline \multicolumn{2}{|l|}{\multirow[b]{2}{*}{Constant Term}} \& 0.0839 \& 0.24236 \& 0.83841 \& 0.24236 \& 0.19941 \& \& <br>
\hline \& \& (0.01532) \& 0.07053 \& (0.04130) \& (0.07053) \& (0.07004) \& \& <br>
\hline \multicolumn{2}{|l|}{Observations} \& 15428 \& 15,428 \& 15428 \& 15,428 \& 15,428 \& \& <br>
\hline \multicolumn{2}{|l|}{R-Square} \& 0.8731 \& 0.8824 \& 0.7165 \& 0.8824 \& 0.8824 \& \& <br>
\hline \multicolumn{2}{|l|}{\# Variables Statiscally Significant} \& All \& Not All \& Not All \& Not All \& All \& \& <br>
\hline \multicolumn{2}{|l|}{Correlation} \& Low \& Strong or High \& Medium \& Strong - High \& Strong-High \& \& <br>
\hline \multicolumn{2}{|l|}{RMSE} \& 0.34025 \& 0.32753 \& 0.9373 \& 0.32753 \& 0.32754 \& \& <br>
\hline \multicolumn{4}{|r|}{Proc Reg with Pooled Data for all the companies (2001) In CLASS-X Model} \& \& \& \& \& <br>
\hline \multicolumn{2}{|l|}{Order by Model quality} \& 1 \& 4 \& 3 \& 4 \& 2 \& \& <br>
\hline
\end{tabular}

### 4.4 CLASS-X Model Equation

At a high level, the equation of CLASS-X is similar to that of the CLASS model. However, the difference is in the underlying elements of the variables used by CLASS-X. Some of the
variables that are in the CLASS-X model are different from the CLASS model. CLASS-X has the form of the general model that we described in the document.

The regression forms of these equations are as follows:

> 1. Net Interest Margin $_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+$ $\beta_{1 c} T_{1 c}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}$
2. Non IntNon Trade Icom Rating $c t$

$$
\begin{aligned}
& =\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+ \\
& \beta_{1 c} T_{1 c}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}
\end{aligned}
$$

3. Return On Trading Asset ${ }_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+$ $\beta_{1 c} T_{1 c}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}$
4. Comp Non - Interest Expense Ration ${ }_{c t}$

$$
\begin{aligned}
& =\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+ \\
& \beta_{1 c} T_{1 c}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}
\end{aligned}
$$

5. Fixed asset NonInt Exp. Ratio ${ }_{c t}$

$$
\begin{aligned}
=\beta_{0 c}+ & \beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+\beta_{1 c} T_{1 c \ldots} \\
& +\beta_{1 c} T_{n t}+\cdots+\beta_{1} X_{1 t}+\beta_{n} X_{n t}+\varepsilon_{c t}
\end{aligned}
$$

6.Other NonIntExp.Ration ${ }_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+$

$$
\beta_{1 c} T_{1 c}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}
$$

7. Return ON AFS Securities ${ }_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\cdots+\beta_{n c} M_{n c t}+\beta_{1 c} B_{1 c t}+\cdots+\beta_{n c} B_{n c t}+$ $\beta_{1 c} T_{1 c}+\cdots+\beta_{1 c} T_{n t}+\beta_{1} X_{1 t}+\cdots+\beta_{n} X_{n t}+\varepsilon_{c t}$

The general form of this equation can be as follows:

$$
\begin{aligned}
& P P N R-K C_{c t}=\beta_{0 c}+\beta_{1 c} M_{1 c t}+\beta_{2 c} B_{2 c t}+\beta_{3 c} T_{3 c t}+\varepsilon_{c t} \\
& l 2 \text { Equations }{ }^{l 0}
\end{aligned}
$$

Equation 4: CLASS-X Model 2 Equations ${ }^{10}$
The PPNR key component equation is: constant or intercept + vector of the macroeconomic values + vector of the balance sheet values ratio + vector of the time control + error term. CLASSX specification provides details about this model. The detailed specifications of this model can be seen in Appendix F.

### 4.5 Model Validation

After building this model with the 5 steps outlined earlier, we followed SR11-7 standards to validate the models in CLASS-X specifications. We followed the basic model validation standard guides (conceptual soundness, outcome analysis, and performance monitoring) that are in the SR11-7 guidelines.

### 4.5.1 Conceptual Soundness

We looked at several key statistic indicators in this model. First, we looked at how the model fits the data by looking at R -squared value. We know that the value of R -squared should be between 0 and 1 , but the closer the value is to 1 , the better. Second, we looked at how statistically

[^7]significant the variables were. We set our standard to a $10 \%$ level of significance. Variables that did not meet this standard couldn't be used in your model. Third, we looked at Root Mean Square Error (RMSE) values to make sure they were less than 2.5 or lower than the highest value we found in the CLASS model. RMSE is one of the most widely used statistics, also known as Root Mean Square Deviation. RMSE measures how much error there is between two datasets comparing a predicted value and an observed, or known, value. Forth, we performed collinearity diagnostics on the model to make sure that the model met these criteria: eigenvector values greater than zero, inflation variance $<=5$, and a condition index less than 15 . Next, we did a complete review of the model from a statistics perspective to decide if it was conceptually sound. We can say that the CLASS-X model passed the first element test of our validation standards.

### 4.5.2 Outcome Analysis

We performed some outcome analyses of the model by comparing the CLASS-X model results with the CLASS model results. We concluded with the following tables:

| R-Square | 0.8731 | 0.8774 | 0.5206 | 0.833 | 0.837 | 0.781 | 0.0321 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| \# Variables Significant | All | All | All | All | All | All | All |
| Strong Correlation | Low | Low | Low | Low | Low | Low | Low |
| RMSE | 0.34025 | 0.5449 | 1.61286 | 0.1706 | 0.05306 | 0.56046 | 2.41591 |
| Proc Reg with Pooled Data for all the companies (2001) In CLASS-X Model |  |  |  |  |  |  |  |

Table 3: CLASS-X Model Summary results

| R-Square | 0.885 | 0.8765 | 0.4495 | 0.8278 | 0.8346 | 0.7721 | 0.0352 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| \# Variables Significant | 12 | 7 | 1 | 7 | 8 | 5 | 3 |
| Strong Correlation | Medium | High | Medium | High | High | Medium | Low |
| RMSE | 0.31839 | 0.54688 | 1.72839 | 0.16753 | 0.05431 | 0.54452 | 2.41203 |
| Proc Reg with Pooled Data for all the companies (2001) In CLASS Model |  |  |  |  |  |  |  |

Table 4: The CLASS model Summary results
We found that the CLASS-X model fits the data better than the CLASS model. While there is not a major difference between the R-square and RMSE values of these two models, CLASS-X regression results are slightly better than those of the CLASS model. We also saw that the variable correlation in the CLASS model variables are strong, and a large number of variables are not statistically significant. The explanatory variables in CLASS-X have a low correlation, and all of them are statistically significant to a $10 \%$ or $1 \%$ level.

With these summary results, we concluded that CLASS-X is a great alternative model for PPNR stress test regression. We will also provide more details in the subsequent sections about the comparison of CLASS-X and the CLASS model. We can say that the model passed the second test element of our validation standards.

### 4.5.3 Performance Monitoring and Ongoing Monitoring

CLASS-X is a new model. For performance monitoring and ongoing monitoring, we looked at the performance of this model in itself, and again at the CLASS model. We knew that CLASS-X fits the data better than the CLASS model. Therefore, we interpolated that CLASS-X has a performance advantage over the CLASS model. During our analysis, we also found that the CLASS model quality deteriorated when we segmented the data, while the quality of CLASS-X did not. Again, we concluded that CLASS-X will perform better with integrated data and sub-data sets. We can say that the model passed the third element of our validation standards.

### 4.6 Comparison of CLASS-X and The CLASS model

We replicated all the regressions of the CLASS model, we compared CLASS-X regression results with the CLASS model, and we found several elements where CLASS-X differed from the CLASS model. The tables in Appendix B, C and D summarize these differences well. While we tried to keep the differences between CLASS and CLASS-X models at a high level, the differences in the details of these two models are significant. Here, we looked at several key statistical differences between the two models.

### 4.6.1 The CLASS Model Specification Details

Here, we looked at the specification details for the seven key components of the CLASS model (Net Interest Margin, Noninterest Nontrading Income Ratio, Return on Trading Asset, Compensation Non-Interest Expense Ratio, Fixed Asset NonInterest Expense Ratio, Other NonInterest Expense Ratio, and Return on AFS Assets for Sale Securities) to see how they were different from the CLASS-X model.

## Overview

1) Net interest margin is one of the key components of PPNR. The regression of this equation helped in understanding how net interest margin will change by changing any of the explanatory variables. It also helped us with the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the net interest margin regression:

|  | Root MSE 0.31839R-Square 0.8850 <br> Dependent Mean3.56927Adj R-Sq0.8849  <br> Coeff Var 8.92037 |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Parameter Estimates |  |  |  |  |  |  |
|  | ParameterStandard |  | t Value | $\operatorname{Pr}>\|t\|$ | Tolerance | Variance Inflation |
| Label | Estimate | Error |  |  |  |  |
| Intercept | 0.23354 | 0.06051 | 3.86 | 0.0001 |  | 0 |
| Term Spread (10Y-3M) | 0.04259 | 0.00722 | 5.90 | <. 0001 | 0.16067 | 6.22402 |
| 3M Treasury Yield | 0.02199 | 0.00596 | 3.69 | 0.0002 | 0.07699 | 12.98892 |
| Lag Net Interest Margin | 0.79281 | 0.00445 | 178.34 | <. 0001 | 0.33358 | 2.99780 |
| Time | -0.00528 | 0.00153 | -3.46 | 0.0005 | 0.11520 | 8.68044 |
| Residential RE Loan Ratio | 0.00476 | 0.00050956 | 9.34 | <. 0001 | 0.44144 | 2.26529 |
| Commercial RE Loan Rati | 00.00648 | 0.00051128 | 12.68 | <. 0001 | 0.39200 | 2.55099 |
| C\&I Loan Ratio | 0.00685 | 0.00069770 | 9.82 | <. 0001 | 0.39004 | 2.56386 |
| Credit Card Loan Ratio | 0.01837 | 0.00067102 | 27.38 | <. 0001 | 0.33771 | 2.96111 |
| Trading Assets Ratio | -0.00626 | 0.00072793 | -8.59 | <. 0001 | 0.14963 | 6.68301 |
| Securities Ratio | 0.00393 | 0.00050969 | 7.71 | <. 0001 | 0.28527 | 3.50545 |
| Asset share | 0.00743 | 0.00056920 | 13.05 | <. 0001 | 0.84112 | 1.18889 |

Collinearity Diagnostics

|  |  | Condition <br> Number Eigenvalue |
| :--- | :--- | :--- |
| 1 | 8.02879 | 1.00000 |
| 2 | 1.11838 | 2.67935 |


|  |  | Condition <br> Index |
| :--- | :---: | :--- |
| 3 | 0.87751 | 3.02483 |
| 4 | 0.55753 | 3.79483 |
| 5 | 0.41689 | 4.38848 |
| 6 | 0.30612 | 5.12125 |
| 7 | 0.25630 | 5.59694 |
| 8 | 0.22553 | 5.96651 |
| 9 | 0.15804 | 7.12760 |
| 10 | 0.03390 | 15.38905 |
| 11 | 0.01849 | 20.84070 |
| 12 | 0.00251 | 56.50496 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are too high (i.e., some values are greater than 5 and greater than 10). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that, while these variables are statistically significant, the VIF values are too high. That is a red flag indicating that we need to investigate this model more.

The eigenvalue should not be too close to zero. Here, you can see the last three values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated and any model with a condition index greater than 30 is not acceptable. Again, these rules are violated for this model. Therefore, we can say that this model needs to be improved or has room for improvement.
2) Noninterest Non-Trading Income Ratio is another key component of PPNR. The regression of this equation helped in understanding how Noninterest Non-Trading Income Ratio will change by changing any of the explanatory variables. It also helped us with the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Noninterest Non-Trading Income Ratio regression:

| Root MSE | 0.54688 | R-Square 0.8765 |
| :--- | ---: | :--- |
| Dependent Mean2.28056 Adj R-Sq0.8764 |  |  |
| Coeff Var | 23.98013 |  |

Parameter Estimates


| Label | Parameter Estimate | Standard Error | $t$ Value | $\operatorname{Pr}>\|t\|$ | Tolerance | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Commercial RE Loan |  |  |  |  |  |  |
| Ratio | -0.00364 | 0.00086865 | -4.19 | <. 0001 | 0.41250 | 2.42427 |
| C\&I Loan Ratio | -0.00087697 | 0.00113 | -0.78 | 0.4364 | 0.43296 | 2.30969 |
| Credit Card Loan Ratio | 0.00990 | 0.00101 | 9.76 | <. 0001 | 0.44694 | 2.23745 |
| Trading Assets Ratio | -0.00146 | 0.00122 | -1.20 | 0.2319 | 0.15893 | 6.29200 |
| Securities Ratio | 0.00309 | 0.00083238 | 3.71 | 0.0002 | 0.28003 | 3.57100 |
| Asset share | -0.00581 | 0.00097434 | -5.96 | <. 0001 | 0.85887 | 1.16432 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 5.50887 | 1.00000 |
| 2 | 1.15005 | 2.18863 |
| 3 | 0.95450 | 2.40239 |
| 4 | 0.90573 | 2.46622 |
| 5 | 0.42776 | 3.58865 |
| 6 | 0.41765 | 3.63181 |
| 7 | 0.23877 | 4.80333 |
| 8 | 0.20836 | 5.14192 |
| 9 | 0.18134 | 5.51163 |
| 10 | 0.00696 | 28.12956 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are too high (i.e., some values are greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. We can also say that some variables are not statistically significant and VIF values are higher than 5 . That is a red flag indicating that we need to investigate this model more.

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is close to zero. Therefore, the model has a strong collinearity. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, the rules are violated for this model. Therefore, we can say that this model needs to be improved or has room for improvement.
3) Trading Income Ratio is a key component of PPNR. The regression of this equation helped in understanding how Trading Income Ratio will change by changing any of the explanatory variables. It also helped us with the sensitivity of financial strength with macroeconomic variables. Below are statistical results of the Trading Income Ratio regression:

| Root MSE | 1.72839 R-Square 0.4495 |
| :--- | ---: |
| Dependent Mean2.25219 Adj R-Sq0.4233 |  |
| Coeff Var | 76.74297 |

Parameter Estimates

|  | ParameterStandard |  |  |  |  |
| :--- | :---: | :--- | :--- | :--- | :--- |
| Variable | Estimate <br> Error | t ValuePr $>\|\boldsymbol{t}\|$ | Tolerance | Variance <br> Inflation |  |
| Intercept | 1.98882 | 0.350665 .67 | $<.0001$ |  | 0 |
| dbspread | -0.67079 | $0.82269-0.82$ | 0.4179 | 0.29393 | 3.40217 |
| dbspread_pos-2.55905 | $1.11491-2.30$ | 0.0251 | 0.29659 | 3.37163 |  |
| l1_cl_tradrat | 0.28407 | 0.099772 .85 | 0.0059 | 0.87721 | 1.13998 |

Collinearity Diagnostics

|  |  |  |
| :--- | :--- | :--- |
| NumberEigenvalue | Condition <br> Index |  |
| 1 | 1.94217 | 1.00000 |
| 2 | 1.66757 | 1.07920 |
| 3 | 0.25365 | 2.76713 |
| 4 | 0.13661 | 3.77055 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are not too high (i.e., some values are greater than 5). We can say that some variables are not statistically significant at a $10 \%$ level. That is a red flag that we need to investigate this model more.

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is reasonable. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Here, we can say that this model adhered to the rules. Therefore, we can say that this model needs to be improved, or has room for improvement, because of variable size and variable statistical significance.
4) Compensation Expense Ratio is another one of the key components of PPNR. The regression of this equation helped in understanding how Compensation Expense Ratio will change by changing any of the explanatory variables. It also helped us to understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Compensation Expense Ratio regression:

| Root MSE | $0.16753 R-$ Square 0.8278 |
| :--- | ---: |
| Dependent Mean1.69380Adj R-Sq0.8277 |  |
| Coeff Var | 9.89060 |

Parameter Estimates

| Label | Parameter Estimate | Standard <br> Error | $t$ Value | $\mathrm{Pr}>\|\mathrm{t}\|$ | Tolerance | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Intercept | 0.26090 | 0.02113 | 12.35 | <. 0001 |  | 0 |
| Stock Market Quarterly Log |  |  |  |  |  |  |
| Change | 0.00345 | 0.00021221 | 16.24 | <. 0001 | 0.99647 | 1.00355 |
| Lag Compensation Expense |  |  |  |  |  |  |
| Ratio | 0.89385 | 0.00331 | 270.27 | <. 0001 | 0.88861 | 1.12535 |
| Residential RE Loan Ratio | -0.00072201 | 0.00026533 | -2.72 | 0.0065 | 0.44571 | 2.24363 |
| Commercial RE Loan Ratio | -0.00109 | 0.00026868 | -4.05 | <. 0001 | 0.40459 | 2.47165 |


| Label | Parameter <br> Estimate | Standard <br> Error | $\boldsymbol{t}$ Value | Pr $>\|\boldsymbol{t}\|$ |  | ToleranceVariance <br> Inflation |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :---: |
| C\&I Loan Ratio | -0.00022850 .00034620 | -0.66 | 0.5093 | 0.43026 | 2.32416 |  |  |
| Credit Card Loan Ratio | -0.00115 | 0.00030405 | -3.78 | 0.0002 | 0.46673 | 2.14255 |  |
| Trading Assets Ratio | -0.00252 | 0.00038658 | -6.52 | $<.0001$ | 0.14792 | 6.76034 |  |
| Securities Ratio | -0.00172 | 0.00026529 | -6.50 | $<.0001$ | 0.25870 | 3.86544 |  |
| Asset share | -0.00002068 | 0.00029345 | -0.07 | 0.9438 | 0.88855 | 1.12543 |  |

Collinearity Diagnostics

|  |  |  |
| :--- | :--- | :--- |
|  |  | Condition <br> NumberEigenvalue |
| 1 | 5.86573 | 1.00000 |
| 2 | 1.08493 | 2.32520 |
| 3 | 0.95347 | 2.48032 |
| 4 | 0.81181 | 2.68803 |
| 5 | 0.43791 | 3.65991 |
| 6 | 0.30404 | 4.39233 |
| 7 | 0.23816 | 4.96282 |
| 8 | 0.20546 | 5.34312 |
| 9 | 0.09289 | 7.94634 |
| 10 | 0.00560 | 32.36171 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are too high (i.e., some values are greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that, while these variables are statistically significant, the VIF values are too high. That is a red flag indicating that we need to investigate this model more.

The eigenvalue should not be too close to zero. Here, you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are violated in this model. Therefore, we can say that this model needs to be improved or has room for improvement.
5) Fixed Asset Expense Ratio is another one of the key components of PPNR. The regression of this equation helped in understanding how Fixed Asset Expense Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Fixed Asset Expense Ratio regression:
Root MSE 0.05431 R-Square 0.8346 Dependent Mean0.44498 Adj R-Sq0.8345

| Root MSE | 0.05431 R-Square 0.8346 |
| :--- | :--- |
| Coeff Var | 12.20513 |

Parameter Estimates

| Label | Parameter Estimate | Standard Error | t Value | $\mathrm{Pr}>\|\mathrm{t}\|$ | Tolerance | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Intercept | 0.13011 | 0.00718 | 18.11 | <. 0001 |  | 0 |
| Real GDP Annualized Log |  |  |  |  |  |  |
| Change | 0.00055199 | 0.00025265 | 2.18 | 0.0289 | 0.87712 | 1.14009 |
| Lag Fixed Asset Expense Ratio | 0.85256 | 0.00365 | 233.50 | <. 0001 | 0.69060 | 1.44802 |
| Time | -0.00186 | 0.00011362 | -16.38 | <. 0001 | 0.60452 | 1.65419 |
| Residential RE Loan Ratio | -0.00032081 | 0.00008521 | -3.76 | 0.0002 | 0.45416 | 2.20189 |
| Commercial RE Loan Ratio | -0.00032763 | 0.00008594 | -3.81 | 0.0001 | 0.41564 | 2.40594 |
| C\&I Loan Ratio | -0.00047036 | 0.00011727 | -4.01 | <. 0001 | 0.39409 | 2.53749 |
| Credit Card Loan Ratio | -0.00055351 | 0.00009785 | -5.66 | <. 0001 | 0.47363 | 2.11137 |
| Trading Assets Ratio | -0.00129 | 0.00012457 | -10.33 | <. 0001 | 0.14971 | 6.67937 |
| Securities Ratio | -0.00085286 | 0.00008585 | -9.93 | <. 0001 | 0.25964 | 3.85153 |
| Asset share | -0.00007559 | 0.00009530 | -0.79 | 0.4277 | 0.88548 | 1.12934 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 7.06574 | 1.00000 |
| 2 | 1.10058 | 2.53377 |
| 3 | 0.83583 | 2.90751 |
| 4 | 0.54549 | 3.59904 |
| 5 | 0.41805 | 4.11116 |
| 6 | 0.32255 | 4.68037 |
| 7 | 0.25558 | 5.25798 |
| 8 | 0.22294 | 5.62964 |
| 9 | 0.14754 | 6.92025 |
| 10 | 0.08047 | 9.37049 |
| 11 | 0.00523 | 36.75640 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are too high (i.e., some values are greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that not all these variables are statistically significant at a $10 \%$ level; one of VIF values is too high. That is a red flag indicating that we need to investigate this model more.

The eigenvalue should not be too close to zero. Here, you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are violated in this model. Therefore, we can say that this model needs to be improved or has room for improvement.
6) All Other Expense Ratio is a key component of PPNR. The regression of this equation helped in understanding how All Other Expense Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the All Other Expense Ratio regression:

| Root MSE | 0.54452 |
| :--- | ---: |
| R-Square 0.7721 |  |
| Dependent Mean 1.54506 Adj R-Sq0.7720 |  |
| Coeff Var | 35.24261 |

Parameter Estimates

| Label | Parameter <br> Estimate | Standard <br> Error |  | t Value Pr $>\|\mathbf{t}\|$ | Tolerance <br> Inflation |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 0.14760 | 0.05963 | 2.48 | 0.0133 | . | 0 |
| Change in bond spread | 0.17857 | 0.01392 | 12.83 | $<.0001$ | 0.99575 | 1.00427 |
| Lag All Other Expense Ratio 0.81574 | 0.00469 | $174.11<.0001$ | 0.60491 | 1.65314 |  |  |
| Residential RE Loan Ratio | -0.00227 | $0.00085333-2.66$ | 0.0078 | 0.45526 | 2.19653 |  |
| Commercial RE Loan Ratio | $-0.000938210 .00085111-1.10$ | 0.2703 | 0.42597 | 2.34756 |  |  |
| C\&I Loan Ratio | -0.00171 | 0.00112 | -1.53 | 0.1266 | 0.43504 | 2.29863 |
| Credit Card Loan Ratio | 0.01530 | 0.00105 | 14.64 | $<.0001$ | 0.41711 | 2.39746 |
| Trading Assets Ratio | -0.000806600 .00121 | -0.67 | 0.5044 | 0.16000 | 6.24982 |  |
| Securities Ratio | 0.00886 | 0.0008608510 .29 | $<.0001$ | 0.25956 | 3.85268 |  |
| Asset share | -0.00369 | $0.00095753-3.85$ | 0.0001 | 0.88164 | 1.13425 |  |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 5.44636 | 1.00000 |
| 2 | 1.11059 | 2.21450 |
| 3 | 0.99956 | 2.33426 |
| 4 | 0.94226 | 2.40419 |
| 5 | 0.50567 | 3.28186 |
| 6 | 0.39133 | 3.73061 |
| 7 | 0.23730 | 4.79076 |
| 8 | 0.20548 | 5.14834 |
| 9 | 0.15430 | 5.94109 |
| 10 | 0.00714 | 27.61189 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are too high (i.e., some values are greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that not all these variables are statistically significant at a $10 \%$ level; one of VIF values is too high. That is a red flag indicating that we need to investigate this model more.

The eigenvalue should not be too close to zero. Here, you can see that the last value in the Collinearity Diagnostics table is close to zero. Therefore, the model has a strong collinearity. Next,
we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are violated in this model. Therefore, we can say that this model needs to be improved or has room for improvement.
7) Return on AFS Asset for Sale, last but not least, is a key component of PPNR. The regression of this equation helped in understanding how Return on AFS Asset for Sale will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Return on AFS Asset for Sale regression:

| Root MSE | 2.41203 | R-Square | 0.0352 |
| :--- | :---: | :---: | :---: |
| Dependent Mean0.20033 | Adj R-Sq | 0.0350 |  |
| Coeff Var | 1204.01453 |  |  |

Parameter Estimates

| Label | Parameter Estimate | Standard Error | t Value Pr > $\mid$ t $\mid$ | Tolerance | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Intercept | 0.27221 | 0.03085 | 8.82 <. 0001 |  | 0 |
| Quarterly change in 10 year |  |  |  |  |  |
| Treasury yield(pct) | -0.58037 | 0.08766 | -6.62<.0001 | 0.93504 | 1.06948 |
| AFS Ratio X Change in bond |  |  |  |  |  |
| Lag Return on AFS | 0.12753 | 0.00984 | $12.96<.0001$ | 0.99326 | 1.00679 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue <br> Index |
| :--- | :--- | :--- |
| 1 | 1.46568 | 1.00000 |
| 2 | 1.03626 | 1.18929 |
| 3 | 0.83040 | 1.32855 |
| 4 | 0.66766 | 1.48164 |

Summary of Findings: In the Parameter Estimates table,, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that all these variables are statistically significant at a $10 \%$ level.

The eigenvalue should not be too close to zero. Here, you can see that the last value in the collinearity diagnostics of this model shows that the model does not have a strong correlation. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. These rules are not violated for this model. Therefore, we can say that this model is reasonable.

In short, in the seven models that we looked at to study PPNR key components, only one is reasonable (i.e., statistically significant). Six of the seven key PPNR component models can be improved.

### 4.6.2 CLASS-X Model Specification Details

Here, we looked at the specification details for the seven key components of the CLASSX model (Net Interest Margin, NonInterest Nontrading Income Ratio, Return on Trading Asset, Compensation Non-Interest Expense Ratio, Fixed Asset NonInt Expense Ratio, Other NonInterest Expense Ratio, and Return on AFS Assets for Sale Securities) to see how they differ from the CLASS model.

1) Net Interest Margin is one of the key components of PPNR/CALLS-X. We tried to improve this model based on the deficiency we have found in the CLASS model. As in the CLASS model, the regression of this equation helped in understanding how Net Interest Margin will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Net Interest Margin regression:

| Root MSE | 0.34025 | R-Square | 0.8731 |
| :--- | ---: | ---: | ---: |
| Dependent Mean3.51095 | Adj R-Sq | 0.8730 |  |
| Coeff Var | 9.69125 |  |  |


$\left.$| Label | Parameter <br> Estimate | Standard <br> Error |  | t Value | $\operatorname{Pr}>\|\boldsymbol{t}\|$ |
| :--- | :---: | :--- | :--- | :--- | :--- | | Variance |
| :--- |
| Inflation | \right\rvert\,


|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 6.23501 | 1.00000 |
| 2 | 0.99040 | 2.50907 |
| 3 | 0.52386 | 3.44995 |
| 4 | 0.42252 | 3.84144 |
| 5 | 0.28776 | 4.65479 |
| 6 | 0.22967 | 5.21039 |
| 7 | 0.18069 | 5.87422 |
| 8 | 0.08148 | 8.74753 |
| 9 | 0.04861 | 11.32597 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that all the variables are statistically significant at a $10 \%$ level. That is not a red flag that could signal us to investigate this model further. All the values are statistically reasonable (i.e., not too high or not too low).

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is not too close to zero. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. These rules are not violated for this model. Therefore, we can say that this model is an improved version of the other model that we see in the CLASS specification. It solves the collinearity issues and makes the explanatory variables statistically significant.
2) Noninterest Non-Trading Income Ratio is the second key component of PPNR/CLASS-X. We tried to improve this model based on the deficiency we found in the CLASS specification. As in the CLASS model, the regression of this equation helped in understanding how Noninterest NonTrading Income Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Noninterest Non-Trading Income Ratio regression:

| Root MSE | 0.56888 |
| :--- | ---: |
| R-Square 0.8784 |  |
| Dependent Mean2.31178 Adj R-Sq0.8784 |  |
| Coeff Var | 24.60790 |

Parameter Estimates

| Label | Parameter <br> Estimate | Standard <br> Error | t Value | Pr $>\|\boldsymbol{t}\|$ | Variance <br> Inflation |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 0.17084 | 0.02012 | 8.49 | $<.0001$ | 0 |
| Real GDP Annualized Log Change | -0.00866 | 0.00360 | -2.40 | 0.0162 | 2.03565 |
| Stock Market Quarterly Log Change | 0.00425 | 0.00084223 | 5.05 | $<.0001$ | 1.35307 |
| AFS Ratio X Change in bond spread X | -0.00274 | 0.00050351 | -5.45 | $<.0001$ | 1.46319 |
| $>0$ Dummy | 0.04283 | 0.00706 | 6.06 | $<.0001$ | 1.77756 |
| Change in Unemployment | 0.00432 | 0.00099778 | 4.33 | $<.0001$ | 1.51763 |
| Year over year HPI |  |  |  |  |  |
| Lag Noninterest Non-Trading Income |  |  | 264.86 | $<.0001$ | 1.48143 |
| Ratio | -0.00373 | 0.00341 | 0.00064028 | -5.83 | $<.0001$ |
| Commercial RE Loan Ratio | 0.01124 | 0.00088816 | 12.66 | $<.0001$ | 1.417461 |
| Credit Card Loan Ratio | 0.00477 | 0.00051594 | 9.24 | $<.0001$ | 1.18529 |
| Securities Ratio | -0.00648 | 0.00101 | -6.39 | $<.0001$ | 1.08540 |
| Asset share |  |  |  |  |  |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 4.65526 | 1.00000 |
| 2 | 2.03483 | 1.51254 |
| 3 | 1.04591 | 2.10972 |
| 4 | 0.90077 | 2.27335 |
| 5 | 0.61335 | 2.75498 |
| 6 | 0.48667 | 3.09282 |
| 7 | 0.42151 | 3.32330 |
| 8 | 0.35891 | 3.60146 |
| 9 | 0.22670 | 4.53158 |
| 10 | 0.17953 | 5.09219 |
| 11 | 0.07657 | 7.79747 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that all the variables are statistically significant at a $10 \%$ level. That is not a red flag signaling us to investigate this model further. All the values are statistically reasonable (i.e., not too high or not too low).

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is not too close to zero. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are not violated in this model. Therefore, we can say that this model is an improved version of the model we see with the CLASS specification. It solves the collinearity issues and makes the explanatory variables statistically significant.
3) Trading Income Ratio is a key component of PPNR/CLASS-X. We tried to improve this model based on the deficiency that we found with the CLASS specification. As in the CLASS model, the regression of this equation helped in understanding how Trading Income Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Trading Income Ratio regression:

| Root MSE | 1.54212 | R-Square 0.5618 |
| :--- | ---: | ---: |
| Dependent Mean2.25219 Adj R-Sq0.5409 |  |  |
| Coeff Var | 68.47204 |  |

Parameter Estimates

| Variable | Parameter <br> Estimate | Standard <br> Error | $\mathbf{t}$ Value | Pr $>\|\boldsymbol{t}\|$ | Variance <br> Inflation |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 3.35361 | 0.24635 | 13.61 | $<.0001$ | 0 |
| unsafe_dbspread_pos-0.08238 | 0.01536 | -5.36 | $<.0001$ | 1.37117 |  |
| yyhpi_zero | 0.17803 | 0.05292 | 3.36 | 0.0013 | 1.72826 |
| yycppi | -0.06624 | 0.01698 | -3.90 | 0.0002 | 1.30799 |

Collinearity Diagnostics

|  |  |  |
| :--- | :--- | :--- |
| NumberEigenvalue |  | Condition <br> Index |
| 1 | 1.87717 | 1.00000 |
| 2 | 1.28701 | 1.20770 |
| 3 | 0.57180 | 1.81187 |
| 4 | 0.26401 | 2.66648 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that Variance Inflation values are not too high (i.e., no values are greater than 5). We can say that all variables are not statistically significant at a $1 \%$ level. This is not red flag to signal us to investigate or refine this model further.

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is reasonable. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Here, we can say that this model adheres to our rules.
4) Compensation Expense Ratio is the fourth key component of PPNR/CLASS-X. We tried to improve this model based on the deficiency that we found with the CLASS specification. As in the CLASS model, the regression of this equation helped with understanding how Compensation Expense Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Compensation Expense Ratio regression:

| Root MSE | 0.17060 R-Square 0.8330 |
| :--- | ---: |
| Dependent Mean1.67798 Adj R-Sq0.8329 |  |
| Coeff Var | 10.16694 |

Parameter Estimates

| Label | Parameter <br> Estimate | Standard <br> Error | $\mathbf{t}$ Value | $\operatorname{Pr}>\|\boldsymbol{t}\|$ | Variance <br> Inflation |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 0.16779 | 0.00705 | 23.78 | $<.0001$ | 0 |
| Real GDP Annualized Log Change | -0.00933 | 0.00107 | -8.75 | $<.0001$ | 1.98393 |
| Stock Market Quarterly Log Change | 0.00343 | 0.00024978 | 13.73 | $<.0001$ | 1.32328 |
| AFS Ratio X Change in bond spread X | -0.00144 | 0.00014713 | -9.82 | $<.0001$ | 1.38927 |
| $>0$ Dummy | -0.00615 | 0.00199 | -3.09 | 0.0020 | 1.56523 |
| Change in Unemployment | 0.90399 | 0.00329 | 274.74 | $<.0001$ | 1.01529 |
| Lag Compensation Expense Ratio | 0.000626780 .00018821 | 3.33 | 0.0009 | 1.00783 |  |
| Residential RE Loan Ratio |  |  |  |  |  |

Collinearity Diagnostics

|  | Condition <br> Index |
| :--- | :--- |
| NumberEigenvalue | 1.00000 |
| 1 | 3.45310 |


|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 2 | 1.78495 | 1.39088 |
| 3 | 0.77551 | 2.11014 |
| 4 | 0.55538 | 2.49350 |
| 5 | 0.22858 | 3.88670 |
| 6 | 0.15497 | 4.72045 |
| 7 | 0.04751 | 8.52509 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated and any values that are greater than 10 are not acceptable. Here, we can say that all the variables are statistically significant at a $1 \%$ level. There is no red flag signaling us to investigate this model further. All the values are statistically reasonable (i.e., not too high or not too low).

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is not too close to zero. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are not violated in this model. Therefore, we can say that this model is an improved version of the model that we saw with the CLASS specification. It solves the collinearity issues and makes the explanatory variables statistically significant. It is a better model than the model in the CLASS specification.
5) Fixed Asset Expense Ratio is another key component of PPNR/CLASS-X. We tried to improve this model based on the deficiency we found in the CLASS specification. As in the CLASS model, the regression of this equation helped with understanding how Fixed Asset Expense Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Fixed Asset Expense Ratio regression:

| Root MSE <br> Dependent Me Coeff Var | $\begin{aligned} & \hline 0.05306 \text { R-S } \\ & \text { n0.42892 Adj } \\ & 12.36983 \end{aligned}$ | $\begin{aligned} & \text { are0.8370 } \\ & \text {-Sq0.8369 } \end{aligned}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Parameter Estimates |  |  |  |  |  |
| Label | Parameter Estimate | Standard Error | t Value | $\operatorname{Pr}>\|t\|$ | Variance Inflation |
| Intercept | 0.02633 | 0.00212 | 12.45 | <. 0001 | 0 |
| Real GDP Annualized Log Change | 0.00222 | 0.00033555 | 6.63 | <. 0001 | 2.03278 |
| Stock Market Quarterly Log Change | 0.00027164 | 0.00008574 | 3.17 | 0.0015 | 1.61203 |
| Change in bond spread | 0.01243 | 0.00202 | 6.15 | <. 0001 | 2.20479 |
| AFS Ratio X Change in bond spread X |  |  |  |  |  |
| >0 Dummy | -0.00018078 | 0.00005656 | -3.20 | 0.0014 | 2.12267 |
| Change in Unemployment | 0.00304 | 0.00063252 | 4.81 | <. 0001 | 1.63839 |
| Lag Fixed Asset Expense Ratio | 0.88305 | 0.00337 | 262.14 | <. 0001 | 1.11238 |
| Residential RE Loan Ratio | 0.00025509 | 0.00006150 | 4.15 | <. 0001 | 1.11235 |


| Label | Parameter <br> Estimate | Standard <br> Error | t Value | $\operatorname{Pr}>\|t\|$Variance <br> Inflation |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Commercial RE Loan Ratio | 0.00022870 | 0.00005901 | 3.88 | 0.0001 | 1.14704 |
| C\&I Loan Ratio | 0.00055893 | 0.00008258 | 6.77 | $<.0001$ | 1.13793 |
| Credit Card Loan Ratio | 0.00016692 | 0.00007312 | 2.28 | 0.0225 | 1.10425 |

Collinearity Diagnostics

|  |  | Condition <br> Number |
| :--- | :--- | :--- |
| 1 | 4.94720 | 1.00000 |
| 2 | 2.28754 | 1.47060 |
| 3 | 1.03634 | 2.18489 |
| 4 | 0.89628 | 2.34941 |
| 5 | 0.58291 | 2.91325 |
| 6 | 0.35183 | 3.74987 |
| 7 | 0.28818 | 4.14330 |
| 8 | 0.21593 | 4.78651 |
| 9 | 0.19756 | 5.00414 |
| 10 | 0.13655 | 6.01906 |
| 11 | 0.05968 | 9.10498 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that all the variables are statistically significant at a $5 \%$ level. There is no red flag signaling us to investigate this model further. All the values are statistically reasonable (i.e., not too high or not too low).

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is not too close to zero. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are not violated in this model. Therefore, we can say that this model is an improved version of the one that we saw in the CLASS specification. It solves the collinearity issues and makes the explanatory variables statistically significant. It is a better model than the model in the CLASS specification.
6) All Other Expense Ratio is one of the key components of PPNR/CLASS-X. We tried to improve this model based on the deficiency we found in the CLASS specification. As in the CLASS model, the regression of this equation helped in understanding how All Other Expense Ratio will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the All Other Expense Ratio regression:

| Root MSE | 0.56046 |
| :--- | ---: |
| R-Square 0.7810 |  |
| Dependent Mean1.54167 Adj R-Sq0.7809 |  |
| Coeff Var | 36.35412 |

Parameter Estimates

| Label | Parameter <br> Estimate | Standard <br> Error | t Value | $\operatorname{Pr}>\|\boldsymbol{t}\|$ | Variance <br> Inflation |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | -0.05116 | 0.01797 | -2.85 | 0.0044 | 0 |
| Real GDP Annualized Log Change | 0.01241 | 0.00350 | 3.55 | 0.0004 | 1.97958 |
| Stock Market Quarterly Log Change | 0.00643 | 0.00091185 | 7.06 | $<.0001$ | 1.63400 |
| Change in bond spread | 0.07949 | 0.02990 | 2.66 | 0.0079 | 4.32171 |
| Change in bond spread X >0 Dummy | 0.19109 | 0.04760 | 4.01 | $<.0001$ | 5.91642 |
| AFS Ratio X Change in bond spread X |  |  |  |  |  |
| $>0$ Dummy | 0.00280 | 0.00069881 | 4.01 | $<.0001$ | 2.90371 |
| Change in Unemployment | 0.03153 | 0.00690 | 4.57 | $<.0001$ | 1.74857 |
| Lag All Other Expense Ratio | 0.81820 | 0.00495 | 165.19 | $<.0001$ | 1.68986 |
| Credit Card Loan Ratio | 0.01691 | 0.00089694 | 18.86 | $<.0001$ | 1.48908 |
| Securities Ratio | 0.01038 | 0.00056680 | 18.32 | $<.0001$ | 1.47376 |
| Asset share | -0.00350 | 0.00097404 | -3.59 | 0.0003 | 1.03091 |

Collinearity Diagnostics

|  |  | Condition <br> Index |
| :--- | :--- | :--- |
| NumberEigenvalue | 1.00000 |  |
| 2 | 2.04552 | 1.16477 |
| 3 | 1.08193 | 1.96908 |
| 4 | 0.90373 | 2.11576 |
| 5 | 0.62035 | 2.55370 |
| 6 | 0.48952 | 2.87477 |
| 7 | 0.33334 | 3.48374 |
| 8 | 0.24363 | 4.07493 |
| 9 | 0.15518 | 5.10580 |
| 10 | 0.10882 | 6.09731 |
| 11 | 0.07460 | 7.36402 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that all the variables are statistically significant at a $1 \%$ level. There is no red flag signaling us to investigate this model further. All the values are statistically reasonable (i.e., not too high or not too low).

The eigenvalue should not be too close to zero. Here, you can see the last value in the Collinearity Diagnostics table is not too close to zero. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. These rules are not violated in this model. Therefore, we can say that this model is an improved version of the model that we saw in the CLASS specification. It solves the collinearity issues and makes the explanatory variables statistically significant. It is a better model than the model in the CLASS specification.
7) Return on AFS Assets for Sale is one of the key components of PPNR/CLASS-X. We tried to improve this model based on the deficiency we found in the CLASS specification. As in the CLASS model, the regression of this equation helped in understanding how Return on AFS Assets for Sale will change by changing any of the explanatory variables. It also helped us understand the sensitivity of financial strength with macroeconomic variables. Below are the statistical results of the Return on AFS Assets for Sale regression:

| Root MSE | 2.41591 | R-Square | 0.0321 |
| :--- | :---: | :---: | :---: |
| Dependent Mean0.20033 | Adj R-Sq | 0.0319 |  |
| Coeff Var | 1205.94681 |  |  |

Parameter Estimates

| Label | ParameterStandard <br> Estimate | Error | t ValuePr $>\|t\| l \mid l$ | Variance <br> Inflation |
| :--- | ---: | :--- | :--- | :--- |
| Intercept | 0.26975 | 0.033218 .12 | $<.00010$ |  |
| AFS Ratio X Change in bond spread X >0 Dummy-0.02575 | $0.00176-14.62<.00011 .02038$ |  |  |  |
| Year over year CPPI | 0.00370 | 0.002351 .58 | 0.11521 .01476 |  |
| Lag Return on AFS | 0.12750 | $0.0098612 .93<.00011 .00741$ |  |  |

Collinearity Diagnostics

|  | NumberEigenvalue | Condition <br> Index |
| :--- | :--- | :--- |
| 1 | 1.44818 | 1.00000 |
| 2 | 1.08490 | 1.15536 |
| 3 | 0.92189 | 1.25335 |
| 4 | 0.54502 | 1.63006 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that the Variance Inflation values are reasonable (i.e., values are not greater than 5). The rule of thumb is that any VIF values that are greater than 5 have to be investigated, and any values that are greater than 10 are not acceptable. Here, we can say that all the variables are statistically significant at a $1 \%$ level. There is no red flag signaling us to investigate this model further. All the values are statistically reasonable (i.e., not too high or not too low).

The eigenvalue should not be too close to zero. Here, the last value in the Collinearity Diagnostics table is not too close to zero. Next, we looked at the condition index. According to the rule of thumb, a model with a condition index greater than 15 needs to be investigated, and any model with a condition index greater than 30 is not acceptable. Again, these rules are not violated in this model. Therefore, we can say that this model is an improved version of the model we saw in the CLASS specification. It solves the collinearity issues and makes the explanatory variables statistically significant. It is a better model than the model in the CLASS specification.

In short, we can say that the models that are in CLASS-X specifications are better than the models that are in CLASS specifications because of variable selection. The statistical analysis results that we have obtained in CLASS-X specifications are also better than those in the CLASS model.

### 4.7 CLASS-X Model 3 Specifications

While finding that CLASS-X Model 1 and Model 2 performed better than the CLASS model, we wanted to continue to look at another approach that can be used for regressions for the seven key PPNR components. We analyzed the different models in VARMAX and used the Bayesian Vector Error Correction model to fit PPNR data for CLASS-X Model 3.

### 4.7.1 CLASS-X Model 3 - Bayesian Vector Correction Model from VARMAX Procedure

This model uses the The Bayesian Vector Correction model from VARMAX procedure to fit PPNR data. Given a multivariate time series, the VARMAX estimates the model parameters and generates forecasts associated with vector autoregressive moving-average processes with exogenous regressors (VARMAX) models. Often, economic or financial variables are not only contemporaneously correlated to each other's past values. In many economic and financial applications, the variables of interest (dependent, response, or endogenous variables) are influenced by variables external to the system under consideration (independent, input, predictor, regressor, or exogenous variables). The VARMAX procedure enables you to model the dynamic relationship both, between the dependent variables and between the dependent and independent variables.

The form of the model can be written as

$$
y t=\sum_{i=1}^{p} \Phi_{i} y_{t-i}+\sum_{i=1}^{p} \theta_{i} x_{t-i}+\varepsilon t-\sum_{i=1}^{p} \Theta_{i} \varepsilon_{t-1}
$$

## Equation 5: CLASS-X Model 3 Equation

where the output variables of interest $\mathrm{yt}=(\mathrm{ylt} \ldots . \mathrm{Ykt})^{\prime}$ can be influenced by other input variables $\mathrm{xt}=(\mathrm{x} 1 \mathrm{t} \ldots$. Xrt), which are determined outside of the system of interest. The variables yt are referred to as dependent response, or endogenous, variables and the variables xt are referred to as independent variables, input, predictor, regressor, or exogenous variables. The unobserved noise variables, $\varepsilon t=(\varepsilon 1 t \ldots \varepsilon k t)$, are a vector white noise process. VARMAX can be written in a different form as well.

The name VARMAX is an abbreviation for Vector Autoregressive Moving Average models with exogenous variables. This output has three main parts - basic statistical properties of the series, by estimation of a particular model, and checks of the fitted model. If the option PRINTALL is included, many more features of the model are presented, leading to a huge output.

A way to reduce the number of parameters in the autoregressive model is to consider Bayesian estimation. The idea is that an informative prior is applied to the autoregressive parameters, where the prior reflects the intuitive feeling that it is more natural to include the parameters for lag 1 in the model than autoregressive parameters for higher lags. In Bayesian terms, this is obtained by a prior that concentrates more around zero for higher lags, so that the evidence from data has to be stronger in order to have a significant estimate at a high lag than for lag 1. This class of model is denoted BVAR models.

In PROC VARMAX, the prior covariance of the autoregressive matrices is as proposed by Litterman (1986). It includes two parameters, $\theta$ and $\lambda$, which could be specified by the user. The PRIOR option to the MODEL statement specifies the BVAR model with default values are $\theta=0.1$ and $\lambda=1$. It is possible to change the prior distribution by specifying the parameters of distribution. Other means of the prior distribution than the default value zero could be applied, but, in this application, it is more interesting to change the variance of the prior. According to the definition
of the prior, the prior distribution becomes wider when $\theta$ and $\lambda$ increase. For large values of $\theta$ and $\lambda$, the result of the Bayesian estimation approaches the result of the maximum likelihood estimation, and more parameters become significant. On the other hand, the shrinkage toward zero is strengthened when smaller values of $\theta$ and $\lambda$ are used. In the next application, the rather small values of $\theta=0.02$ and $\lambda=0.5$ are applied.

VARMAX models are defined in terms of the orders of the autoregressive or movingaverage process (or both). When you use the VARMAX procedure, these orders can be specified by options or they can be automatically determined. Criteria for automatically determining these orders include the following - Akaike information criterion (AIC), corrected AIC (AICC), HannanQuinn (HQ) criterion, final prediction error (FPE), and Schwarz Bayesian criterion (SBC), also known as Bayesian information criterion (BIC).

For stationary vector time series (or nonstationary series made stationary by appropriate differencing), the VARMAX procedure provides for vector autoregressive and moving-average (VARMA) and Bayesian vector autoregressive (BVAR) models. To cope with the problem of high dimensionality in the parameters of the VAR model, the VARMAX procedure provides both, the vector error correction model (VECM) and the Bayesian vector error correction model (BVECM). Bayesian models are used when prior information about the model parameters is available. The VARMAX procedure also allows independent (exogenous) variables, with their distributed lags, to influence dependent (endogenous) variables in various models, such as VARMAX, BVARX, VECMX, and BVECMX models.

Forecasting is one of the main objectives of multivariate time series analysis. After successfully fitting the VARMAX, BVARX, VECMX, and BVECMX models, the VARMAX procedure computes predicted values based on the parameter estimates and the past values of the vector time series. The VARMAX procedure parameter estimation methods are Least Squares (LS) or Maximum Likelihood (ML). The kind of models supported by the VARMAX procedure are - Vector Autoregressive Process, Bayesian Vector Autoregressive Process, Vector Error Correction Model, Bayesian Vector Error Correction Model, and Vector Autoregressive Process with Exogenous Variables. We leveraged BVECMX (Bayesian Vector Error Correction Model), which uses the ML method. The results of this model (CLASS-X Model 3) can be seen in Appendix D of this document.

### 4.8 Table Comparison of CLASS and CLASS-X Models

Below we show the attributes that we used to summarize the differences between the CLASS model and CCAR-X model. As you can see in the table, the CLASS model has a topdown structure and CLASS-X is a bottom up, top-down model. Both use public data, and CLASSX leveraged some data from the CLASS model. The CLASS model focuses on the 200 largest financial companies, while CLASS-X replicated the regressions of the CLASS model and performed econometric analyses on the 19 companies that were part of the initial CCAR stress test.

CLASS-X focuses more on the econometric analysis of the seven key PPNR components. Detail comparisons of the regression results of these two models can be seen in Appendix B and D of this document. In the table below we summarized how the CLASS-X model is different from the CLASS model.

|  | CLASS Model | CLASS-X Model | DFAST/CCAR |
| :--- | :--- | :--- | :--- |
| Model | Top-down models based on aggregated <br> outcomes (e.g., net charge-offs) for <br> broad income categories and loan and <br> securities securities portfolios | Top-down models based on the <br> specifivation of CLASS Model and <br> Bottom up based on the data from <br> FRY9C reports | Bottom-up models focused on the risk <br> characteristics of individual loans, <br> securities, and trading positions |
| Data | Publicly available balance sheet and <br> income statement regulatory report <br> data from Call and Y-9C filings | Publicly available balance sheet and <br> income statement regulatory report <br> data from Call and Y-9C filings | Detailed supervisory information from <br> individual BHCs, often at the level of |
| individual loans or securities |  |  |  |

Table 5: CLASS-X should be look at as an alternative model regression for The CLASS model
This table summarizes the comparison of attributes of the CLASS and CLASS-X models.

### 4.9 Forecast with PPNR CLASS

We wanted to forecast each one of the seven key PPNR components for the following scenarios - base, redux, and historical. We also looked at the sensitivity for assets growth, provision assumption and payout for Tier 1 common ratio. We documented our findings in Appendix E and Figures $12,13,15,16,17,18,19$, and 20 of the document.

### 4.10 Fitted and CLASS-X Model

We fit our CLASS-X model for one PPNR component, and we forecasted for the seven key PPNR components. We documented our findings in Appendix E and Figures 12, 13, 15, 16, $17,18,19$, and 20 of this document.

### 4.11 Conclusion

We conclude that the CLASS specification is a good stress test model, if you want to stress test aggregate PPNR data. However, if you segment the data, CLASS-X is a better specification. If you also segment the data to an individual company, CLASS-X is again better than the CLASS specification. The strong variable correlation within the CLASS model specifications could
produce unexpected results when you segment the data to a sub-dataset. CLASS-X also performs well with PPNR aggregate data.

## Chapter 5: Model Testing and Evaluation or Validation

### 5.1 Model Structure

In this chapter, we provide more details on how to validate the CLASS-X model. The structure of the models that we have created for our research is documented in Section 1 of this document. Like PPNR/CLASS specifications, CLASS-X specifications have the following models - 1) Net Interest Margin, 2) Noninterest Nontrading Income Ratio, 3) Return on Trading Asset, 4) Compensation Non-Interest Expense Ratio, 5) Fixed Asset NonInterest Expense Ratio, 6) Other NonInterest Expense Ratio, and 7) Return on AFS Assets for Sale Securities. Reviewing the 5 steps that we used to develop these models could be very helpful in validating these models.

### 5.2 Processing Input Data

The inputs for the equations can be summarized as follows - we have the macroeconomic variables, the balance sheet values for the financial institutions (HBCs), the lag for the dependent variables, and the time control variable. These variables are clearly displayed in PPNR/CLASS specifications.

We tried to understand the impact the independent variables have on the dependent variables.

### 5.3 Model Formulation

The formulations of the models that we used in this research are in Section 1.1.1 of the document. It is closely related to the PPNR/CLASS model.

### 5.4 Underlying Input Estimation

Most of the input variables we used in this research are feeder inputs that we found when we consolidated our dataset.

### 5.5 Adjustments and Special Cases

We did not make any major adjustments in the data in addition to filling some of the blank fields that were in the raw data.

### 5.6 Sensitivity Analysis

In Appendix E Figures 19, 20 and 21, we performed a scenario analysis on several variables. Based on the regressions that we performed with the consolidated data, we verified the conclusion that these models are sensitive to a variety of model assumptions about asset growth, loan loss provisioning, and capital distributions.

In Figure 18, for asset growth assumption, we have verified the asset growth rate assumption. Recall that the CLASS model assumes asset growth of $1.25 \%$ per quarter ( $5 \%$ per year). In the figure, we compare our Tier 1 common equity ratio projections under this baseline assumption to projections under three other asset growth rates, ranging from $2.5 \%$ per quarter to $1.25 \%$ per quarter. As the figure shows, the path of the projected capital ratio is, quantitatively,
very sensitive to which assumption is chosen - after nine quarters, the Tier 1 common equity ratio is around $13 \%$ under a $-1.25 \%$ asset growth rate, but only $9 \%$ under a $2.5 \%$ growth rate. This variation is driven primarily by the mechanical fact that the Tier 1 common ratio is directly expressed as a ratio of risk-weighted assets; high asset growth thus acts to reduce the Tier 1 common ratio, while asset shrinkage increases it. Asset growth assumptions also affect the numerator of the capital ratio through their effect on projected dollars of losses, revenues, and expenses. For example, a given projected ROA will, by definition, imply a higher dollar value of net income when assets are higher. See Appendix E Figure 19.

In Figure B, for provisioning assumption, we verified how the model projections are affected by the choice of loan loss provisioning rule. We compared our benchmark assumption for provisions (that provision equal net charge-offs as long as the ALLL stays in a "tunnel" between $100 \%$ and $250 \%$ of the next four quarters of projected net charge-offs) to a "four quarter" rule that sets ALLL equal to the next four quarters of projected net charge-offs under the scenario in question, and to a rule that provision expense is always set equal to net charge-offs.

Among these three approaches, the "provision expense $=$ NCO" rule produced the smallest decline in the industry capital ratio because it leaves ALLL constant at its last historical value, rather than revising ALLL upwards in line with the high-projected future net charge-offs as the adverse macroeconomic scenario plays out. See Appendix E Figure 20.

In Figure C, for capital distribution rules assumption, we considered three alternate capital distribution rules: (i) dividends remain fixed at their last historical value, (ii) dividends are equal to the benchmark rule used by the CLASS model (i.e. dividends adjust gradually towards a payout ratio of $45 \%$ of net income), and (iii) dividends are set equal to zero over the entire scenario. Comparing the two extreme scenarios under the crisis redux scenario, the industry Tier 1 common ratio is about 75 basis points higher under the "zero dividend" assumption than under the "constant dividends" assumption. The rule used by the CLASS model is in between these extremes, although closer to the "constant dividends" assumption, reflecting the model assumption of a slow adjustment speed for dividends. (See Appendix E Figure 21.) The code to test the model is in SAS.

### 5.7 Stress Testing

In our test for the data that we forecasted, we did not do back testing. (See Appendix E.)

### 5.8 Performance Metrics

We looked at the results of our back testing, and we also looked at the results of our forecast. We concluded that the performance of our models is reasonable.

### 5.9 Model Performance

The forecasts of our models are close to the actual data.

### 5.10 Model Change/Mitigation Performance

We suggest that these models are calibrated quarterly, of every other quarter.

### 5.11 Benchmarking

We looked at other studies on the PPNR key components, the trends (upward or downward) that we found are almost the same as other research studies. We found that the CLASS model deteriorated when we segmented the data, while CLASS-X is stable with the same segmented data. Table 20 in Appendix D has the detailed results, when we segmented the data for the 19 companies and performed the regressions with the CLASS and CLASS-X models.

### 5.12 Testing Dataset

We have done some line plots in the macroeconomics data to have a sense of the time series data. The results of this test are in Section 3.1.1.

### 5.13 Modeling Software used

We used several information technology tools in this research. For data extraction, we used Excel. For analytics and modeling, we used SAS for managing the models created, and we used Predix (a cloud computing technology) to develop a risk management system for the models. We used STATA for reverse engineering.

### 5.14 Assumptions

The assumption that we made in our models is the following: macroeconomic variables (three months treasury bill, GDP, and unemployment rate) will not change in an unreasonable fashion (i.e., more than 2 or 3 points in a quarter).

### 5.15 Limitations

This research is based on the PPNR data that we extracted from Federal Reserve Company, market return data from Yahoo finance, and FRED data for the macroeconomics data. The result of this research is based on the quality or completeness of these data. It is important to mention that Federal Reserve Company receives the data quarterly from the SIFI companies that are required to fill out the FRY 9C report quarterly to show the health of their financial institutions. They also need to show their company can survive an adverse situation or severely adverse situation.

### 5.15.1 Long Forecast Horizon

It is requested by the Federal Reserve that the SIFI companies have 9 quarters of financial reserve to survive an adverse scenario. Sometimes, it is good to forecast for a long period, to stress test the financial health of a company.

### 5.15.2 Expert Judgement

The formula for PPNR is not a straight forward formula. We had some conversations with the CLASS model team about variables.

### 5.16 Applicability to Purpose

The models that are in Equation 1 can be used in capital planning for individual financial businesses that want to study their PPNR for planning purposes. These models can also help businesses with creating their policy and procedures to help them manage their business better.

### 5.17 Uncertainty

Of course, there could be uncertainty that could change the outside scope of any assumptions, or change the approach we used in this research. It is important for a model user to understand the model well before using it.

### 5.18 Expert Components

While the Federal Reserve team provides a framework for a PPNR model (the CLASS model), there is still work that needs to be done to improve the CLASS model. Using some of the components in our econometrics analysis, to evaluate the financial health of the 19 initial companies that were part of PPNR stress testing can be very helpful for other research. This
research can also help us visualize the financial strength (upward or downward) of the US economy.

### 5.19 Overrides/Adjustments

We did not make any major adjustments in the data that we used for this research after extracting them from their sources. However, we could not verify each DataStream because the Federal Reserve Company had already consolidated the data by the time we received it. We found some outliers, but we used the data that we had.

### 5.20 Methodology Used to Validate CLASS-X Specification

Below is the description of the methodology that we developed to select the best model for CLASS-X specifications:

1) Replicate the 22 regressions of the CLASS model: In this step, we used STATA to perform a reverse engineering in the CLASS specification to study each model of the specification.
2) Study the regression results for the 22 models: In this step, we studied the parameter estimates of the variable for each one of the models. We performed a multi-collinearity study on the variables, and we looked at the level of statistical significance (e.g., $1 \%, 5 \%$, or $10 \%$ ) of the variables.
3) Summarize the regressions need in each model: After steps 1 and 2, we started understanding the areas where the CLASS model needed to be improved. We formulated a high-level approach to improve the CLASS model
4) Analyze and try different techniques to select variables for CLASS-X specifications: In this step, we used several techniques (forward, backward, stepwise, AIC, and others) to select variables for the CLASS-X models. (See Appendix D Table 17)
5) Select the best model for each one of the key PPNR components: We selected models with the best AIC values and lower percentage in variables correlation.
6) Refine the seven models selected by reducing and strong correlation and the explanatory variable: We refined the models in the CLASS-X specification to make sure these models were statistically sound and met the criteria of SR11-7 standards.
7) Finalize the CLASS-X specifications: We made sure the CLASS-X specifications are conceptually sound, statistically better than its parent (CLASS), and capable of performing well.

### 5.21 Summary and Conclusion

While it is important to come up with new ways to improve the parameters of a regression, it is also important to document how the improvement is made. In this document, we described the methodology that we followed to improve the equations that we developed for CLASS-X. In short, we can say that CLASS-X is, statistically, a better model than the CLASS model.

## Chapter 6: Model Implementation Planning and Execution

### 6.1 List of Models

Here, we provide some guidelines on how this research can be used to implement CCAR/PPNR/CLASS-X model key components within an organization.

The following are the models that we created in our econometrics analysis - 1) Net Interest Margin, 2) NonInterest Nontrading Income Ratio, 3) Return on Trading Asset, 4) Compensation Non-Interest Expense Ratio, 5) Fixed asset Noninterest Expense Ratio, 6) Other NonInterest Expense Ratio, and 7) Return on AFS Assets for Sale Securities. If you want to implement CLASSX, you will need to deploy these models. The specification of CLASS-X can also be seen in Appendix D Table 17 of this document.

### 6.2 Implementation

These models are in SAS. They can be used in other tools as well, if needed (JAVA, R, Matlab, and others). The following are the steps that can be used to improve these models - 1) review CLASS-X specification, 2) build your regressions according to the specification, 3) compare actual data with forecast data, 4) review discrepancies between forecast and actual, and 5) calibrate the model to make the next forecast close to actual. This is an ongoing monitoring process for model improvement. It is a simple and straight-forward approach to implementing the CLASS-X model. For a financial institution, your FRY 9C report has all the data you need to implement this model.

### 6.3 System Used to Manage the Models

To use these models individually, you can launch them in an SAS tool. To institutionalize these models in a large organization, we would like to propose a framework to help you manage your enterprise risk wisely. Below is the proposed risk management framework that can be used at a large scale to manage these models and control your enterprise's financial risks.

## Model Risk Management Framework



## Technology

| Model | Document | Validation | Change | Issues | Workflo | Access | Reporting |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Inventory | Repository | Schedule | Mgmt. | Mgmt. | w Mgmt. | Control |  |

Figure 5: Model Risk Management Framework
These teams should work together to make an enterprise's risk management model succeed:

- Oversight Committee
- $1^{\text {st }}$ Line of Defense
- $2^{\text {nd }}$ Line of Defense
- $3^{\text {rd }}$ Line of Defense
- Business Processes
- Technology

We will provide some details about this framework in the subsequent sections.

### 6.3.1 Functionality

The technology that supports the framework should create the functionalities that each team needs to do their job effectively.

### 6.3.2 System Design

here are different ways that you can design a system to support this framework. Below is a snapshot of an advanced approach:

## PPNR- Architecture Framework



Figure 6: Architecture Framework for PPNR implementation

### 6.3.3 Architecture

You can deploy the models as services. That will help different processes use these models and get the same results.

### 6.3.4 Database Entity Diagram

The databases should manage the data of these models (training, testing, and production).

### 6.3.5 Data Dictionary

The data dictionary should be online to help users understand the model better and quickly.

### 6.3.6 Implementation and Deployment

These models can be used individually or can be deployed in a distributed or multi-layer environment.

### 6.4 Different Components of Decisions Support Systems

All decision support systems share specific features while varying greatly in application and complexity. A typical Decision Support System (DSS) has four components - data management, model management, knowledge management, and user interface management. These components work in synchronization to make the system effective. Below is a simple diagram that can be used to visualize a DSS:


Figure 7: Simple DSS Decision Support Systems

### 6.4.1 Data Management Component

The data management component performs the function of storing and maintaining the information that you want your Decision Support System to use. The data management component, therefore, consists of both, the DSS information and the DSS database management system. The information you use in your Decision Support System comes from several sources:

Organizational information: You may want to use virtually any information available in the organization for your Decision Support System. What you use, of course, depends on what you need and whether it is available. You can design your DSS to access this information directly from your company's database and data warehouse. However, specific information is often copied to the DSS database to save the time of searching through the organization's database and data warehouses.

External information: Some decisions require input from external sources of information. Various branches of federal government, data bureaus, and the internet, to mention just a few, can provide additional information for the use of a Decision Support System.

Reference data or Personal information: You can incorporate your own insights, experience, and personal information into your Decision Support System. You can design your DSS so that you enter this personal information only as needed, or you can keep the information in a personal database that is accessible by the Decision Support System. It is important to mention that data can be in different structures or formats.

### 6.4.2 Model Management Component

The model management component consists of both, the Decision Support System models, and the DSS model management system. A model is a representation of some event, fact, or situation. As it is not always practical, or wise, to experiment with reality, people build models and use them for experimentation. Models can take various forms.

Businesses use models to represent variables and their relationships. For example, you would use a statistical model called analysis of variance to determine whether newspaper, TV, and billboard advertising are equally effective in increasing sales. The results of these models can help business managers make better decisions.

Decision Support Systems help in various decision-making situations by utilizing models that allow you to analyze information in many different ways. The models you use in a Decision Support System depend on the decision you are making and, consequently, the kind of analysis you require. For example, you would use what-if analysis to see what effect the change of one or more variables will have on other variables, or optimization to find the most profitable solution given operating restrictions and limited resources. Spreadsheet software such as Excel and more advanced analytic tools (SAS, Matlab, R, and others) can be used as a Decision Support System for what-if analysis.

The model management system stores and maintains the Decision Support System's models. Its function of managing models is similar to that of a database management system. The model management component can not select the best model for you to use for a particular problem, that requires your expertise, but it can help you create and manipulate models quickly and easily. Therefore, you will be able to get all the information you need at your finger tips to make reasonable decision.

### 6.4.3 User Interface Management Component

The user interface management component allows you to communicate with the Decision Support System. It consists of the user interface management system. This is the component that allows you to combine your know-how with the storage and processing capabilities of the computer.

The user interface is the part of the system you see through when entering information, commands, and models. This is the only component of the system with which you have direct contract. If you have a Decision Support System with a poorly designed user interface, if it is too rigid or too cumbersome to use, you simply won't use it no matter what its capabilities. The best user interface uses your terminology and methods, is flexible, consistent, simple, and adaptable.

For an example of the components of a Decision Support System, let's consider that Land's End has a DSS and tens of millions of names in its customer database. It sells a wide range of women's, men's, and children's clothing, as well as various household wares. To match a customer with the right catalog, Land's End has identified 20 different specialty target markets. Customers in these target markets receive catalogs of merchandise that they are likely to buy, saving Land's End the expense of sending catalogs of all products to all 20 million customers. To predict customer demand, Land's End needs to continuously monitor buying trends. And to meet that demand, Land's End must accurately forecast sales levels. To accomplish these goals, it uses a Decision Support System which performs three tasks:

Data management: The Decision Support System stores customer and product information. In addition to this organizational information, Land's End also needs external information, such as demographic, and industry and style trend information.

Model management: The Decision Support System has to have models to analyze this information. The models create new information that decision makers need to plan product lines and inventory levels. For example, Land's End uses a statistical model called regression analysis to determine trends in customer buying patterns and forecasting models to predict sales levels.

User interface management: A user interface enables Land's End decision makers to access information and to specify the models they want to use to create the information they need (dsssystem, 2010).

### 6.4.4 Knowledge Management Component

The knowledge management component, like that in an expert system, provides information about the relationship among data that is too complex for a database to represent. It consists of rules that can constrain possible solutions, as well as alternative solutions and methods for evaluating them.

For example, when analyzing the impact of a price reduction, a Decision Support System should signal if the forecasted volume of activity exceeded the volume that the staff projected they can service. Such signaling requires the Decision Support System to incorporate some rules of thumb about an appropriate ratio of staff to sales volume. Such rules of thumb, also known as heuristics, make up the knowledge base (dsssystem, 2010) .


Figure 8: Decision System Activities

These four components that we describe here are greatly describe a DDS system. In this research paper, we focused on business modeling for seven key components of PPNR.

### 6.5 Summary

The guidelines provided in this chapter can be changed to accommodate the environment where the models will be deployed. For a small organization, you might need a lower-scale enterprise risk framework model. Small or large enterprises with ongoing monitoring should be critical in making sure they monitor their environment properly.

## Chapter 7: Conclusion and Findings

### 7.1 Research Findings Summary

In this chapter, we want to provide a summary of our findings. We also want to outline some future research that can be done on CLASS or CLASS-X specifications. While we are weighing risk and return, it is important to mention to manage your risk wisely to avoid any unexpected results and disasters

Below is a summary of our findings for the alternative PPNR econometric models that we created for this research.

### 7.2 Sensitivity Analysis

Like CLASS specifications, the CLASS-X specifications that we created are sensitive to a variety of modeling assumptions (asset growth, provisioning rule, and dividends payout). While we assume an asset growth of $1.25 \%$ per quarter (or $5 \%$ per year) for Tier 1 common equity ratio, we have seen the changes when we make an assumption of $2.5 \%$ to $-1.25 \%$ growth per quarter. We have seen the changes in provisioning when we compare our benchmark assumption for provision (that provision equal net charge-offs as long as the ALLL stays in a "tunnel" between $100 \%$ and $250 \%$ of the next four quarters of projected net charge-offs) to a "four quarter" rule that sets ALLL equal to the next four quarters of projected net charge-offs under the scenario in question, and to a rule that provision expense is always set equal to net charge-offs. Among these three approaches, the "provision expense $=$ NCO" rule produces the smallest decline in the industry capital ratio, because it leaves ALLL constant at its last historical value, rather than revising ALLL upwards in line with the high, projected, future net charge-offs as the adverse macroeconomic scenario plays out. We saw a similar behavior in the CLASS model as well.

In Figure C, for the capital distribution rules assumption, we considered three alternate capital distribution rules: (i) dividends remain fixed at their last historical value, (ii) dividends are equal to the benchmark rule used by the CLASS model (i.e. dividends adjust gradually towards a payout ratio of $45 \%$ of net income), and (iii) dividends are set equal to zero over the entire scenario. Comparing the two extreme scenarios under the crisis redux scenario, the industry Tier 1 common ratio is about 75 basis points higher under the "zero dividend" assumption than under the "constant dividends" assumption. The rule used by the CLASS model is in between these extremes, although closer to the "constant dividends" assumption, reflecting the model assumption of a slow adjustment speed for dividends. We saw a similar behavior in the CLASS model as well.

This is a clear indication that the CLASS and CLASS-X model projections are sensitive to these elements (asset growth, loan loss provisioning and capital distributions or dividends payout). It is shown that changes in the assumption of these factors change the PPNR model projections.

### 7.3 Scenario Analysis

If we increase the growth assumptions, provisioning assumption, or capital payout, they will have an impact on the PPNR/CLASS model projections. The impact could be positive or negative, based on how we make our assumption (i.e., increase or decrease the values).

### 7.4 Suggested Other Research

There is a list of other research that can be done on this topic (PPNR). To mention a few of them, we can outline the following topics:

- Data Automation for PPNR Econometric Analysis
- PPNR Models Management
- Deep Theoretical Econometrics Analysis for PPNR
- PPNR Models Validation and Calibration
- Deployment and Management of PPNR Models
- Data Integration Within PPNR Components
- Reporting Analysis of PPNR Data

These research topics can touch different critical points that could help the advancement of information technology, risk management, analytics, and others.

In short, this research has been an interesting journey. We collected data from several sources (PPNR, market data, and financial data) and consolidated them into one source. We did preliminary data analysis by line plot to look at the nature of the data (linear, time series, panel data, and others). We continued our data analysis by looking at parameter estimates of different regressions and comparing their results. We forecasted with data from different regression results to look at discrepancies, and tried to find the regression, or the model, that could best fit the data.

We used different techniques to select variables for CLASS-X models and went through multi-collinearity study for the variables selected to make sure that we has a specification that was statistically reasonable and met the criteria of SR11-7 (conceptual soundness, outcome analysis, and ongoing monitoring). Last, we presented CLASS-X as an alternative solution to the CLASS model.

We documented our findings and proposed other researches that can be done in that area. It will be a good framework in MRM (Model Risk Management) for model selection and eCap (Economic Capital Planning). It will enhance the discipline and create a reference point for Model Risk Managers and researchers. Now, they can use CLASS-X for regressions of CCAR/PPNR key components model.

## Glossary

## AAPEMA

Average Absolute Percentage Error Moving Average

## ARIMA

ARIMA stands for Autoregressive Integrated Moving Average models. Univariate (single vector) ARIMA is a forecasting technique that projects the future values of a series based entirely on its own inertia. Its main application is in the area of short term forecasting requiring at least 30 historical data points.

## BHC

Bank Holding Company Financial Institutions
CLASS
Capital and Loss Assessment under Stress Scenarios Model

## CLASS-X

Capital and Loss Assessment under Stress Scenarios eXtended Model

## Compensation Noninterest Expense Ratio

Noninterest Expense Fixed operating costs that a financial institution must incur, such as anticipated bad debt provisions. Noninterest expenses can include employee salaries and benefits, equipment and property leases, taxes, loan loss provisions and professional service fees. Compensation Noninterest Expense Ratio= (Compensation Expense/Total Assets)

## CCAR

Comprehensive Capital Analysis and Review (CCAR) is a regulatory framework introduced by the Federal Reserve in order to assess, regulate, and supervise large banks and financial institutions - collectively referred to in the framework as Bank Holding Companies (BHCs).

## FR Y9C

Document to Report Financial statement to Federal Reserve Company

## Fixed Asset Noninterest Expense Ratio

Assets that are purchased for long-term use and are not likely to be converted quickly into cash, such as land, buildings, and equipment.
Fixed Asset Noninterest Expense Ratio = (Fixed Asset Expense/Total Assets)

## GDP

The gross domestic product (GDP) is one of the primary indicators used to gauge the health of a country's economy. It represents the total dollar value of all goods and services produced over a specific timeperiod; you can think of it as the size of the economy.

## Net Interest Margin

Net interest margin (NIM) is a measure of the difference between the interest income generated by banks or other financial institutions and the amount of interest paid out to their lenders (for example, deposits), relative to the amount of their (interest-earning) assets.
Net Interest Margin $=($ Net interest Income/Interest Earning Assets $)$

## Noninterest Nontrading Income Ratio

Non-interest income is bank and creditor income derived primarily from fees including deposit and transaction fees, insufficient funds (NSF) fees, annual fees, monthly account service charges, inactivity fees, check and deposit slip fees, and so on. Institutions charge fees that provide non-interest income as a way of generating revenue and ensuring liquidity in the event of increased default rates. Credit card issuers also charge penalty fees, including late fees and over-the-limit fees. While trading income is the oncome generated on trades.
Noninterest Nontrading Income Ratio $=(($ NonInterest Income - Trading Income $) /$ Total assets $)$

## Other Noninterest Expense Ratio

Any other Noninterest Expense Ratio
Other Noninterest Expense Ratio = ((Amortization Impair. + Goodwill Impair + Other Noninterest Expense)/Total assets)

## Percentage Residential RE Loans

Proportion of Residential Real Estate Loans for company c and timeperiod t .

## Percentage Commercial Loans

Proportion of Commercial Real Estate Loans for company c and timeperiod t.

## Percentage Commercial Industrial Loans

Proportion of C \& L Loans for company c and timeperiod t .

## Percentage Credit Card Loans

Proportion of Credit Card Loans for company c and timeperiod t .

## Percentage Trading Assets

Proportion of Trading Assets for company c and timeperiod t .

## Percentage Firm Assets

Firm Assets as \% of industry for company c and timeperiod t.)

## PPNR

Pre-Provision Net Revenue

## Return on Trading Assets

ROA gives an idea as to how efficient management is at using its assets to generate earnings. Calculated by dividing a company's annual earnings by its total assets, ROA is displayed as a percentage. Sometimes this is referred to as "return on investment"
Return on net assets (RONA) is a measure of financial performance calculated as net income divided by fixed assets and net working capital. RONA can be used to discern how well a company is performing versus others in its industry. It reveals if a company and its management are deploying assets in economically valuable ways or if the company is performing poorly versus its peers.
Return on Trading Assets = (Trading Income/Trading Assets)

## Return on AFS Securities

Return on Available-for-sale (AFS) portfolios
Return on AFS Securities $=($ Realized Net Gains on AFS Securities/Total Available for Sale Securities $)$

## T-Bill

A Treasury bill (T-Bill) is a short-term debt obligation backed by the U.S. government with a maturity of less than one year, sold in denominations of $\$ 1,000$ up to a maximum purchase of $\$ 5$ million. T-bills have various maturities and are issued at a discount from par.

## Unemployment Rate

The unemployment rate is the share of the labor force that is jobless, expressed as a percentage. ... In the U.S., the U3 or U-3 rate, which the Bureau of Labor Statistics (BLS) releases as part of its monthly employment situation report, is the most commonly cited national rate.

## VaR

Value at Risk Model to measure risk of investments

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## Appendix A: Models Development Steps Process

## Model Development and Processing

Observation Window
Here, we would like to provide a snapshot of the period of observation in the dataset. We looked at the data from 2003 to 2015 . We pulled out the PPNR data from the Federal Reserve data collection. These data come from the quarterly report (FR Y9C) that is required by Financial Services Holding Company to fill out to US Federal Reserve Company. We gathered macroeconomic data and market return data for each one of the 19 companies that were part of the original PPNR/CLASS model.
Observation Population
Most of the companies (19 initial companies) have data from the period mentioned above (from 2003 to 2015) or 46 quarters. However, some companies have less than 46 quarters because they are new in reporting to the Federal Reserve data quarterly. There are also cases where a company is a new entity that needs to follow the SIFI - Systemic Important Financial Institution rules.
Sourcing
Below is a short diagram of our dataflow.


We did our Analysis, Modeling and Data Analytics to report our findings. Section 4 has the model details.

Quality
The data quality was not too poor. However, sometimes we find a few banks fields that we had to clear up or fill. We use the average method (average the values of the fields before and after or the values of the fields Left to right) to clean up the fields that we had to fill.

Recording Transparency
We do a reverse engineering between the FRY 9C report and the PPNR data that we pull out from the Federal Reserve Company to get the meaning of the fields.

Ongoing Collection

We pull out the data once and consolidate them to do our research. If we had to do ongoing monitory, we will automate a process to refresh and expand the data.

## PPNR Prelimination works

We selected the macroeconomics data in the same range (quarterly) as the PPNR data.
Bhcf0403 Bhcf0406 Bhcf0409 Bhcf0412
Bhcf0503 Bhcf0506 Bhcf0509 Bhcf0512
Bhcf0603 Bhcf0606 Bhcf0609 Bhcf0612
Bhcf0703 Bhcf0706 Bhcf0709 Bhcf0712
Bhcf0803 Bhcf0806 Bhcf0809 Bhcf0812
Bhcf0903 Bhcf0906 Bhcf0909 Bhcf0912
Bhcf1003 Bhcf1006 Bhcf1009 Bhcf1012
Bhcf1103 Bhcf1106 Bhcf1109 Bhcf1112
Bhcf1203 Bhcf1206 Bhcf1209 Bhcf1212
Bhcf1303 Bhcf1306 Bhcf1309 Bhcf1312
Bhcf1403 Bhcf1406 Bhcf1409 Bhcf1412
Bhcf1503 Bhcf1506 Bhcf1509 Bhcf1512
We can briefly explain these files as follows:
Bhcf0403 = Bank Holding Company data for first quarter 2003 - (First File)
: :
: :
Bhcf1315 = Bank Holding Company data for fourth quarter 2015 - (Last File)
These files are the output of FR Y-9C, which is the report that is required by Federal Reserve Bank for Bank Holding Companies to fill out quarterly.

## Data Analysis

We gathered several types of data (PPNR, market data, and financial data). We analyzed that data thoroughly and created these variables for the PPNR calculation.

| FR Y9C <br> Code | Descriptions |
| :--- | :--- |
| BHCK4074 | Net interest income (item 1.h minus item 2.f). |
| BHCK4073 | Total interest expense (sum of items 2.a through 2.e) |
| BHCKA220 | Trading revenue |
| BHCK4079 | Total noninterest income (sum of items 5.a through 5.l). |
| BHCK4135 | Salaries and employee benefits |
| BHCK4217 | Expenses of premises and fixed assets (net of rental income) <br> (excluding salaries and employee benefits and mortgage interest) |
| BHCK4092 | Other noninterest expense |
| BHCK4093 | Total noninterest expense (sum of items 7.a through 7.d) |
| BHCK1773 | Available-for-sale securities (from Schedule HC-B, column D) |
| BHCK1410 | Loans secured by real estate |


| BHCK2122 | (total of column A must equal Schedule HC, sum of items 4.a and 4.b) |  | $\begin{array}{r} \text { 11) } \\ \text { d 4.b) } \\ \hline \end{array}$ |
| :---: | :---: | :---: | :---: |
| BHCK1763 | $\begin{array}{lc} \text { Commercial } & \text { and } \\ \text { To U.S. addressees (domicile) } \end{array}$ | industrial | loans |
| BHCK1764 | Commercial and To non-U.S. addressees (domicile) | industrial | loans |
| BHCKB538 | Credit cards |  |  |
| BHCK3545 | Trading assets (from Schedule HC-D) |  |  |
| BHCK2170 | Total assets (sum of items 1 through 11) |  |  |

Table 1: Variables from PPNR data
Table 6: Variables from PPNR data

These variables are from the FR Y9C report:
NetIntMargin $=$ BHCK4074/BHCK4073;
NonIntNonTradeRatio = BHCKA220/BHCK4079;
RetOnTradeAssets = BHCKA220/BHCK3545;
CompNonIntExpRatio $=($ BHCK4135 + BHCK4217 + BHCK4092 $) /$ BHCK4093;
FixedAssetNoIntExpRatio $=$ BHCK4135/BHCK4093;
OtherNonIntExpRatio $=$ BHCK4092/BHCK4093;
ReturnOnAFSSecurities $=$ BHCK1773/BHCK2170;
PctResidentialRELoans $=$ BHCK1410/BHCK2122;
PctCommercialRELoans $=\mathbf{1}$ - $($ BHCK1410/BHCK2122);
PctCILoans $=($ BHCK1763 + BHCK1764 $) /$ BHCK2122;
PctCreditCardLoans = BHCKB538/BHCK2122;
PctTradingAssets $=$ BHCK3545/BHCK2122;
PctAssetAsInd $=$ BHCK2170/367359787151;
Total Asset Amount of the 19 companies is: $\mathbf{3 6 7 , 3 5 9 , 7 8 7 , 1 5 1}$

Line regression of the Macroeconomic Variables
Below are some line plots of the macroeconomic variables:

| Treasomomumpor | comat |
| :---: | :---: |
|  |  |
|  | $\ldots \infty$ |
|  |  |
| $\cdots$ " |  |


|  | Tem sprrad Line Plot |
| :---: | :---: |
|  |  |
|  |  |

Figure 9: Line Plots for the Macroeconomic Variables

## Work Process

We used historical data from several sources in this study and followed a simple process, as displayed below:


Figure: 5: Work and Methodology
We performed the following steps for our data analysis - 1. data investigation, 2. data preparation, 3. model planning, 4. analysis of individual findings, and 5. consolidation or analysis of findings.

## Data Investigation

We started the process by investigating the sources for the data that we needed. We then extracted the PPNR text files data from the Federal Reserve.

Here are the PPNR text files:
Bhcf0403 Bhcf0406 Bhcf0409 Bhcf0412
Bhcf0503 Bhcf0506 Bhcf0509 Bhcf0512
Bhcf0603 Bhcf0606 Bhcf0609 Bhcf0612
Bhcf0703 Bhcf0706 Bhcf0709 Bhcf0712
Bhcf0803 Bhcf0806 Bhcf0809 Bhcf0812
Bhcf0903 Bhcf0906 Bhcf0909 Bhcf0912
Bhcf1003 Bhcf1006 Bhcf1009 Bhcf1012
Bhcf1103 Bhcf1106 Bhcf1109 Bhcf1112
Bhcf1203 Bhcf1206 Bhcf1209 Bhcf1212
Bhcf1303 Bhcf1306 Bhcf1309 Bhcf1312
Bhcf1403 Bhcf1406 Bhcf1409 Bhcf1412
Bhcf1503 Bhcf1506 Bhcf1509 Bhcf1512
The consolidated dataset has 133,446 observations and 1,417 variables. The data is made up of more than 200 US major financial institutions. For CLASS and CCAR, 19 companies were used in that study. Here are the macroeconomic files that we extracted for this document:

| Name | Description |
| :--- | :--- |
| tb3mQ | Three Months Treasury Bill |
| gdpc96 | Gross Domestic Product |
| Gs10 | 10 Years Treasury Interest |
| TedValue | Term Spread |
| UnRate | Un-employment Rate |

## Table 7: Macroeconomic Variables

We keep the macroeconomic variables ready for PPNR in this research. As mentioned, the data used in this research come from three difference sources:

| Items | Sources | Description |
| :--- | :--- | :--- |
| 1 | FRED | Macroeconomics data |
| 2 | Yahoo Finance | Stock Return data or Market Return data |
| 3 | PPNR Federal Reserve <br> Data | PPNR Data |

Table 8: Data Sources for the Dissertation

Variable Details:

| Items | Description | Definition | Use/Not <br> Use in <br> Equation | Data <br> Source |
| :--- | :--- | :--- | :--- | :--- |
| 1 | Date | Date | Y | PPNR |
| 2 | RSSD9001 | Date in the Raw data form | N | PPNR |
| 3 | RSSD9017 | Company Name | N | PPNR |
| 4 | NetIntMargin | Net Interest margin | Y | PPNR |
| 5 | NonIntNonTradeRatio | NonInterest Non. Trade <br> Ratio | Y | PPNR |
| 6 | RetOnTradeAssets | Ret On Trade Assets | Y | PPNR |
| 7 | CompNonIntExpRatio | Comp. NonInt Exp. Ratio | Y | PPNR |
| 8 | FixedAssetNoIntExpRatio | Fixed Asset Not IntExp <br> Ratio | Y | PPNR |
| 9 | OtherNonIntExpRatio | Other Non. Int Exp. Ratio | Y | PPNR |
| 10 | ReturnOnAFSSecurities | Return On AFS Securities | Y | PPNR |
| 11 | PctResidentialRELoans | \%Residential RE Loans | Y | PPNR |
| 12 | PctCommercialRELoans | \% Commercial RE Loans | Y | PPNR |
| 13 | PctCILoans | \% CILoans | Y | PPNR |
| 14 | PctCreditCardLoans | \%CreditsCardLoans | Y | PPNR |
| 15 | PctTradingAssets | \%TradingAssets | Y | PPNR |
| 16 | PctAssetAsInd | \%Asset As in Industry - <br> Fraction | N | PPNR |
| 17 | PctValue | \%Asset As in Industry | Y | PPNR |
| 18 | Category | Flag to control subject <br> Category | Y | PPNR |
| 19 | GDPValue | Gross Domestic Product | Y | FRED |
| 20 | GS10 | Ten Year Treasury <br> Interest | N | FRED |
| 21 | TB3 | Three Months Treasury <br> Bill | Y | FRED |
| 22 | TEDValue | Term Spread | Y | FRED |
| 23 | UNRate | StockReturnValue | Return on the Company | Y |
| 24 | FRED |  |  |  |
|  | Yahoo |  |  |  |

Table 9: Variables from the three data sources and record sample
The variables in this table that are not used are kept in this table for control purposes (to help us identify records during analysis or data management).

The details about how we use this model is in this Appendix of the document. Analysis of variance table (include R-square and Adjusted R-Square)

| Root MSE | 0.39207 | R-Square 0.9614 |
| :--- | :---: | :--- |
| Dependent Mean2.87819 | Adj R-Sq 0.9553 |  |
| Coeff Var | 13.62217 |  |

As you know, R -Square is from 0 to 1 . The closer the value is to 1 , the better the R -Square is. In this experiment, R-Square is less than .5 which can be an indicator that R-Square is not a strong. The same analysis goes to Adj R-Sq.
Standard Error of the Coefficients, p-values
The standard error of the coefficients is low and p-values is less than 0.05 for most of the variables which indicates that the coefficient value that we get we do not receive that value by chance.

| Parameter Estimates |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Variable | Parameter DFEstimate | Standard Error | Pr | Variance Inflation |
| Intercept | 1 -16.10147 | 72.70068 | -5.96<.0001 | 0 |
| PctResidentialRELoans | $1-0.26559$ | 1.93670 | -0.14 0.8916 | 2.30457 |
| PctCILoans | -9.75529 | 3.56224 | -2.74 0.0093 | 4.20042 |
| PctTradingAssets | -3.64535 | 1.08127 | -3.37 0.0017 | 4.60357 |
| GDPvalue | 0.00148 | 0.0001375 | 610.76 <.0001 | 2.28634 |
| Tb3value | -0.17573 | 0.07714 | -2.28 0.0284 | 5.83423 |
| Unratevalue | 0.17841 | 0.08238 | $\begin{array}{ll}2.17 & 0.0367\end{array}$ | 6.80482 |

Table showing the number of observations and the dependent variable
We have one dependent variables and 6 independent variables as seen in the previous section equation.

Line plot of the dependent variable and each independent variable: This is the line plot with all the independent variables

Scatter plot of predicted vs actual: Below is a scatter plot of Predicted Vs Actual. Tables (with ods output statement) with the following columns.

Below is a snapshort of the variables:

|  |  | (2) STDP | (12) LCLM | (12) | (12) LCL | (12) UCL | 3) R | ST | (12) STUDENT |  | ) H | S | I |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1.0328896964 | 0.2352646294 | 0.5566213535 | 1.5091580392 | 0.1072522884 | 1.9585271043 | 0.1962254526 | 0.3136416283 | 0.6256358689 | 0.031462347 | 0.3600654421 | 0.306633624 | 0.6205532224 |
| 2 | 1.1374202427 | 0.2131894453 | 0.7058407739 | 1.5689997115 | 0.2339635949 | 2.0408768905 | 0.0741599223 | 0.3290452511 | 0.2253790992 | 0.0030461366 | 0.295664759 | 0.1052906599 | 0.2225426032 |
| 3 | 0.7619283142 | 0.1524242017 | 0.4533616499 | 1.0704949785 | -0.089650492 | 1.6135071203 | 0.2044116158 | 0.3612303692 | 0.5658760537 | 0.0081448659 | 0.1511388182 | 0.2408068836 | 0.5607483112 |
| 4 | 0.9000394104 | 0.1366161283 | 0.6234745175 | 1.1766043033 | 0.0595269378 | 1.740551883 | 0.0030869656 | 0.3675004086 | 0.008399897 | $1.3929585 \mathrm{E}-6$ | 0.1214149347 | 0.0035135648 | 29 |
| 5 | 0.8346846286 | 0.1194949852 | 0.5927796779 | 1.0765895793 | 0.0049310014 | 1.6644382558 | 0.0095566474 | 0.3734186195 | 0.0255923163 | $9.5813911 \mathrm{E}-6$ | 0.0928896922 | 0.0105352649 | 0252535479 |
| 6 | 0.8739701495 | 0.1382572924 | 0.5940828937 | 1.1538574053 | 0.0323586283 | 1.7155816707 | -0.088286835 | 0.3668861376 | -0.240638243 | 0.0011747481 | 0.1243495617 | -0.100824292 | 969 |
| 7 | 0.7883689349 | 0.1634865465 | 0.4574077243 | 1.1193301455 | -0.071577807 | 1.6483156772 | -0.169633345 | 0.3563603036 | -0.476016389 | 0.0068128868 | 0.1738730225 | -0.20533568 | -0.471117981 |
| 8 | 0.509919616 | 0.144356219 | 0.217685727 | 0.8021535046 | -0.335878068 | 1.3557173001 | 0.0822107359 | 0.3645295581 | 0.2255255688 | 0.0011394599 | 0.1355623736 | 0.0951031439 | 0.2226874232 |
| 9 | 0.594010 | 0.1476119215 | 0.29518612 | 0.8928355478 | -0.254086615 | 1.4421082858 | -0.010851216 | 0.3632233989 | -0.029874772 | 0.0000210575 | 0.1417460714 | -0.012643363 | -0.029479409 |
| 10 | 0.6616962278 | 0.1492218596 | 0.3596123661 | 0.9637800894 | -0.187555052 | 1.5109475075 | -0.096662556 | 0.3625649645 | -0.266607547 | 0.001720046 | 0.1448548563 | -0.113036432 | -0.263322555 |
| 11 | 0.273129666 | 0.1629787 | -0.05680365 | 0.6030629893 | -0.586422003 | 1.1326813372 | 0.3120576311 | 0.3565928057 | 0.8751091612 | 0.0228530134 | 0.1727946816 | 0.3772432601 | 0.8723528261 |
| 12 | 0.5380631785 | 0.1557306263 | 0.2228030 | 0.8533233496 | -0.315963784 | 1.3920901407 | 0.0309945385 | 0.3598172993 | 0.0861396562 | 0.0001985602 | 0.1577670207 | 0.0368004332 | 0.085006983 |
| 13 | 0.6903409 | 0.1430978953 | 0.400654 | 0.9800274566 | -0.154580013 | 1.535261838 | -0.115858256 | 0.3650253542 | -0.317397833 | 0.0022117208 | 0.1332093338 | -0.133663479 | 0.313609682 |
| 14 | 0.6894010469 | 0.1441415763 | 0.397601681 | 0.9812004128 | -0.156246602 | 1.5350486961 | -0.099085136 | 0.3646144852 | -0.271753153 | 0.0016487767 | 0.1351595379 | -0.114570421 | -0.268414562 |
| 15 | 0.5145 | 0.2210657625 | 0.0670173995 | 0.9620658786 | -0.396639474 | 1.4257227525 | 0.264958007 | 0.3238061851 | 0.8182611055 | 0.0445818894 | 0.3179150862 | 0.3884531114 | 0.8146314356 |
| 16 | 0.576384 | 0.2593662645 | 0.051324637 | 1.1014437417 | -0.375277836 | 1.5280462146 | 0.3086942285 | 0.2940232265 | 1.0498974253 | 0.1225347863 | 0.437617961 | 0.5489048495 | 1.0513516349 |
| 17 | 2.0891588214 | 0.1760115756 | 1.732842014 | 2.4454756279 | 1.2191388543 | 2.9591787886 | -1.14142811 | 0.3503433203 | -3.258027324 | 0.3827420535 | 0.2015350676 | -1.429528166 | -3.787016229 |
| 18 | 1.9998 | 0.2004 | 1.5940 | 2.4056411431 | 1.1083823 | 2.8912597975 | -0.862521495 | 0.3369485425 | -2.559801829 | 0.3313327687 | 0.2614237667 | 1.167816478 | 2.776609043 |
| 19 | 2.4087653212 | 0.1858249565 | 2.0325823638 | 2.7849482787 | 1.5304221684 | 3.2871084741 | 0.5326692038 | 0.3452384718 | 1.5429022177 | 0.0985254609 | 0.2246343895 | 0.6869910098 | 1.5725180674 |
| 20 | 2.7605086586 | 0.1969268573 | 2.361851078 | 3.1591662391 | 1.8723076998 | 3.6487096174 | 0.3354856524 | 0.3390285088 | 0.9895499751 | 0.0471970534 | 0.252277236 | 0.4486765263 | 0.9892720709 |
| 21 | 2.7631555204 | 0.174988 | 2.40891053 | 3.1174005 | 1.8939820127 | 3.6323290281 | 0.4900841756 | 0.3508556183 | 1.3968257881 | 0.0693340944 | 0.1991982109 | 0.611991859 | 1.4151329136 |
| 22 | 3.2161109297 | 0.1596066708 | 2.8930041168 | 3.5392177426 | 2.3591563864 | 4.0730654729 | 0.1616361423 | 0.3581148245 | 0.451352838 | 0.0057808512 | 0.1657182131 | 0.1937428635 | 0.4465730466 |
| 23 | 3.79805 | 0.1340280 | 3.5267332203 | 4.069384389 | 2.9592556995 | 4.6368619101 | 0.5901389622 | 0.3684521692 | 1.6016704785 | 0.0484928163 | 0.1168582842 | 0.6682267995 | 1.6366655794 |
| 24 | 4.061410946 | 0.132387 | 3.793407182 | 4.3294147109 | 3.2236764457 | 4.8991454478 | 0.2343568493 | 0.3690449304 | 0.635036089 | 0.0074136473 | 0.1140144242 | 0.2645154229 | 0.6299763371 |
| 25 | 3.8196141585 | 0.1695024386 | 3.4764744109 | 4.1627539061 | 2.9549072931 | 4.6843210239 | 0.3898737125 | 0.3535384564 | 1.10277596 | 0.0399351319 | 0.1869046325 | 0.4794932158 | 1.1060107677 |
| 26 | 3.741394896 | 0.160908271 | 3.415653130 | 4.0671366622 | 2.8834433974 | 4.5993463954 | 0.2625156306 | 0.3575318797 | 0.7342439807 | 0.0155994736 | 0.1684321154 | 0.315687553 | 0.7297132561 |
| 27 | 3.5685499318 | 0.1597590975 | 3.2451345472 | 3.8919653164 | 2.7114789968 | 4.4256208668 | -0.194855323 | 0.3580468512 | -0.54421739 | 0.0084236104 | 0.1660348908 | -0.233649251 | $-0.539113935$ |
| 28 | 3.8875791254 | 0.1200870896 | 3.6444755221 | 4.1306827288 | 3.0574752532 | 4.7176829976 | -0.64091609 | 0.3732286267 | -1.717221147 | 0.0436111121 | 0.0938125202 | -0.707266548 | -1.764314262 |
| 29 | 3.9286593989 | 0.111127878 | 3.7036927711 | 4.1536260266 | 3.1036848173 | 4.7536339804 | -0.587339792 | 0.3759934994 | -1.562100921 | 0.0304512768 | 0.0803367405 | -0.638646576 | -1.593419205 |

These are fit statistics. You should use a small hold out sample (last four observations) and make forecasts from them.

## Plots Definitions:

Please see these snapshots below for the following plots. That will help to visualize the definitions of these plots:
a. Scatter plot of predicted values vs residuals - Shows a plot of Predicted next residual
b. Scatter plot of Rstudent by predicted values - Shows a plot of Rstudent by predicted values
c. Cooks D plot - Show a Cooks D Plot
d. Plot of press residuals - Shows a residual plot
e. DFFITS plot - Shows the DFFTS plot
f. DFBETAS plot - shows the DFBETAS plot
g. Q-Q Plot of residuals Shows of the Q-Q Plot of Residual
h. Histogram of residuals - Shows a histogram of residuals
i. Outlier and leverage diagnostics plot - shows an outlier plot



Figure 10: Preliminary Analysis of the CLASS Variables

## Collinearity Diagnostics

Multicollinearity (also collinearity) is a phenomenon in which two or more predictor variables in a multiple regression model are highly correlated, meaning that one can be linearly predicted from the others with a substantial degree of accuracy. The coefficient estimates of the multiple regression may change erratically in response to small changes in the model or the data. Multicollinearity does not reduce the predictive power or reliability of the model as a whole, at least within the sample dataset; it only affects calculations regarding individual predictors. That is, a multiple regression model with correlated predictors can indicate how well the entire bundle of predictors predicts the outcome variable, but it may not give valid results about any individual predictor, or about which predictors are redundant with respect to others [13].


Figure 11: Preliminary study of Collinearity Diagnostics

Collinearity is a linear association between two explanatory variables. Two variables are perfectly collinear if there is an exact linear relationship between them.
Detection of Multicollinearity
Indicators that multicollinearity may be present in a model:

1. Large changes in the estimated regression coefficients when a predictor variable is added or deleted. 2. Insignificant regression coefficients for the affected variables in the multiple regression, but a rejection of the joint hypothesis that those coefficients are all zero (using an F-test).3. If a multivariable regression finds an insignificant coefficient of a particular explanatory, yet a simple linear regression of the explained variable on this explanatory variable shows its coefficient to be significantly different from zero, this situation indicates multicollinearity in the multivariable regression. 4. Some authors have suggested a formal detection-tolerance or the variance inflation factor (VIF) for multicollinearity:
tolerance $=1-\mathrm{Rj}^{\wedge} 2, \mathrm{VIF}=1 /$ tolerance ,
where $\mathrm{Rj}^{\wedge} 2$ is the coefficient of determination of a regression of explanatory j on all the other explanators. A tolerance of less than 0.20 or 0.10 and/or a VIF of 5 or 10 and above indicates a multicollinearity problem (O'Brien, 2007).
2. Condition number test: The standard measure of ill-conditioning in a matrix is the condition index. It will indicate that the inversion of the matrix is numerically unstable with finite-precision numbers (standard computer floats and doubles). This indicates the potential sensitivity of the computed inverse to small changes in the original matrix. The Condition Number is computed by finding the square root of (the maximum eigenvalue divided by the minimum eigenvalue). If the Condition Number is above 30, the regression may have significant multicollinearity; multicollinearity exists if, in addition, two or more of the variables related to the high condition number have high proportions of variance explained. One advantage of this method is that it also shows which variables are causing the problem (Belsley, 1991).
6.Farrar-Glauber test: If the variables are found to be orthogonal, there is no multicollinearity; if the variables are not orthogonal, then multicollinearity is present. C. Robert Wichers has argued that Farrar-Glauber partial correlation test is ineffective in that a given partial correlation may be compatible with different multicollinearity patterns (Farrar \& Glauber, 1967). The Farrar-Glauber test has also been criticized by other researchers (Wichers, 1975) (Kumar, 1975).
We assess the impact of each independent variable on the dependent variable : a.) Make a unit change in one explanatory variable and estimate the effect on the explanatory variable (report whether it is in dollars, millions of dollars, etc. ) We will use SAS for this analysis.
Here is the result:

| Parameter Estimates | Parameter Standard |  |  |  |  |  |  |
| :--- | ---: | :--- | :--- | :--- | :--- | :--- | :---: |
| DFEstimate | Error |  | t ValuePr $>\|\boldsymbol{t}\|$ | Variance <br> Inflation |  |  |  |
| Variable | 1 | -16.101472 .70068 | -5.96 | $<.0001$ | 0 |  |  |
| Intercept | 1 | -0.26559 | 1.93670 | -0.14 | 0.8916 | 2.30457 |  |
| PctResidentialRELoans | -9.75529 | 3.56224 | -2.74 | 0.0093 | 4.20042 |  |  |
| PctCILoans | 1 | -3.64535 | 1.08127 | -3.37 | 0.0017 | 4.60357 |  |
| PctTradingAssets | 1 | 0.00148 | 0.0001375610 .76 | $<.0001$ | 2.28634 |  |  |
| GDPvalue | 1 | -0.17573 | 0.07714 | -2.28 | 0.0284 | 5.83423 |  |
| Tb3value | 1 | 0.17841 | 0.08238 | 2.17 | 0.0367 | 6.80482 |  |
| Unratevalue |  |  |  |  |  |  |  |

For example, we can say that 1 unit change in the dependent variables will change the pctCILoans by 9.75 and PctTradingAsset by 3.64 .

Meta Data
. Below is a snapshot of the meta-data:

| Date | Company Name | Data Field 1 | Data Field 2 | Data Field n |
| :--- | :--- | :--- | :--- | :--- |
| 1991Q1 | Company 1 | Data | Data | Data |
| 1991Q1 | Company 2 | Data | Data | Data |
| 1991Q1 | Company n | Data | Data | Data |
| 1991Q2 | Company 1 | Data | Data | Data |
| 1991Q2 | Company 2 | Data | Data | Data |
| 1991Q2 | Company n | Data | Data | Data |
| $\ldots$ | $\ldots$ | Data | Data |  |
| 2013Q3 | Company 1 | Data | Data | Data |
| 2013Q3 | Company 2 | Data | Data | Data |
| 2013Q3 | Company n | Data | Data | Data |

This table could provide you a visual presentation of the data structure. In short, these are some of the steps that we follow to replicate CLASS model and Present CLASS-X model as an alternative for CLASS model.

# Appendix B: The CLASS model Specification Results <br> Appendix: Estimated econometric models 

Appendix Table 1: PPNR Components and Securities Specifications

|  | Net Interest Margin | Noninterest <br> Noutrading <br> Income <br> Ratio | Return on <br> Trading <br> Assets | Compensation Nonint. Exp. <br> Ratio | Fived Asset <br> Nonint. Exp. <br> Ratio | Other <br> Nonint. <br> Exp. Ratio | Retum on AFS <br> Securities |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Macroeconomic variables |  |  |  |  |  |  |  |
| Anmulized Real GDP growth (\%) |  |  |  |  | $\begin{aligned} & 0.000552 \\ & (0.000665) \end{aligned}$ |  |  |
| Term Spread ( 10 year minus 3 months. pct. pt) 3 Month Treasury Yield (\%) | $\begin{aligned} & 0.0426^{* * *} \\ & (0.0139) \\ & 0.0220^{* *} \\ & (0.0106) \end{aligned}$ |  |  |  |  |  |  |
| Quarterly change in 10 year Treasury yield (pct. pt) |  |  |  |  |  |  | $\begin{aligned} & -0.580^{+* *} \\ & (0.161) \end{aligned}$ |
| Stock Murket retums (quarterly, \%) |  | $\begin{aligned} & 0.00407^{*} \\ & (0.00245) \end{aligned}$ |  | $\begin{aligned} & 0.00345^{*+*} \\ & (0.000886) \end{aligned}$ |  |  |  |
| Quarterly change in BBB bond sprend (pct. pt) Quarterly change in BBB Spread if change is positive (else zero) |  |  | $\begin{aligned} & -0.671 \\ & (0.452) \\ & -2.559 * * * \\ & (0.588) \end{aligned}$ |  |  | $\begin{aligned} & 0.179 * \\ & (0.0939) \end{aligned}$ |  |
| Quanterly change in BBB Spread if change is positive a Risky AFS Ratio |  |  |  |  |  |  | $\begin{aligned} & -0.0310^{* * *} \\ & (0.0030) \end{aligned}$ |
| Time-series coutrols <br> Laged dependert triable |  |  |  |  |  |  |  |
| Lagged dependent variable Time trend (armuni, 1991:Q1 $=0$ ) | $\begin{aligned} & 0.793^{* * *} \\ & (0.0390) \\ & -0.00528^{*} \\ & (0.00317) \end{aligned}$ | $\begin{aligned} & 0.904^{* * *} \\ & (0.0143) \end{aligned}$ | $\begin{aligned} & 0.284 \\ & (0.181) \end{aligned}$ | $\begin{aligned} & 0.894^{* * *} \\ & (0.0175) \end{aligned}$ | $\begin{aligned} & 0.853^{* * *} \\ & (0.0221) \\ & -0.00186^{* * *} \\ & (0.000348) \end{aligned}$ | $\begin{aligned} & 0.816^{* * *} \\ & (0.0340) \end{aligned}$ | $\begin{aligned} & 0.128 \\ & (0.0951) \end{aligned}$ |
| Balance sheet ratios (as \% of interest earning assets) |  |  |  |  |  |  |  |
| Residential Real Estate Loans | $\begin{aligned} & 0.00476^{* * *} \\ & (0.00141) \end{aligned}$ | $\begin{aligned} & -0.00155 \\ & (0.00185) \end{aligned}$ |  | $\begin{aligned} & -0.000722 \\ & (0.000918) \end{aligned}$ | $\begin{aligned} & -0.000321 \\ & (0.000207) \end{aligned}$ | $\begin{aligned} & -0.00227 \\ & (0.00211) \end{aligned}$ |  |
| Commercial Real Estate Loans | $\begin{aligned} & 0.00648^{* * *} \\ & (0.00162) \end{aligned}$ | $\begin{aligned} & -0.00364^{* *} \\ & (0.00174) \end{aligned}$ |  | $\begin{aligned} & -0.00109^{*} \\ & (0.000647) \end{aligned}$ | $\begin{aligned} & -0.000328 \\ & (0.000201) \end{aligned}$ | $-0.000938$ <br> (0.00136) |  |
| Commercial and Industrial Loans | $\begin{aligned} & 0.00685^{* * *} \\ & (0.00134) \end{aligned}$ | $\begin{aligned} & -0.000877 \\ & (0.00189) \end{aligned}$ |  | $\begin{aligned} & -0.000229 \\ & (0.00147) \end{aligned}$ | $\begin{aligned} & -0.000470^{+} \\ & (0.000252) \end{aligned}$ | $\begin{aligned} & -0.00171 \\ & (0.00202) \end{aligned}$ |  |
| Credit Card Loans | $\begin{aligned} & 0.0184^{+* *} \\ & (0.00369) \end{aligned}$ | $\begin{aligned} & 0.00990^{* * *} \\ & (0.00245) \end{aligned}$ |  | $-0.00115$ <br> (0.00105) | $\begin{aligned} & -0.000554^{* * *} \\ & (0.000170) \end{aligned}$ | $\begin{aligned} & 0.0153^{* * *} \\ & (0.00337) \end{aligned}$ |  |
| Trading Assets | $\begin{aligned} & -0.00626^{*+*} \\ & (0.00161) \end{aligned}$ | $\begin{aligned} & -0.00146 \\ & (0.00223) \end{aligned}$ |  | $\begin{aligned} & -0.00252^{+*} \\ & (0.00110) \end{aligned}$ | $\begin{aligned} & -0.00129^{*+*} \\ & (0.000459) \end{aligned}$ | $\begin{aligned} & -0.000807 \\ & (0.00201) \end{aligned}$ |  |
| Secunities Ratio | $\begin{aligned} & 0.00393^{* * *} \\ & (0.00118) \end{aligned}$ | $\begin{aligned} & 0.00309 \\ & (0.00201) \end{aligned}$ |  | $\begin{gathered} -0.00172^{*} \\ (0.00103) \end{gathered}$ | $\begin{aligned} & -0.000853^{* * *} \\ & (0.000244) \end{aligned}$ | $\begin{aligned} & 0.00886^{* * *} \\ & (0.00241) \end{aligned}$ |  |
| Other |  |  |  |  |  |  |  |
| Asset Share (firm assets as $\%$ of industry assets) | $\begin{aligned} & 0.00743^{* * *} \\ & (0.00141) \end{aligned}$ | $\begin{aligned} & -0.00581^{* * *} \\ & (0.00181) \end{aligned}$ |  | $\begin{aligned} & -2.07 \mathrm{e}-05 \\ & (0.000840) \end{aligned}$ | $\begin{aligned} & -7.56 \mathrm{e}-05 \\ & (0.000159) \end{aligned}$ | $\begin{aligned} & -0.00369^{* *} \\ & (0.00175) \end{aligned}$ |  |
| Constant Term | $\begin{aligned} & 0.234^{*} \\ & (0.124) \end{aligned}$ | $\begin{aligned} & 0.233^{*} \\ & (0.127) \end{aligned}$ | $\begin{aligned} & 1.989^{* * *} \\ & (0.602) \end{aligned}$ | $\begin{aligned} & 0.261^{*+*} \\ & (0.0964) \end{aligned}$ | $\begin{aligned} & 0.130^{* * *} \\ & (0.0253) \end{aligned}$ | $\begin{aligned} & 0.148 \\ & (0.111) \end{aligned}$ | $\begin{aligned} & 0.272^{* * * *} \\ & (0.0535) \end{aligned}$ |
| Observations | 17,565 | 17,565 | 67 | 17,565 | 17,565 | 17,565 | 12,875 |
| $\mathrm{R}^{2}$ | 0.885 | 0.876 | 0.449 | 0.828 | 0.835 | 0.772 | 0.0352 |

PPNR Model Securities specifications for all companies

Our Replication Research results for the CLASS model:


Table 10: Regression results of the replication of PPNR specifications for all companies

PPNR specifications for 19 original CCAR companies

| Legend | ***p<0.01 ${ }^{* * \mathrm{p}}<0.05{ }^{*} \mathrm{p}<0.1$ |  | Correlation - High |  |  | => . 9 | Medium |  |  | $<.9$ or $>.5$ | Low |  |  | $=<.5$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Annualized Real GDP growth (\%) |  |  |  |  |  |  |  |  |  | 0.000128 |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  | (0.00079) |  |  |  |  |  |
| Term Spread (10 year minus 3 months, pct. pt) |  | 0.04327 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | (0.02025) |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 3 Month Treasury Yield (\%) |  | 0.02659 | * |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | (0.01687) |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Quarterly change in 10 year Treasury yield (pct. pt) |  |  |  |  |  |  |  |  |  |  |  |  |  | -0.59781 | *** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  | (0.14208) |  |
| Stock Market returns (quarterly, \%) |  |  |  | 0.00425 |  |  |  | 0.00394 | *** |  |  |  |  |  |  |
|  |  |  |  | (0.00198) |  |  |  | (0.00075) |  |  |  |  |  |  |  |
| Quarterly change in BBB bond spread (pct. pt) |  |  |  |  |  | -0.58118 |  |  |  |  |  | 0.16853 | *** |  |  |
|  |  |  |  |  |  | (6.80726) |  |  |  |  |  | (0.03709) |  |  |  |
| Quarterly change in BBB Spread if change is positive (else zero) |  |  |  |  |  | -3.45592 | * |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  | (9.63915) |  |  |  |  |  |  |  |  |  |
| Quarterly change in BBB Spread if change is positive x Risky AFS Ratio |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Annualized change in Unemployment (\%) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Home price growth (\%, year-over-year) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Home price growth if growth is negative (else zero) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Commercial property price growth (\%, year-over-year) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Commercial Property Price Growth if negative else 0 |  |  |  |  |  |  |  |  |  |  |  |  |  | -0.01313 | *** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  | (0.00239) |  |
| Time-Series Controls |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Lagged dependent variable |  | 0.82968 | *** | 0.85386 | *** | 0.53691 |  | 0.76089 | *** | 0.78997 | *** | 0.77046 | *** | 0.24182 | *** |
|  |  | (0.01455) |  | (0.01451) |  | (0.02736) |  | (0.01817) |  | (0.01709) |  | (0.01795) |  | (0.03038) |  |
| Time Trend(Annual 1991Q1=0) |  | -0.0042 |  |  |  |  |  |  |  | -0.0037 | *** |  |  |  |  |
|  |  | (0.00487) |  |  |  |  |  |  |  | (0.00057) |  |  |  |  |  |
| Balance sheet Ratios (as \% of Interest earning |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Residential Real Estate Loans |  | 0.00487 | * | 0.000387 |  |  |  | 0.00159 |  | 0.000934 |  | -0.007 |  |  |  |
|  |  | (0.00174) |  | (0.00328) |  |  |  | (0.00124) |  | (0.00036) |  | (0.00340) |  |  |  |
| Commercial Real Estate Loans |  | 0.01206 | *** | -0.00483 |  |  |  | -0.00872 |  | -0.00128 | ** | 0.01189 |  |  |  |
|  |  | (0.00305) |  | (0.00549) |  |  |  | (0.00220) | *** | (0.00061) |  | (0.00567) |  |  |  |
| Commercial and Industrial Loans |  | 0.00313 |  | -0.00235 |  |  |  | -0.00341 | ** | -0.0013 | ** | -0.00465 |  |  |  |
|  |  | (0.00256) |  | (0.00393) |  |  |  | (0.00153) |  | (0.00054) |  | (0.00403) |  |  |  |
| Credit Card Loans |  | 0.02387 | *** | 0.01832 | * |  |  | 0.00163 | * | 0.000716 | ** | 0.02314 | *** |  |  |
|  |  | (0.00315) |  | (0.00546) |  |  |  | (0.00200) |  | (0.00058) |  | (0.00572) |  |  |  |
| Trading Assets |  | -0.00175 |  | 0.000749 |  |  |  | -0.00483 |  | -0.00053 |  | 0.00156 |  |  |  |
|  |  | (0.00217) |  | (0.00400) |  |  |  | (0.00161) |  | (0.00044) |  | (0.00410) |  |  |  |
| Security Ratio |  | 0.00568 | * | 0.00781 | ** |  |  | -0.00441 | *** | -0.00076 |  | 0.01726 | *** |  |  |
|  |  | (0.00146) |  | (0.00257) |  |  |  | (0.00105) |  | (0.00029) |  | (0.00298) |  |  |  |
| Asset Share (firm assets as \% of industry assets) |  | 0.00566 |  | -0.0161 | ** |  |  | -0.00882 | *** | -0.002 | * | $4.51 \mathrm{E}-05$ |  |  |  |
|  |  | (0.00296) |  | (0.00548) |  |  |  | (0.00212) |  | (0.00062) |  | (0.00554) |  |  |  |
| Constant Term |  | 0.00758 |  | 0.29629 |  | 6.86957 | *** | 0.66323 | *** | 0.1766 | *** | 0.01362 |  | 0.27663 | *** |
|  |  | (0.17683) |  | (0.18045) | * | (2.39376) |  | (0.09010) |  | (0.02765) |  | (0.17940) |  | (0.05125) |  |
| Observations |  | 1,257 |  | 1,257 |  | 993 |  | 1,257 |  | 1,257 |  | 1,257 |  | 993 |  |
| R-Square |  | 0.9208 |  | 0.8472 |  | 0.2806 |  | 0.7319 |  | 0.8188 |  | 0.8477 |  | 0.1014 |  |
| \#Variables Significant |  | 4 |  | 4 |  | 2 |  | 7 |  | 8 |  | 6 |  | 4 |  |
| Strong Correlation |  | High |  | High |  | High |  | High |  | Medium |  | Medium |  | Low |  |
| RMSE |  | 0.5896 |  | 1.13786 |  | 61.05825 |  | 0.42999 |  | 0.12396 |  | 1.17194 |  | 2.82557 |  |
| Proc Reg with Pooled Data for all the 19 initial companies that were part of CCAR |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

Table 11: Regression results of the replication of PPNR specifications for 19 companies

## Regression results specifications for Company 1



Table 12: Regression results of the replication of PPNR specifications for company 1

PPNR specifications for company 2


Table 13: Regression results of the replication of PPNR specifications for company 2

PPNR specifications for company 19


Table 14: Regression results of the replication of PPNR specifications for company 19

## Appendix C: The CLASS Model Specification with Proc Panel



Table 15: Proc panel Regression results of the replication of PPNR specifications for all companies

Appendix C: The CLASS model Specifications with Proc
Panel


Table 16: Proc panel Regression results of the replication of PPNR specifications for 19 companies

## Appendix D: CLASS-X Model Specifications

CLASS-X Model Specifications


Table 17: CLASS-X Model specifications


Table 18: CLASS-X Process - steps for Variables selections

CLASS-X Model Specifications - Results of the regressions


Table 19: CLASS-X Model Specifications - Results of the regressions

CLASS-X Model Specifications results with the 19 CCAR Companies


Table 20: CLASS-X Model Specifications results with the 19 CCAR Companies

Analysis of Variance Inflation and Eigenvalues

| Label | Parameter | Standard | t Value | $\mathrm{Pr}>\|\mathrm{t}\|$ | Variance | Number | Eigenvalue |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Estimate | Error |  |  | Inflation |  |  |
| Intercept | 0.19941 | 0.07004 | 2.85 | 0.0044 | 0 | 1 | 8.53132 |
| Stock Market Quarterly Log Change | 0.00102 | 0.000459 | 2.22 | 0.0262 | 1.21474 | 2 | 1.53576 |
| 3M Treasury Yield | -0.02084 | 0.00342 | -6.09 | <. 0001 | 3.90386 | 3 | 1.11146 |
| 10Y Treasury Yield | 0.04825 | 0.0083 | 5.81 | <. 0001 | 12.31365 | 4 | 0.86293 |
| AFS Ratio X Change in bond spread | 0.00157 | 0.000287 | 5.47 | <. 0001 | 1.39666 | 5 | 0.78022 |
| Year over year HPI | 0.00118 | 0.000534 | 2.21 | 0.0273 | 1.31273 | 6 | 0.50912 |
| Lag Net Interest Margin | 0.78812 | 0.00479 | 164.6 | <. 0001 | 2.99294 | 7 | 0.45856 |
| Time | -0.00449 | 0.00183 | -2.45 | 0.0143 | 9.01488 | 8 | 0.41941 |
| Residential RE Loan Ratio | 0.00437 | 0.000549 | 7.96 | <. 0001 | 2.29284 | 9 | 0.27355 |
| Commercial RE Loan Ratio | 0.00654 | 0.000547 | 11.97 | <. 0001 | 2.66224 | 10 | 0.23138 |
| C\&I Loan Ratio | 0.00752 | 0.000756 | 9.94 | <. 0001 | 2.45739 | 11 | 0.1802 |
| Credit Card Loan Ratio | 0.01885 | 0.000727 | 25.93 | <. 0001 | 2.93295 | 12 | 0.05978 |
| Trading Assets Ratio | -0.00653 | 0.000792 | -8.25 | <. 0001 | 6.95373 | 13 | 0.03055 |
| Securities Ratio | 0.00393 | 0.000555 | 7.07 | <. 0001 | 3.64234 | 14 | 0.01376 |
| Asset share | 0.00762 | 0.000613 | 12.44 | <. 0001 | 1.21153 | 15 | 0.00198 |

Table 21: Analysis of Variance Inflation and Eigenvalues

## CLASS-X - Model 3 The Bayesian Vector Correction model from VAMAX procedure

This model uses The Bayesian Vector Correction model from VAMAX procedure to fit PPNR data. Given a multivariate time series, the VARMAX estimates the model parameters and generates forecasts associated with vector autoregressive moving-average processes with exogenous regressors (VARMAX) models. Often, economic or financial variables are not only contemporaneously correlated to each other's past values. In Many economic and financial applications, the variables of interest (dependent, response, or endogenous variables) are influence by variables external to the system under consideration (independent, input, predictor, regressor, or exogenous variables).

We leveraged BVECMX Bayesian Vector Error Correction model which uses the ML method. Below are the results of our findings:


MARMAX Procedure
Type of Model BVECMX $(1,0)$
Estimation MethodMaximum Likelihood Estimation Cointegrated Rank 1
Prior Lambda 0.5
Prior Theta 0.2

Table 23: CLASS-X Model 3 Method

| Model Parameter Estimates |  |  |  |
| :---: | :---: | :---: | :---: |
| Equation | ParameterEstimate | Standard Error | $t$ Value Pr $\gg\|t\|$ Variable |
| D_cl_nim |  |  |  |
|  | AR1_1_1-0.03578 | 0.01015 | cl_nim(t-1) |
|  | AR1_1_2-0.36842 | 0.10455 | cl_nintrat(t-1) |
|  | AR1_1_30.00009 | 0.00003 | cl_tradrat(t-1) |
|  | AR1_1_4-0.31489 | 0.08936 | cl_nie_comp(t-1) |
|  | AR1_1_57.05976 | 2.00332 | cl_nie_fass(t-1) |
|  | AR1_1_6-0.04937 | 0.01401 | cl_nie_allother(t-1) |
|  | AR1_1_70.06119 | 0.01736 | cl_afs_return(t-1) |
| D_cl_nintrat |  |  |  |
|  | AR1_2_10.00437 | 0.02099 | cl_nim(t-1) |
|  | AR1_2_20.04503 | 0.21616 | cl_nintrat(t-1) |
|  | AR1_2_3-0.00001 | 0.00005 | cl_tradrat(t-1) |
|  | AR1_2_40.03849 | 0.18475 | cl_nie_comp(t-1) |
|  | AR1_2_5-0.86292 | 4.14204 | cl_nie_fass(t-1) |
|  | AR1_2_60.00603 | 0.02897 | cl_nie_allother(t-1) |
|  | AR1_2_7-0.00748 | 0.03590 | cl_afs_return(t-1) |
| D_cl_tradrat |  |  |  |
|  | AR1_3_140.66554 | 19.37010 | cl_nim(t-1) |
|  | AR1_3_2418.73849 | 199.45651 | cl_nintrat(t-1) |
|  | AR1_3_3-0.10415 | 0.04961 | cl_tradrat(t-1) |
|  | AR1_3_4357.89750 | 170.47629 | cl_nie_comp(t-1) |
|  | AR1_3_5-8023.9190 | 13822.01047 | 7 cl_nie_fass(t-1) |
|  | AR1_3_656.11270 | 26.72800 | cl_nie_allother(t-1) |
|  | AR1_3_7-69.54444 | 33.12591 | cl_afs_return(t-1) |
| D_cl_nie_comp |  |  |  |
|  | AR1_4_10.00717 | 0.00367 | cl_nim(t-1) |
|  | AR1_4_20.07381 | 0.03776 | cl_nintrat(t-1) |
|  | AR1_4_3-0.00002 | 0.00001 | cl_tradrat(t-1) |
|  | AR1_4_40.06308 | 0.03228 | cl_nie_comp(t-1) |
|  | AR1_4_5-1.41433 | 0.72363 | cl_nie_fass(t-1) |
|  | AR1_4_60.00989 | 0.00506 | cl_nie_allother(t-1) |
|  | AR1_4_7-0.01226 | 0.00627 | cl_afs_return(t-1) |
| D_cl_nie_fass |  |  |  |
|  | AR1_5_10.00584 | 0.00124 | cl_nim(t-1) |
|  | AR1_5_20.06012 | 0.01278 | cl_nintrat(t-1) |
|  | AR1_5_3-0.00001 | 0.00000 | cl_tradrat(t-1) |
|  | AR1_5_40.05139 | 0.01093 | cl_nie_comp(t-1) |
|  | AR1_5_5-1.15206 | 0.24496 | cl_nie_fass(t-1) |
|  | AR1_5_60.00806 | 0.00171 | cl_nie_allother(t-1) |
|  | AR1_5_7-0.00999 | 0.00212 | cl_afs_return(t-1) |
| D_cl_nie_allother |  |  |  |
|  | AR1_6_1-0.01157 | 0.01398 | cl_nim(t-1) |
|  | AR1_6_2-0.11918 | 0.14398 | cl_nintrat(t-1) |
|  | AR1_6_30.00003 | 0.00004 | cl_tradrat(t-1) |


| Model Parameter Estimates |  |  |  |
| :---: | :---: | :---: | :---: |
| Equation | Parameter Estimate | Standard <br> Error | t Value Pr > $\mid$ t Variable $^{\text {a }}$ |
|  | AR1_6_4-0.10187 | 0.12306 | cl_nie_comp(t-1) |
|  | AR1_6_52.28380 | 2.75892 | cl_nie_fass(t-1) |
|  | AR1_6_6-0.01597 | 0.01929 | cl_nie_allother(t-1) |
|  | AR1_6_70.01979 | 0.02391 | cl_afs_return(t-1) |
| D_cl_afs_return |  |  |  |
|  | AR1_7_10.15863 | 0.20385 | cl_nim(t-1) |
|  | AR1_7_21.63348 | 2.09908 | cl_nintrat(t-1) |
|  | AR1_7_3-0.00041 | 0.00052 | cl_tradrat(t-1) |
|  | AR1_7_41.39614 | 1.79409 | cl_nie_comp(t-1) |
|  | AR1_7_5-31.30100 | 40.22279 | cl_nie_fass(t-1) |
|  | AR1_7_60.21889 | 0.28129 | cl_nie_allother(t-1) |
|  | AR1_7_7-0.27129 | 0.34862 | cl_afs_return(t-1) |

Table 24: CLASS-X Model 3 Parameter Estimates

Information Criteria
AICC -15.5957
HQC - 15.4084
AIC -17.6175
SBC -12.1369
FPEC $2.606 \mathrm{E}-8$

Table 25: CLASS-X Model 3 Information Criteria

The values for information creation is very low or lower with BVECM model.

| Cross Correlations of Residuals |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Lag | Variable | cl_nim | cl_nintrat | cl_tradrat | cl_nie_comp | cl_nie_fass | cl_nie_allother | cl_afs_return |
| 0 | cl_nim | 1.00000 | 0.10169 | 0.01602 | 0.09927 | 0.38024 | 0.30003 | 0.35295 |
|  | cl_nintrat | 0.10169 | 1.00000 | 0.22683 | 0.32934 | 0.54745 | 0.48103 | 0.12320 |
|  | cl_tradrat | 0.01602 | 0.22683 | 1.00000 | -0.05764 | 0.05128 | 0.01651 | -0.01856 |
|  | cl_nie_comp | 0.09927 | 0.32934 | -0.05764 | 1.00000 | 0.33798 | 0.31867 | -0.06930 |
|  | cl_nie_fass | 0.38024 | 0.54745 | 0.05128 | 0.33798 | 1.00000 | 0.61231 | 0.02882 |
|  | cl_nie_allother | 0.30003 | 0.48103 | 0.01651 | 0.31867 | 0.61231 | 1.00000 | -0.13122 |
|  | cl_afs_return | 0.35295 | 0.12320 | -0.01856 | -0.06930 | 0.02882 | -0.13122 | 1.00000 |
| 1 | cl_nim | -0.15751 | 0.05734 | -0.08786 | 0.17574 | 0.21000 | 0.06592 | -0.01755 |
|  | cl_nintrat | -0.12018 | -0.31404 | -0.13642 | -0.09920 | -0.12500 | -0.04103 | -0.04095 |
|  | cl_tradrat | -0.00357 | 0.04235 | -0.19016 | 0.08692 | 0.03505 | -0.00065 | -0.02779 |
|  | cl_nie_comp | -0.09351 | 0.02134 | -0.01565 | -0.10752 | 0.04779 | 0.04077 | -0.06633 |
|  | cl_nie_fass | -0.11444 | -0.18898 | -0.12412 | -0.00983 | -0.10109 | -0.08139 | 0.00214 |
|  | cl_nie_allother | 0.06026 | -0.19366 | -0.00079 | 0.01558 | 0.02254 | 0.07909 | 0.01879 |
|  | cl_afs_return | -0.08121 | -0.05372 | -0.05974 | 0.00347 | -0.04662 | -0.03598 | -0.09404 |
| 2 | cl_nim | 0.01681 | -0.04853 | 0.04769 | -0.16672 | -0.21814 | -0.16026 | -0.01766 |
|  | cl_nintrat | 0.12665 | -0.18552 | 0.08245 | -0.11443 | -0.08477 | -0.07772 | -0.13695 |
|  | cl_tradrat | -0.04690 | -0.16255 | -0.20126 | 0.03376 | -0.06583 | -0.10938 | -0.07424 |
|  | cl_nie_comp | 0.08099 | -0.21510 | 0.03482 | -0.23554 | -0.14974 | -0.18291 | 0.00673 |
|  | cl_nie_fass | -0.03092 | -0.11448 | 0.01556 | -0.14935 | -0.18010 | -0.03941 | -0.10547 |
|  | cl_nie_allother | -0.00667 | -0.15384 | 0.17000 | 0.00209 | -0.08197 | 0.00225 | -0.12091 |
|  | cl_afs_return | -0.00450 | 0.05756 | 0.02992 | -0.08362 | -0.12931 | -0.07844 | -0.19173 |
| 3 | cl_nim | -0.07938 | 0.02369 | 0.00320 | -0.07000 | -0.09692 | 0.10429 | -0.10177 |
|  | cl_nintrat | -0.07625 | 0.07348 | -0.09006 | 0.09819 | 0.06839 | -0.05761 | 0.04699 |
|  | cl_tradrat | 0.03135 | -0.10656 | 0.02746 | 0.07719 | -0.00142 | -0.14723 | 0.01699 |
|  | cl_nie_comp | -0.10442 | 0.07813 | -0.09723 | -0.04007 | 0.02459 | 0.00626 | -0.05040 |
|  | cl_nie_fass | 0.05777 | 0.11994 | 0.08299 | 0.02567 | -0.04117 | -0.06413 | 0.09480 |
|  | cl_nie_allother | 0.02621 | 0.21603 | 0.09298 | 0.03917 | 0.07438 | -0.08280 | -0.02298 |
|  | cl_afs_return | -0.18408 | 0.00048 | -0.09787 | 0.04646 | -0.02844 | 0.19140 | -0.08570 |

Table 26: CLASS-X Model 3 Cross Correlations of Residuals

Below is the schematic representation of cross correlations of residuals.
Schematic Representation of Cross Correlations of Residuals

| Variable/Lag | 0 | 1 | 2 | 3 |
| :---: | :---: | :---: | :---: | :---: |
| cl_nim | +. . . +++ | . . . . . | ....-. | . . . . . |
| cl_nintrat | . +++++ . | .-.... | . . . . . | . |
| cl_tradrat | . ++ . . | - | . . . . . | . . . . . |
| cl_nie_comp | .+.+++. | . . . . . | .-.-.. | - |
| cl_nie_fass | ++. +++. | . . . . . | . . . . . | - |
| cl_nie_allother | ++. +++. | . . . . . | . . . . . | .+.... |
| cl_afs_return | +.....t | . . . . . | . . . . | . . . . . |

+ is > $2^{*}$ std error, - is < -2** std error, . is between

| Portmanteau Test for Cross Correlations |  |  |  |
| :--- | ---: | ---: | ---: |
| of Residuals |  |  |  |
| Up To Lag | DF | Chi-Square | Pr $>$ ChiSq |
| $\mathbf{2}$ | 49 | 108.61 | $<.0001$ |
| $\mathbf{3}$ | 98 | 156.95 | 0.0001 |


| Univariate Model ANOVA Diagnostics |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Variable | R-Square | Standard Deviation | F Value | $\mathrm{Pr}>\mathrm{F}$ |
| cl_nim | 0.5045 | 0.06934 | 1.70 | 0.0407 |
| cl_nintrat | 0.3972 | 0.14337 | 1.10 | 0.3723 |
| cl_tradrat | 0.7418 | 132.29615 | 4.79 | <. 0001 |
| cl_nie_comp | 0.6444 | 0.02505 | 3.02 | 0.0001 |
| cl_nie_fass | 0.4952 | 0.00848 | 1.64 | 0.0525 |
| cl_nie_allother | 0.7724 | 0.09550 | 5.66 | <. 0001 |
| cl_afs_return | 0.5961 | 1.39228 | 2.46 | 0.0015 |

Table 28: Portmanteau Test and Univariate Model ANOVA

| Variable | Obs | Time | Forecast | $95 \%$ Confidence Limits |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
| cl_nim | 91 | $2013: 43.62616$ | 3.16474 | 4.08758 |  |
|  | 92 | $2014: 13.60771$ | 1.60537 | 5.61006 |  |
|  | 93 | $2014: 23.61131$ | -6.54852 | 13.77115 |  |
|  | 94 | $2014: 33.61590$ | -81.16164 | 88.39344 |  |
|  | 95 | $2014: 43.63391$ | -581.94321 | 589.21102 |  |
| cl_nintrat | 91 | $2013: 41.75205$ | 0.92132 | 2.58278 |  |
|  | 92 | $2014: 11.77019$ | -1.15949 | 4.69987 |  |
|  | 93 | $2014: 21.83122$ | -13.42493 | 17.08736 |  |
|  | 94 | $2014: 31.91286$ | -92.04002 | 95.86575 |  |
|  | 95 | $2014: 41.98274$ | -565.68480 | 569.65028 |  |
|  | 91 | $2013: 4-2.39705$ | -1084.85123 | 1080.05714 |  |
| cl_tradrat | 92 | $2014: 1-22.19306$ | -4690.42882 | 4646.04270 |  |
|  | 93 | $2014: 2-18.38968$ | -36595.88154 | 36559.10218 |  |
|  | 94 | $2014: 3-26.95348$ | -250454.3527 | 250400.44570 |  |
|  | 95 | $2014: 4-32.05344$ | -1691343.888 | 1691279.7808 |  |
|  | 91 | $2013: 41.63847$ | 1.53528 | 1.74166 |  |
| cl_nie_comp | 92 | $2014: 11.65031$ | 1.15036 | 2.15026 |  |
|  | 93 | $2014: 21.66400$ | -2.86989 | 6.19788 |  |
|  | 94 | $2014: 31.67970$ | -24.58593 | 27.94532 |  |
|  | 95 | $2014: 41.69627$ | -176.80579 | 180.19832 |  |
| cl_nie_fass | 91 | $2013: 40.35923$ |  |  |  |
|  | 92 | $2014: 10.36140$ | 0.19229 | 0.53050 |  |
|  | 93 | $2014: 20.35984$ | -1.81991 | 2.53960 |  |
|  | 94 | $2014: 30.36111$ | -5.68044 | 6.40266 |  |
|  | 95 | $2014: 40.36109$ | -40.67419 | 41.39637 |  |
|  |  |  |  |  |  |
| cl_nie_allother91 | $2013: 41.30402$ | 0.75781 | 1.85023 |  |  |


| Variable | Obs Time | Forecast | $\mathbf{9 5 \%}$ Confidence Limits |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
|  | 92 | $2014: 11.26446$ | -0.18857 | 2.71749 |
|  | 93 | $2014: 21.22455$ | -5.56657 | 8.01567 |
|  | 94 | $2014: 31.20324$ | -49.31826 | 51.72474 |
|  | 95 | $2014: 41.17173$ | -308.05355 | 310.39702 |
| cl_afs_return | 91 | $2013: 40.19522$ | -6.21051 | 6.60094 |
|  | 92 | $2014: 10.85545$ | -32.67011 | 34.38102 |
|  | 93 | $2014: 21.30197$ | -201.49395 | 204.09788 |
|  | 94 | $2014: 31.58262$ | -1282.91854 | 1286.08377 |
|  | 95 | $2014: 41.90854$ | -8459.66585 | 8463.48293 |

Table 29: Snapshot of Forecast Data with CLASS-X Model 3


Figure 12: Prediction error diagnostics for Net Interest Margin


Figure 13: Plot of fitted data with CLASS-X Model 3 form Net Interest Margin

Graphs for forecast the seven Key PPMR Components with CLASS-X Model 3.

|  |  |
| :---: | :---: |
| Projections of PPNR - Net Interest Margin by Year | Projections of PPNR - Noninterest Non-Trading Income Ratio by Year |
| 1 - Net Interest Margin | 2 - Noninterest Non-Trading Income Ratio |



Figure 14: Forecast for Seven Key PPNR Components with CLASS-X Model 3

Here we show a different way to do regression of PPNR. The CLASS model with VARMAX BVECM. We have used Maximum Likelihood method while The CLASS model used Ordinary Least Square Regression. So far, we have shown several alternatives Models of The CLASS model. In short this is a summary of our CLASS-X Model 3 with VARMAX procedure with BVECM Model.

## Appendix E: Forecast with Key PPNR Components



Figure 15: Net Interest Margin


Figure 16: Return On Trading Asset


Figure 17: Non-Trading Non-interest Income Ratio

Projections of PPNR - Non-Interest Expense Ratio Graph


Figure 18 : Non-interest expense ratio



[^8]

Figure 21: Return On Assets for Sale

## Appendix F: Sensitivity Analysis to Assumptions





Figure 24: Dividends Payout Rule

## Appendix G: Results of CLASS and The CLASS models Regressions for the 19 CCAR Stress Test Companies

## Results of The CLASS model regressions for the 19 CCAR Stress Test Companies

 1) Net Interest MarginOverview
Again Net Interest Margin is one of the key components of PPNR. The regression of this equation will help to understand how Net interest margin will change by changing any of the explanatory variables. Also it will help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Net Interest Margin regression for the 19 CCAR Stress Test Companies.

| Root MSE | 0.58960 | R-Square 0.9215 |
| :--- | ---: | :--- |
| Dependent Mean3.10432 Adj R-Sq0.9208 |  |  |
| Coeff Var | 18.99276 |  |

Parameter estimates

|  | ParameterStandard <br> Lstimate |  |  | Error | t ValuePr $>\|\boldsymbol{t}\|$ |
| :--- | :--- | :--- | :--- | :--- | :--- | Tolerance | Variance |
| :--- |
| Inflation |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :---: | :--- |
| 1 | 8.68406 | 1.00000 |
| 2 | 1.18529 | 2.70675 |
| 3 | 0.67690 | 3.58177 |
| 4 | 0.45888 | 4.35023 |
| 5 | 0.42936 | 4.49727 |
| 6 | 0.21416 | 6.36789 |
| 7 | 0.15167 | 7.56678 |
| 8 | 0.08547 | 10.07984 |
| 9 | 0.06352 | 11.69212 |
| 10 | 0.03018 | 16.96215 |
| 11 | 0.01830 | 21.78150 |
| 12 | 0.00220 | 62.87476 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that some values of the Variance Inflation are too high (i.e., some values are greater than 5 and greater than 10). The rule of thumb that any VIF values that are greater than five have to be investigated and any value that are greater than 10 are not acceptable. Also we can say that some variables are not statistically significant at $10 \%$ level.
The Eigenvalue should not be too close to zero. Here you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore the model has a strong collinearity. Next we look at the condition Index. According to the rule of thumb a model with a condition index greater than 15 needs to be investigated and any model with a condition index greater than 30 are not acceptable. Again the rules are violated for this model. Therefore we can say that this model deteriorates we segment the data.
2) Non Interest Non Trade Ratio

Overview
Again Non Interest Non Trade Ratio is one of the key components of PPNR. The regression of this equation will help to understand how Non Interest Non Trade Ratio will change by changing any of the explanatory variables. Also it will help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Non Interest Non Trade Ratio regression for the 19 CCAR Stress Test Companies.

| Root MSE | 1.13786 R-Square 0.8483 |
| :--- | ---: |
| Dependent Mean2.58222 Adj R-Sq0.8471 |  |
| Coeff Var | 44.06527 |

Parameter estimates

| Label | Parameter <br> Estimate | Standard <br> Error |  |  | t Value Pr $>\|\boldsymbol{t}\|$ | Toleranc <br> Variance | Inflation |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 0.29629 | 0.18045 | 1.64 | 0.1009 | . | 0 |  |
| Stock Market Quarterly Log Change | 0.00425 | 0.00198 | 2.14 | 0.0326 | 0.97632 | 1.02426 |  |
| Lag Noninterest | Non-Trading |  |  |  |  |  |  |
| Income Ratio | 0.85386 | 0.01451 | 58.86 | $<.0001$ | 0.57968 | 1.72508 |  |
| Residential RE Loan Ratio | 0.00038717 | 0.00328 | 0.12 | 0.9061 | 0.31464 | 3.17828 |  |
| Commercial RE Loan Ratio | -0.00483 | 0.00549 | -0.88 | 0.3797 | 0.32740 | 3.05437 |  |
| C\&I Loan Ratio | -0.00235 | 0.00393 | -0.60 | 0.5504 | 0.42521 | 2.35180 |  |
| Credit Card Loan Ratio | 0.01832 | 0.00546 | 3.35 | 0.0008 | 0.62905 | 1.58970 |  |
| Trading Assets Ratio | 0.00074923 | 0.00400 | 0.19 | 0.8513 | 0.14171 | 7.05683 |  |
| Securities Ratio | 0.00781 | 0.00257 | 3.04 | 0.0024 | 0.21052 | 4.75015 |  |
| Asset share | -0.01610 | 0.00548 | -2.94 | 0.0034 | 0.40708 | 2.45653 |  |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :---: | :--- |
| 1 | 6.31406 | 1.00000 |
| 2 | 1.09949 | 2.39640 |
| 3 | 0.97971 | 2.53867 |
| 4 | 0.64338 | 3.13271 |
| 5 | 0.45030 | 3.74459 |
| 6 | 0.18956 | 5.77138 |
| 7 | 0.14657 | 6.56354 |
| 8 | 0.11469 | 7.41968 |
| 9 | 0.05478 | 10.73594 |


| NumberEigenvalue | Condition <br> Index |
| :--- | :--- |
| 10 | 0.00747 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that some variables are not statistically significant at $10 \%$ level.

The eigenvalue should not be too close to zero. Here you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we look at the condition Index. According to the rule of thumb a model with a condition index greater than 15 needs to be investigated and any model with a condition index greater than 30 are not acceptable. Again, the rules are violated for this model deteriorates when we segment the data.

## 3) Return on Trade Assets

Overview
Again, Return on Trade Assets is one of the key components of PPNR. The regression of this equation will help to understand how Return on Trade Assets will change by changing any of the explanatory variables. It will also help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Return on Trade Assets regression for the 19 CCAR Stress test Companies.

Parameter estimates

| Root MSE | 61.05825 |
| :--- | ---: |
| R-Square0.2828 |  |
| Dependent Mean13.40601 Adj R-Sq0.2806 |  |
| Coeff Var | 455.45439 |


|  | ParameterStandard <br> Estimate |  | Error | t ValuePr $>\|\boldsymbol{t}\|$ | Tolerance | Variance <br> Inflation |
| :--- | ---: | :--- | :--- | :--- | :--- | :--- |
| Variable | 6.86957 | 2.393762 .87 | 0.0042 | . | 0 |  |
| Intercept | 6.38718 | $6.80726-0.09$ | 0.9320 | 0.33146 | 3.01699 |  |
| dbspread | -0.58118 | $6.83915-0.36$ | 0.7200 | 0.33136 | 3.01789 |  |
| dbspread_pos-3.45592 | 9.639 |  |  |  |  |  |
| l1_cl_tradrat | 0.53691 | 0.0273619 .63 | $<.0001$ | 0.99948 | 1.00052 |  |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue <br> Index |
| :--- | :---: | :--- |
| 1 | 1.86183 | 1.00000 |
| 2 | 1.15624 | 1.26896 |
| 3 | 0.82720 | 1.50025 |
| 4 | 0.15472 | 3.46893 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that some variables are not statistically significant at $10 \%$ level.

## 4) Compensation NonInterest Expense

Overview
Compensation NonInterest Expense Ratio is one of the key components of PPNR. The regression of this equation will help to understand how Compensation NonInterest Expense will change by changing any of the explanatory variables. It will also help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Compensation NonInterest Expense regression for the 19 CCAR stress test companies.

| Root MSE | 0.42999 |
| :--- | ---: |
| R-Square 0.7338 |  |
| Dependent Mean1.62960 Adj R-Sq0.7319 |  |
| Coeff Var | 26.38595 |

Parameter estimates

|  | $\begin{array}{l}\text { ParameterStandard } \\ \text { Estimate }\end{array}$ |  |  | Error |
| :--- | ---: | :--- | :--- | :--- | :--- | :--- | :--- |$)$

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :---: | :--- |
| 1 | 6.50515 | 1.00000 |
| 2 | 1.09487 | 2.43751 |
| 3 | 0.97986 | 2.57660 |
| 4 | 0.51609 | 3.55032 |
| 5 | 0.42559 | 3.90961 |
| 6 | 0.19083 | 5.83848 |
| 7 | 0.14588 | 6.67782 |
| 8 | 0.09630 | 8.21902 |
| 9 | 0.04094 | 12.60532 |
| 10 | 0.00449 | 38.05481 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that some variables are not statistically significant at $10 \%$ level.

The eigenvalue should not be too close to zero. Here you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we look at the condition Index. According to the rule of thumb a model with a condition index greater than 15 needs to be investigated and any model with a condition index greater than

30 are not acceptable. Again, the rules are violated with this model deteriorates when we segment the data.

## 5) Fixed Asset Noninterest Expense Ratio

Overview
Fixed Asset Noninterest Expense Ratio is one of the key components of PPNR. The regression of this equation will help to understand how Fixed Asset Noninterest Expense Ratio will change by changing any of the explanatory variables. It will also help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Fixed Asset Noninterest Expense Ratio regression for the 19 CCAR stress test companies.


Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 7.69990 | 1.00000 |
| 2 | 1.11908 | 2.62308 |
| 3 | 0.61881 | 3.52747 |
| 4 | 0.54679 | 3.75258 |
| 5 | 0.42455 | 4.25869 |
| 6 | 0.21703 | 5.95644 |
| 7 | 0.15690 | 7.00544 |
| 8 | 0.10469 | 8.57593 |
| 9 | 0.07394 | 10.20464 |
| 10 | 0.03425 | 14.99313 |
| 11 | 0.00405 | 43.58669 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that some variables are not statistically significant at $10 \%$ level.

The eigenvalue should not be too close to zero. Here you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we look at the condition Index. According to the rule of thumb a model with a condition index greater than 15 needs to be investigated and any model with a condition index greater than 30 are not acceptable. Again, the rules are violated for this model deteriorates when we segment the data.

## 6) Other NonInterest Expense Ratio

Overview
Other NonInterest Expense Ratio is one of the key components of PPNR. The regression of this equation will help to understand how Other NonInterest Expense Ratio will change by changing any of the explanatory variables. It will also help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Other NonInterest Expense Ratio regression for the 19 CCAR stress test companies.

| Root MSE | 1.17194 | R-Square 0.8488 |
| :--- | ---: | :--- |
| Dependent Mean 1.63352 Adj R-Sq0.8477 |  |  |
| Coeff Var | 71.74292 |  |

Parameter estimates

| Label | $\begin{array}{l}\text { Parameter } \\ \text { Estimate }\end{array}$ | $\begin{array}{l}\text { Standard } \\ \text { Error }\end{array}$ |  | t ValuePr $>\|\boldsymbol{t}\|$ | Tolerance |
| :--- | :---: | :--- | :--- | :--- | :--- | \(\left.\begin{array}{l}Variance <br>


Inflation\end{array}\right]\)| Intercept | 0.01362 | 0.179400 .08 | 0.9395 |  | 0 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Change in bond spread | 0.16853 | 0.037094 .54 | $<.0001$ | 0.98536 | 1.01486 |
| Lag All Other Expense Ratio0.77046 | 0.0179542 .91 | $<.0001$ | 0.37826 | 2.64369 |  |
| Residential RE Loan Ratio | -0.00700 | $0.00340-2.06$ | 0.0395 | 0.31150 | 3.21028 |
| Commercial RE Loan Ratio | 0.01189 | 0.005672 .10 | 0.0362 | 0.32540 | 3.07313 |
| C\&I Loan Ratio | -0.00465 | $0.00403-1.15$ | 0.2488 | 0.42958 | 2.32785 |
| Credit Card Loan Ratio | 0.02314 | 0.005724 .04 | $<.0001$ | 0.60745 | 1.64624 |
| Trading Assets Ratio | 0.00156 | 0.004100 .38 | 0.7043 | 0.14252 | 7.01632 |
| Securities Ratio | 0.01726 | 0.002985 .80 | $<.0001$ | 0.16643 | 6.00854 |
| Asset share | 0.000045120 .005540 .01 | 0.9935 | 0.42262 | 2.36617 |  |

Collinearity Diagnostics

|  |  | Condition <br> Index |
| :--- | :---: | :--- |
| NumberEigenvalue | 6.07943 | 1.00000 |
| 2 | 1.13202 | 2.31741 |
| 3 | 1.00915 | 2.45445 |
| 4 | 0.83895 | 2.69192 |
| 5 | 0.44787 | 3.68430 |
| 6 | 0.18021 | 5.80824 |
| 7 | 0.14640 | 6.44404 |
| 8 | 0.09778 | 7.88492 |
| 9 | 0.06045 | 10.02824 |
| 10 | 0.00773 | 28.03861 |

Summary of Findings: In the Parameter Estimates table, we want to highlight that some values of the Variance Inflation are too high (i.e., some values are greater than 5). The rule of thumb that any VIF values that are greater than five have to be investigated and any value that are greater than 10 are not acceptable. Also, we can say that some variables are not statistically significant at $10 \%$ level.

The eigenvalue should not be too close to zero. Here you can see the last two values in the Collinearity Diagnostics table are close to zero. Therefore, the model has a strong collinearity. Next, we look at the condition Index. According to the rule of thumb a model with a condition index greater than 15 needs to be investigated and any model with a condition index greater than 30 are not acceptable. Again, the rules are violated for this model. Therefore, relative to the results that we got before the segmentation we can say that this model deteriorates when we segment the data.

## 7) Return on AFS Securities

Overview
Return on AFS Securities is one of the key components of PPNR. The regression of this equation will help to understand how Return on AFS Securities will change by changing any of the explanatory variables. Also, it will help us with the sensitivity analysis of financial strength with the explanatory variables. Below are statistical results of the Return on AFS Securities regression for the 19 CCAR stress test companies.


Collinearity Diagnostics

|  | NumberEigenvalue | Condition <br> Index |
| :--- | :---: | :--- |
| 1 | 1.52345 | 1.00000 |
| 2 | 1.10563 | 1.17384 |
| 3 | 0.79006 | 1.38862 |
| 4 | 0.58086 | 1.61950 |

Summary of Findings: The statistical results of this model is reasonable when we segment the data for the 19 CCAR stress test companies.

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

## CLASS Specification Details for Some Companies (Company 1)

1) Net Interest Margin

Overview
Below are the regression results for the seven key PPNR components for 1 company.

$$
\text { Root MSE } \quad 0.35178 \text { R-Square } 0.9548
$$

Dependent Mean2.35336 Adj R-Sq0.9484
Coeff Var 14.94780
Parameter estimates

| Label | $\begin{array}{l}\text { ParameterStandard } \\ \text { Estimate } \\ \text { Error }\end{array}$ |  |  | $\mathbf{t}$ ValuePr $>\|\boldsymbol{t}\|$ ToleranceInflation |
| :--- | :--- | :--- | :--- | :--- |$]$| Variance |
| :--- |
| Intercept |

Collinearity Diagnostic

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 10.37750 | 1.00000 |
| 2 | 0.81793 | 3.56196 |
| 3 | 0.44123 | 4.84969 |
| 4 | 0.19270 | 7.33846 |
| 5 | 0.07857 | 11.49248 |
| 6 | 0.03664 | 16.82844 |
| 7 | 0.02114 | 22.15860 |
| 8 | 0.01740 | 24.41882 |
| 9 | 0.00788 | 36.29678 |
| 10 | 0.00476 | 46.69863 |
| 11 | 0.00367 | 53.16212 |
| 12 | 0.00057867 | 133.91587 |

Summary Findings:
2) Noninterest Nontrade Ratio

Overview

| Root MSE | 0.75638 | R-Square 0.7047 |
| :--- | ---: | ---: |
| Dependent Mean2.03508 Adj R-Sq0.6715 |  |  |
| Coeff Var | 37.16706 |  |

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

Parameter estimates


Summary Findings
3) Return On Trade Assets

Overview

| Root MSE | 1.38178 |
| :--- | ---: |
| R-Square 0.4139 |  |
| Dependent Mean2.09181 Adj R-Sq0.3860 |  |
| Coeff Var | 66.05679 |

Parameter estimates

| Variable | ParameterStandard <br> Estimate <br> Error |  | $\mathbf{t}$ Value | Pr $>\|\boldsymbol{t}\|$ | Tolerance | Variance <br> Inflation |
| :--- | ---: | :--- | :--- | :--- | :--- | :--- |
| Intercept | 1.79876 | 0.307855 .84 | $<.0001$ |  | 0 |  |
| dbspread | -0.37196 | $0.65242-0.57$ | 0.5706 | 0.29871 | 3.34768 |  |
| dbspread_pos-2.06438 | $0.89992-2.29$ | 0.0251 | 0.29095 | 3.43700 |  |  |
| l1_cl_tradrat | 0.28606 | 0.101172 .83 | 0.0063 | 0.91070 | 1.09805 |  |

Collinearity Diagnostics

| NumberEigenvalue | Condition <br> Index |
| :--- | :--- |
| 1 | 2.01949 |

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

|  |  |  |
| :--- | :--- | :--- |
| NumberEigenvalue |  |  | \(\left.\begin{array}{l}Condition <br>


Index\end{array}\right]\)| 2 | 1.61968 | 1.11662 |
| :--- | :--- | :--- |
| 3 | 0.23547 | 2.92858 |
| 4 | 0.12537 | 4.01356 |

Summary Findings
4) Compensation NonInterest Expense Ratio

Overview

> | Root MSE | 0.49204 |
| :--- | ---: |
| R-Square 0.4984 |  |
| Dependent Mean 1.49437 Adj R-Sq 0.4420 |  |
| Coeff Var | 32.92636 |

Parameter estimates

|  | ParameterStandard <br> Estimate |  |  | Error | $\boldsymbol{t}$ ValuePr $>\|\boldsymbol{t}\|$ |
| :--- | ---: | :--- | :--- | :--- | :--- | Tolerance | Variance |
| :--- |
| Inflation |

Collinearity Diagnostic

|  |  | Condition <br> Number Eigenvalue |
| :--- | :--- | :--- |
| 1 | 8.21799 | 1.00000 |
| 2 | 0.99528 | 2.87349 |
| 3 | 0.38254 | 4.63496 |
| 4 | 0.23116 | 5.96243 |
| 5 | 0.07818 | 10.25231 |
| 6 | 0.04866 | 12.99557 |
| 7 | 0.02137 | 19.60865 |
| 8 | 0.01300 | 25.14151 |
| 9 | 0.01105 | 27.27658 |
| 10 | 0.00076058 | 103.94688 |

Summary Findings
5) Fixed Assets Noninterest Expense Ratio

Overview

| Root MSE | 0.16915 |
| :--- | ---: |
| R-Square 0.7629 |  |
| Dependent Mean0.45847 Adj R-Sq0.7329 |  |
| Coeff Var | 36.89462 |

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

Parameter estimates

| Label | Parameter <br> Estimate | Standard <br> Error | t Value Pr $>\|\mathbf{t}\|$ | Tolerance | Variance <br> Inflation |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 1.09463 | 0.25702 | 4.26 | $<.0001$ | . | 0 |
| Real GDP Annualized Log Change-0.000335670.00294 | -0.11 | 0.9095 | 0.56218 | 1.77880 |  |  |
| Lag Fixed Asset Expense Ratio | 0.21632 | 0.11235 | 1.93 | 0.0578 | 0.24154 | 4.14003 |
| Time | -0.00947 | 0.00501 | -1.89 | 0.0624 | 0.03930 | 25.44684 |
| Residential RE Loan Ratio | 0.00125 | 0.00317 | 0.39 | 0.6942 | 0.74002 | 1.35132 |
| Commercial RE Loan Ratio | 0.00482 | 0.00787 | 0.61 | 0.5421 | 0.25451 | 3.92913 |
| C\&I Loan Ratio | -0.01355 | 0.00492 | -2.76 | 0.0073 | 0.05315 | 18.81435 |
| Credit Card Loan Ratio | -0.01970 | 0.00653 | -3.01 | 0.0035 | 0.48987 | 2.04136 |
| Trading Assets Ratio | -0.00302 | 0.00292 | -1.03 | 0.3042 | 0.07043 | 14.19929 |
| Securities Ratio | -0.00804 | 0.00281 | -2.86 | 0.0054 | 0.20365 | 4.91050 |
| Asset share | -0.01937 | 0.00737 | -2.63 | 0.0104 | 0.06058 | 16.50824 |

Collinearity Diagnostic

|  |  | Condition <br> Index |
| :--- | :--- | :--- |
| NumberEigenvalue | 1.00000 |  |
| 1 | 9.40980 | 3.59594 |
| 3 | 0.72771 | 4.74830 |
| 4 | 0.41735 | 6.11447 |
| 5 | 0.25169 | 10.78933 |
| 6 | 0.08083 | 12.80884 |
| 7 | 0.05735 | 20.41707 |
| 8 | 0.01957 | 21.94424 |
| 9 | 0.00918 | 32.01504 |
| 10 | 0.00351 | 51.74113 |
| 11 | 0.00045133 | 144.39193 |

Summary Findings
6) Other NonInterest Expense Ratio

Overview


Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies
$\left.\begin{array}{llll}\hline \text { Label } & \begin{array}{l}\text { ParameterStandard } \\ \text { Estimate }\end{array} \text { Error } & \text { t ValuePr }>|\mathbf{t}| \text { Tolerance }\end{array} \quad \begin{array}{l}\text { Variance } \\ \text { Inflation }\end{array}\right]$

Collinearity Diagnostic

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 8.12363 | 1.00000 |
| 2 | 1.01259 | 2.83243 |
| 3 | 0.39014 | 4.56318 |
| 4 | 0.21568 | 6.13716 |
| 5 | 0.10423 | 8.82828 |
| 6 | 0.07045 | 10.73798 |
| 7 | 0.05046 | 12.68858 |
| 8 | 0.01966 | 20.32718 |
| 9 | 0.01223 | 25.77594 |
| 10 | 0.00094029 | 92.94902 |

Summary Findings
7) Return on AFS Securities

Overview

| Root MSE | 2.74118 | R-Square0.1524 |
| :--- | ---: | ---: |
| Dependent Mean0.55589 | Adj R-Sq0.1121 |  |
| Coeff Var | 493.11315 |  |

Parameter estimates

|  |  |  |  |  |  |
| :--- | :---: | :--- | :--- | :--- | :--- |
| Variable | ParameterStandard <br> Estimate | Error | t ValuePr $>\|\boldsymbol{t}\|$ | Tolerance | Variance <br> Inflation |
| Intercept | 0.37597 | 0.140232 .68 | 0.0094 |  | 0 |
| d10y | -0.82146 | $0.34778-2.36$ | 0.0213 | 0.92059 | 1.08627 |
| unsafe_dbspread_pos-0.00471 | $0.00779-0.61$ | 0.5472 | 0.92208 | 1.08450 |  |
| l1_cl_afs_return | 0.26006 | 0.115972 .24 | 0.0285 | 0.99218 | 1.00788 |

Collinearity Diagnostic

|  |  | Condition <br> Index |
| :--- | :--- | :--- |
| NumberEigenvalue | 1.78877 | 1.00000 |
| 2 | 1.01296 | 1.32887 |
| 3 | 0.69224 | 1.60749 |
| 4 | 0.50603 | 1.88013 |

In short, we can see the results of the seven previous regressions and assess that the CLASS model deteriorates further when we segment the data to analyze one company.

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

## Results of CLASS-X Model regressions for the 19 CCAR Stress Test companies

1) Net Interest Margin Model

Overview

|  | Root MSE | 0.62504 |
| :--- | :--- | ---: |
|  | R-Square0.9169 |  |
|  | Dependent Mean3.06781 Adj R-Sq0.9163 |  |
| Coeff Var | 20.37406 |  |
|  |  |  |


| Label | Parameter <br> Estimate | Standard <br> Error | t Value | $\mathrm{Pr}>\|\mathbf{t}\|$ | Tolerance Inflation |  |
| :--- | :---: | :--- | :--- | :--- | :--- | :--- |
| Intercept | 0.03617 | 0.04614 | 0.78 | 0.4333 | . | 0 |
| 3M Treasury Yield | 0.00744 | 0.00575 | 1.29 | 0.1961 | 0.71163 | 1.40522 |
| AFS Ratio X Change in bond |  |  |  |  |  |  |
| spread X >0 Dummy | 0.00128 | 0.00054365 | 2.35 | 0.0192 | 0.95029 | 1.05231 |
| Lag Net Interest Margin | 0.90848 | 0.01174 | 77.40 | $<.0001$ | 0.53768 | 1.85985 |
| Residential RE Loan Ratio | 0.00177 | 0.00159 | 1.12 | 0.2645 | 0.43241 | 2.31262 |
| Commercial RE Loan Ratio | 0.00547 | 0.00310 | 1.77 | 0.0776 | 0.32473 | 3.07945 |
| C\&I Loan Ratio | 0.00566 | 0.00230 | 2.46 | 0.0142 | 0.44386 | 2.25298 |
| Securities Ratio | 0.00284 | 0.00099636 | 2.85 | 0.0044 | 0.54922 | 1.82076 |
| Asset share | 0.00327 | 0.00279 | 1.17 | 0.2415 | 0.50850 | 1.96657 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :---: | :--- |
| 1 | 6.22323 | 1.00000 |
| 2 | 1.00371 | 2.49002 |
| 3 | 0.62018 | 3.16774 |
| 4 | 0.48128 | 3.59592 |
| 5 | 0.39766 | 3.95597 |
| 6 | 0.11057 | 7.50206 |
| 7 | 0.07246 | 9.26721 |
| 8 | 0.05537 | 10.60187 |
| 9 | 0.03554 | 13.23210 |

Summary Findings: For a Net Interest Margin model, we have found that the results of the regression (R-squared, RMSE, Variance Inflation, Eigenvalue, Condition Index, and others) are in a reasonable standard of a good model.
2) NonInterest Nontrade Ratio

Overview

| Root MSE | 1.17671 | R-Square 0.8518 |
| :--- | ---: | :--- |
| Dependent Mean2.61131 Adj R-Sq0.8505 |  |  |
| Coeff Var | 45.06187 |  |

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

Parameter Estimates

| Label | ParameterStandard |  |  |  | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Estimate | Error | $t$ Value | $\mathrm{Pr}>\|t\|$ |  |
| Intercept | 0.35693 | 0.08248 | 4.33 | <. 0001 | 0 |
| Real GDP Annualized Log Change | -0.01355 | 0.01081 | -1.25 | 0.2101 | 2.29063 |
| Stock Market Quarterly Log Change | 0.00471 | 0.00246 | 1.92 | 0.0556 | 1.46404 |
| AFS Ratio X Change in bond spread $\mathrm{X}>0$ Dummy | -0.00327 | 0.00124 | -2.63 | 0.0085 | 1.61485 |
| Change in Unemployment | 0.07352 | 0.01975 | 3.72 | 0.0002 | 1.98039 |
| Year over year HPI | 0.00697 | 0.00277 | 2.51 | 0.0121 | 1.69181 |
| Lag Noninterest Non-Trading Income Ratio | 0.83797 | 0.01561 | 53.69 | <. 0001 | 1.84157 |
| Commercial RE Loan Ratio | -0.00883 | 0.00422 | -2.09 | 0.0364 | 1.62818 |
| Credit Card Loan Ratio | 0.02265 | 0.00518 | 4.37 | <. 0001 | 1.30521 |
| Securities Ratio | 0.00941 | 0.00162 | 5.80 | <. 0001 | 1.74818 |
| Asset share | -0.01973 | 0.00506 | -3.90 | 0.0001 | 1.84736 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue <br> Index |
| :--- | :--- | :--- |
| 1 | 4.97986 | 1.00000 |
| 2 | 2.30510 | 1.46982 |
| 3 | 0.94439 | 2.29632 |
| 4 | 0.79188 | 2.50772 |
| 5 | 0.53625 | 3.04737 |
| 6 | 0.41348 | 3.47042 |
| 7 | 0.36258 | 3.70603 |
| 8 | 0.31338 | 3.98631 |
| 9 | 0.21117 | 4.85612 |
| 10 | 0.10430 | 6.90969 |
| 11 | 0.03760 | 11.50785 |

Summary Findings: For a NonInterest Nontrade Ratio Model we have found that the results of the regression (R-Squared, RMSE, Variance Inflation, Eigenvalue, Condition Index and others) are in a reasonable standard of a good model.
3) Return On Trade Assets

| Root MSE | 1.31703 | R-Square 0.4675 |
| :--- | ---: | :--- |
| Dependent Mean2.09181 Adj R-Sq0.4422 |  |  |
| Coeff Var | 62.96119 |  |

Overview
Parameter Estimates

| ParameterStandard |  |  |  |  | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Variable | Estimate | Error | $t$ Valu | ePr > $\|t\|$ |  |
| Intercept | 2.72317 | 0.210 | 612.92 | <. 0001 | 0 |
| unsafe_dbspread_po | -0.06157 | 0.012 | 2-4.80 | <. 0001 | 1.28591 |
| yyhpi_zero | 0.12631 | 0.043 | 92.89 | 0.0053 | 1.61487 |
| yусррі | -0.03417 | 0.014 | 3-2.37 | 0.0209 | 1.29491 |

Collinearity Diagnostics

|  |  | Condition <br> Index |
| :--- | :--- | :--- |
| NumberEigenvalue |  | 1.76605 |
|  | 1.00000 |  |
| 3 | 1.31129 | 1.16052 |
| 4 | 0.64940 | 1.64909 |

Summary Findings: For a Return on Trade Assets model, we have found that the results of the regression (RMSE, Variance Inflation, Eigenvalue, Condition Index, and others) are in a reasonable standard of a good model.
Overview

| Root MSE | 0.45143 | R-Square 0.7254 |
| :--- | ---: | :--- |
| Dependent Mean 1.62575 | Adj R-Sq 0.7240 |  |
| Coeff Var | 27.76749 |  |


| Label | Parameter Estimate | Standard Error | $t$ Value $\operatorname{Pr}>\|\mathrm{t}\|$ |  | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Intercept | 0.27734 | 0.02904 | 9.55 | <. 0001 | 0 |
| Real GDP Annualized Log Change | -0.01751 | 0.00407 | -4.30 | <. 0001 | 2.20910 |
| Stock Market Quarterly Log Change | 0.00478 | 0.00092914 | 5.15 | <. 0001 | 1.41944 |
| AFS Ratio X Change in bond spread |  |  |  |  |  |
| X >0 Dummy | -0.00179 | 0.00046306 | -3.87 | 0.0001 | 1.52392 |
| Change in Unemployment | -0.01201 | 0.00688 | -1.75 | 0.0812 | 1.63319 |
| Lag Compensation Expense Ratio | 0.83341 | 0.01587 | 52.50 | <. 0001 | 1.04509 |
| Residential RE Loan Ratio | 0.00173 | 0.00074824 | 2.31 | 0.0208 | 1.03002 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 3.32638 | 1.00000 |
| 2 | 1.96802 | 1.30009 |
| 3 | 0.77285 | 2.07462 |
| 4 | 0.50461 | 2.56750 |
| 5 | 0.24088 | 3.71611 |
| 6 | 0.15078 | 4.69688 |
| 7 | 0.03649 | 9.54824 |

Summary Findings: For a Compensation NonInterest Expense Ratio model, we have found that the results of the regression (RMSE, Variance Inflation, Eigenvalue, Condition Index, and others) are in a reasonable standard of a good model.
4) Fixed Asset Noninterest Expense Ratio

Overview

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies


Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 5.26466 | 1.00000 |
| 2 | 2.48800 | 1.45465 |
| 3 | 1.05330 | 2.23568 |
| 4 | 0.65892 | 2.82664 |
| 5 | 0.52059 | 3.18009 |
| 6 | 0.30615 | 4.14684 |
| 7 | 0.23431 | 4.74015 |
| 8 | 0.17783 | 5.44108 |
| 9 | 0.11937 | 6.64103 |
| 10 | 0.11488 | 6.76959 |
| 11 | 0.06200 | 9.21485 |

Summary Findings: For a Fixed Asset Noninterest Expense Ratio model, we have found that the results of the regression (R-Squared, RMSE, Variance Inflation, Eigenvalue, Condition Index, and others) are in a reasonable standard of a good model.
5) Other NonInterest Expense Ratio

Overview

| Root MSE | 1.20717 R-Square0.8549 |
| :--- | :--- |
| Dependent Mean1.64154 Adj R-Sq0.8536 |  |
| Coeff Var $\quad 73.53867$ |  |

Parameter Estimates

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

| Label | Parameter <br> Estimate | Standard <br> Error | t Value Pr $>\|\|t\|$ | Variance <br> Inflation |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | -0.12845 | 0.06437 | -2.00 | 0.0462 | 0 |
| Real GDP Annualized Log Change | 0.00195 | 0.01085 | 0.18 | 0.8574 | 2.19443 |
| Stock Market Quarterly Log Change | 0.00962 | 0.00284 | 3.39 | 0.0007 | 1.85475 |
| Change in bond spread | 0.06201 | 0.08115 | 0.76 | 0.4450 | 4.56518 |
| Change in bond spread X >0 Dummy | 0.25630 | 0.13918 | 1.84 | 0.0658 | 7.06214 |
| AFS Ratio X Change in bond spread X >0 |  |  |  |  |  |
| Dummy | 0.00199 | 0.00202 | 0.98 | 0.3256 | 4.07252 |
| Change in Unemployment | 0.00788 | 0.01977 | 0.40 | 0.6904 | 1.88479 |
| Lag All Other Expense Ratio | 0.79036 | 0.01848 | 42.77 | $<.0001$ | 2.62965 |
| Credit Card Loan Ratio | 0.02138 | 0.00524 | 4.08 | $<.0001$ | 1.26868 |
| Securities Ratio | 0.01754 | 0.00209 | 8.38 | $<.0001$ | 2.76611 |
| Asset share | -0.00257 | 0.00418 | -0.62 | 0.5385 | 1.19950 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 4.35346 | 1.00000 |
| 2 | 3.15606 | 1.17448 |
| 3 | 1.06883 | 2.01819 |
| 4 | 0.76935 | 2.37878 |
| 5 | 0.58223 | 2.73445 |
| 6 | 0.37169 | 3.42236 |
| 7 | 0.25795 | 4.10820 |
| 8 | 0.18607 | 4.83701 |
| 9 | 0.11611 | 6.12314 |
| 10 | 0.08140 | 7.31313 |
| 11 | 0.05684 | 8.75179 |

Summary Findings: For the Other NonInterest Expense Ratio model, we have found that the results of the regression (R-Squared, RMSE, Variance Inflation, Eigenvalue, Condition Index, and others) are in a reasonable standard of a good model.
6) Return on AFS Securities

Overview

| Root MSE | 2.84982 | R-Square0.0887 |
| :--- | ---: | ---: |
| Dependent Mean0.29480 | Adj R-Sq0.0859 |  |
| Coeff Var | 966.70900 |  |

Parameter Estimates

| Label | Parameter <br> Estimate | Standard <br> Error | $\mathbf{t}$ Value Pr $>\|\mathbf{t}\|$ | Variance <br> Inflation |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Intercept | 0.27715 | 0.053215 .21 | $<.0001$ | 0 |

Appendix G: Results of CLASS and CLASS-X Model regressions for the 19 CCAR Stress Test Companies

| Label | Parameter Estimate | Standard Error | t Valu | $\operatorname{Pr}>\|t\|$ | Variance Inflation |
| :---: | :---: | :---: | :---: | :---: | :---: |
| AFS Ratio X Change in bond spread |  |  |  |  |  |
| X >0 Dummy | -0.01001 | 0.00232 | -4.32 | <. 0001 | 1.02759 |
| Year over year CPPI | 0.00316 | 0.00344 | 0.92 | 0.3583 | 1.01250 |
| Lag Return on AFS | 0.24219 | 0.03068 | 7.89 | <. 0001 | 1.02206 |

Collinearity Diagnostics

|  |  | Condition <br> NumberEigenvalue |
| :--- | :--- | :--- |
| 1 | 1.42515 | 1.00000 |
| 2 | 1.12163 | 1.12721 |
| 3 | 0.88452 | 1.26933 |
| 4 | 0.56869 | 1.58304 |

Summary Findings: For a Return on AFS Securities model, we have found that the results of the regression (R-Squared, RMSE, Variance Inflation, Eigenvalue, Condition Index, and others) are in a reasonable standard of a good model.

## Appendix H: Analysis of Several Types of Models

In this appendix, we will provide several examples of models for regressions and data analysis. We will present Random Coefficient, Mixed Model, Markov Vector Autoregression and other models.

## 1) Random Coefficient

Below is a sample random coefficient data to explain how Random Coefficient analysis is done with SAS Proc Mixed model.

```
data rc;
    input Batch Month @ @;
    Monthc = Month;
    do i=1 to 6;
        input Y @ @;
        output;
    end;
    datalines;
    1 0 101.2 103.3 103.3 102.1 104.4 102.4
    1}11998.8 99.4 99.7 99.5
    1 3 98.4 99.0 97.3 99.8
    1 6 101.5 100.2 101.7 102.7
    1 9 96.3 97.2 97.2 96.3
    1 12 97.3 97.9 96.8 97.7 97.7 96.7
    2 0 102.6 102.7 102.4 102.1 102.9 102.6
    2 1 1 99.1 99.0 99.9 100.6
    2 3 105.7 103.3 103.4 104.0
    2 6 101.3 101.5 100.9 101.4
    2 9 94.1 96.5 97.295.6
    2 12 93.1 92.8 95.4 92.2 92.2 93.0
    3 0 105.1 103.9106.1 104.1 103.7 104.6
    3 1 102.2 102.0 100.8 99.8
    3 3 101.2 101.8 100.8 102.6
    3 6 101.1 102.0 100.1 100.2
    3}99100.9 99.5 102.2 100.8
    3 12 97.8 98.3 96.9 98.4 96.9 96.5
proc mixed data=rc;
    class Batch;
    model Y = Month / s;
    random Int Month / type=un sub=Batch s;
    run;
```

The two random effects are Int and Month, modeling random intercepts and slopes, respectively. Note that Intercept and Month are used as both fixed and random effects. The TYPE=UN option in the RANDOM statement specifies an unstructured covariance matrix for the random intercept
and slope effects. In mixed model notation, G is block diagonal with unstructured $2 \times 2$ blocks. Each block corresponds to a different level of Batch, which is the SUBJECT= effect. The unstructured type provides a mechanism for estimating the correlation between the random coefficients. The S option requests the production of the random-effects parameter estimates. (SAS/STAT(R) 9.2 User's Guide, Second Edition - Example 56.5)

Here are the results of the regression.
The Mixed Procedure

| Model Information |  |
| :--- | :--- |
| Data Set | WORK.RC |
| Dependent Variable | Y |
| Covariance Structure | Unstructured |
| Subject Effect | Batch |
| Estimation Method | REML |
| Residual Variance Method | Profile |
| Fixed Effects SE Method | Model-Based |
| Degrees of Freedom Method | Containment |
| Class Level Information   <br> Class Levels Values  $\quad$Batch3 123 |  |

## Dimensions

Covariance Parameters 4
Columns in X 2
Columns in Z Per Subject2
Subjects 3
Max Obs Per Subject 36
Number of Observations
Number of Observations Read 108
Number of Observations Used 84
Number of Observations Not Used 24
Iteration History
Iteration Evaluations -2 Res Log Like Criterion

| 0 | 1 | 367.02768461 |
| :--- | :--- | :--- |
| 1 | 1 | 350.328135770 .00000000 |

Convergence criteria met.

## Covariance Parameter Estimates

Cov Parm Subject Estimate
UN $(1,1)$ Batch 0.9768
UN $(2,1)$ Batch -0.1045
UN(2,2) Batch 0.03717
Residual 3.2932


Batch is the only classification variable in this analysis, and it has three levels. The "Dimensions" table indicates that there are three subjects (corresponding to batches). The 24 observations not used correspond to the missing values of Y in the input data set. We see only one iteration is required for convergence. The Estimate column the estimated elements of the unstructured 22 matrix comprising the blocks of G. It is important to note that the random coefficients are negatively correlated. The null model likelihood ratio test indicates a significant improvement over the null model consisting of no random effects and a homogeneous residual error. The fixed-effects estimates represent the estimated means for the random intercept and slope, respectively. The random-effects estimates represent the estimated deviation from the mean intercept and slope for each batch. Both statistics test the null hypothesis that the slope assigned to Month equals 0 , and this hypothesis can barely be rejected at the $5 \%$ level.

It is also possible to fit a random coefficients model with error terms that follow a nested structure (Fuller and Battese 1973). The following SAS sample statements represent one way of doing this:
proc mixed data=rc;
class Batch Monthc;
model Y = Month / s;
random Int Month Monthc / sub=Batch s;
run;

Below is the result of the regression:

The Mixed Procedure


AICC (smaller is better)283.2
BIC (smaller is better) 280.2

| Solution for Fixed Effects |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Intercept | Estimate Standa 102560.7287 | t Value $\mathrm{Pr}>\|\mathrm{t}\|$ |  |  |
|  |  | 2 | 140. | <. 0001 |
| Month | -0.5003 0.1259 | 2 | -3.97 | 0.0579 |

Solution for Random Effects
Effect BatchMonthc Estimate Std Err Pred DFt Value Pr > $|t|$

| Intercept 1 |  | 0 | . | . | . |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Month | 1 |  | -0.00028 | 0.09268 | $66-0.00$ | 0.9976 |
| Monthc | 1 | 0 | 0.2191 | 0.7896 | 660.28 | 0.7823 |
| Monthc | 1 | 1 | -2.5690 | 0.7571 | $66-3.39$ | 0.0012 |
| Monthc | 1 | 3 | -2.3067 | 0.6865 | $66-3.36$ | 0.0013 |
| Monthc | 1 | 6 | 1.8726 | 0.7328 | 662.56 | 0.0129 |
| Monthc | 1 | 9 | -1.2350 | 0.9300 | $66-1.33$ | 0.1888 |
| Monthc | 1 | 12 | 0.7736 | 1.1992 | 660.65 | 0.5211 |
| Intercept 2 |  | 0 | . | . | . |  |
| Month | 2 |  | -0.07571 | 0.09268 | $66-0.82$ | 0.4169 |
| Monthc | 2 | 0 | -0.00621 | 0.7896 | $66-0.01$ | 0.9938 |
| Monthc | 2 | 1 | -2.2126 | 0.7571 | $66-2.92$ | 0.0048 |
| Monthc | 2 | 3 | 3.1063 | 0.6865 | 664.53 | $<.0001$ |
| Monthc | 2 | 6 | 2.0649 | 0.7328 | 662.82 | 0.0064 |
| Monthc | 2 | 9 | -1.4450 | 0.9300 | $66-1.55$ | 0.1250 |
| Monthc | 2 | 12 | -2.4405 | 1.1992 | $66-2.04$ | 0.0459 |
| Intercept 3 |  | 0 | . | . |  |  |
| Month | 3 |  | 0.07600 | 0.09268 | 660.82 | 0.4152 |
| Monthc | 3 | 0 | 1.9574 | 0.7896 | 662.48 | 0.0157 |
| Monthc | 3 | 1 | -0.8850 | 0.7571 | $66-1.17$ | 0.2466 |
| Monthc | 3 | 3 | 0.3006 | 0.6865 | 660.44 | 0.6629 |
| Monthc | 3 | 6 | 0.7972 | 0.7328 | 661.09 | 0.2806 |
| Monthc | 3 | 9 | 2.0059 | 0.9300 | 662.16 | 0.0347 |
| Monthc | 3 | 12 | 0.002293 | 1.1992 | 660.00 | 0.9985 |

Type 3 Tests of Fixed Effects
Effect Num DF Den DF F Value Pr > F

| Month1 | 2 | 15.78 | 0.0579 |
| :--- | :--- | :--- | :--- |

For this analysis, the Newton-Raphson algorithm requires five iterations and nine likelihood evaluations to achieve convergence. The missing value in the Criterion column in iteration 1 indicates that a boundary constraint has been dropped. The estimate for the Intercept variance component equals 0 . The random-effects solution provides the empirical best linear unbiased predictions (EBLUPs) for the realizations of the random intercept, slope, and nested errors. The better-fitting covariance model affects the standard errors of the fixed-effects parameter estimates more than the estimates themselves. You can use these values to compare batches and months. This occurs frequently in practice and indicates that the restricted likelihood is maximized by setting this variance component equal to 0 . The test of Month is similar to that of the previous model, although it is no longer significant at the $5 \%$ level.

## 2. Mixed Model - Data Analysis for One of Key PPNR components (Net Interest Margin).

Below is the regression that we have used for the data analysis:
ods graphics on;
proc mixed data=moddata PLOTS(MAXPOINTS=NONE) plots(only)=All; class date entity;
model cl_nim = spread cpr_t3m 11_cl_nim time rat_rre rat_cre rat_ci rat_cc
rat_trad rat_inv assetshare /influence(effect=entity);
weight intearn_assetshare;
repeated date / subject=cl_nim;
run;
ods graphics off;
Results of the Analysis.

| Model Information |  |
| :--- | :--- |
| Data Set | WORK.MODDATA |
| Dependent Variable | cl_nim |
| Weight Variable | intearn_assetshare |
| Covariance Structure | Autoregressive |
| Subject Effect | cl_nim |
| Estimation Method | REML |
| Residual Variance Method | Profile |
| Fixed Effects SE Method | Model-Based |
| Degrees of Freedom MethodBetween-Within |  |


| Dimensions |  |
| :--- | :--- |
| Covariance Parameters1 |  |
| Columns in X | 12 |
| Columns in Z | 0 |
| Subjects | 17565 |
| Max Obs Per Subject | 1 |

Number of Observations
Number of Observations Read 18291
Number of Observations Used 17565
Number of Observations Not Used726

| Iteration History |  |  |  |
| :--- | :--- | :---: | :---: |
| IterationEvaluations-2 Res Log Like | Criterion |  |  |
| 0 | 1 |  |  |$\quad 48561.87612906$

Convergence criteria met.

| Covariance Parameter Estimates |  |  |
| :--- | :--- | :--- |
| Cov Parm | Subject | Estimate |
| date | cl_nim | 0.1014 |


| Fit Statistics |  |
| :--- | ---: |
| -2 Res Log Likelihood 48561.9 |  |
| AIC (smaller is better) | 48563.9 |
| AICC (smaller is better) 48563.9 |  |
| BIC (smaller is better) | 48571.6 |

Null Model Likelihood Ratio Test DF Chi-Square $\quad$ Pr $>$ ChiSq $0 \quad 0.00 \quad 1.0000$

| Effect | F Value | Pr $>$ F |
| :--- | :--- | :--- |
| spread | 34.83 | $<.0001$ |
| cpr_t3m | 13.62 | 0.0002 |
| l1_cl_nim31804.1 | $<.0001$ |  |
| time | 11.98 | 0.0005 |
| rat_rre | 87.24 | $<.0001$ |
| rat_cre | 160.70 | $<.0001$ |
| rat_ci | 96.44 | $<.0001$ |
| rat_cc | 749.41 | $<.0001$ |
| rat_trad | 73.85 | $<.0001$ |
| rat_inv | 59.50 | $<.0001$ |
| assetshare 170.41 | $<.0001$ |  |




Fixed Effects Deletion Estimates for cl_nim



With all of these results, we can say it is clear that Proc Mixed is a good model for data analysis. It provides a flexible way to analyze the data.

## 3. Markov-switching vector autoregression (MSVAR) Estimator

Below is the SAS codes that we executed:

## data switch;

input date monyy. bor /* borrow */
rate /* mortgage rates */
starts /* housing starts */
dep /* deposit */
loans /* real estate loans */;
format date monyy7.;
label bor = "borrow";
label rate = "Mortgage Rates";
label starts = "Housing Starts";
label dep = "Deposit";
label loans = "Real Estate Loans";
datalines;
Jan73 $45.7 \quad 7.55146 .6596 .3104 .2$

```
Feb73 49.2 7.56 138.0 598.4 105.6
Mar73 50.5 7.63 200.0 602.4 107.3
Apr73 50.1 7.73 205.0 611.8 109
May73 52.8 7.79 234.0 613.8 110.8
Jun73 55.8 7.89 202.6 622.5 112.9
Jul73 58.9 8.19 202.6 630.2 115
Aug73 60.2 8.85 197.2 629.3 117.1
Sep73 62.9 9.18 148.4 638 119.1
Oct73 65.2 8.97 147.1 647 120.8
Nov73 71.3 8.86 133.3 648.6 122.4
Dec73 71.3 8.78 90.4 663.2 123.6
:
:
:
;
```

title1 'Switching Regression Example';
proc model data=switch; parms $\operatorname{sig} 1=10$ sig2 $=10$ int1 b11 b13 int2 b21 b23 p; bounds 0.0001 < sig1 sig2;
/*\%PUT _all_;*/
decjanfeb $=(\operatorname{month}($ date $)=12 \mid \operatorname{month}($ date $)<=2) ;$
$\mathrm{a}=\mathrm{p} * \operatorname{dif}($ rate $) ; \quad / *$ Upper bound of integral */ $\mathrm{d}=\operatorname{probnorm}(\mathrm{a}) ; \quad / *$ Normal CDF as an approx of switch */
/* Regime 1 */
$\mathrm{y} 1=$ int $1+$ zlag(starts) $*$ b $11+$ decjanfeb $*$ b13;
/* Regime 2 */
$\mathrm{y} 2=$ int $2+$ zlag(starts) $* \mathrm{~b} 21+$ decjanfeb $* \mathrm{~b} 23$;
/* Composite regression equation */
starts $=(1-\mathrm{d}) * \mathrm{y} 1+\mathrm{d} * \mathrm{y} 2$;
/* Resulting log-likelihood function */
$\log \mathrm{L}=(1 / 2) *((\log (2 * 3.1415))+$ $\log \left((\operatorname{sig} 1 * * 2) *((1-\mathrm{d}) * * 2)+(\operatorname{sig} 2 * * 2) *\left(\mathrm{~d}^{*} * 2\right)\right)$
$+\left(\right.$ resid.starts* ${ }^{*} /\left(\left(\operatorname{sig} 1^{* *}\right)^{*}((1-\mathrm{d}) * * 2)+\right.$ $(\operatorname{sig} 2 * * 2) *\left(\mathrm{~d}^{* *} 2\right)$ ) $)$ *resid.starts) ) ;
errormodel starts ~ general( $\operatorname{logL}$ );
fit starts / method=marquardt converge=1.0e-5;
/* Test for significant differences in the parms */
test int $1=$ int $2, / \mathrm{lm}$;
test $\mathrm{b} 11=\mathrm{b} 21, / \mathrm{lm}$;
test b13 = b23,/lm;
test $\operatorname{sig} 1=\operatorname{sig} 2, / \mathrm{lm}$;
run;

Here are the results that we get.

## Switching Regression Example

## The MODEL Procedure

| Model Summary |  |
| :--- | :---: |
| Model Variables | 1 |
| Parameters | 9 |
| Equations | 1 |
| Number of Statements19 |  |
| Program Lag Length | 1 |

Model Variables starts
Parameters(Value)sig1(10) sig2(10) int1 b11 b13 int2 b21 b23 p Equations starts

The Equation to Estimate is starts $=\mathrm{F}($ int1, b11, b13, int2, b21, b23, p, sig1, sig2)

The estimation lag length 1
NOTE: At Liklhood Iteration 59 CONVERGE=0.00001 Criteria Met.

## Switching Regression Example

The MODEL Procedure
Liklhood Estimation Summary

> Data Set Options
> DATA=SWITCH

| Minimization Summary |  |
| :--- | :--- |
| Parameters Estimated 9 |  |
| Method | Marquardt |
| Iterations | 59 |
| Subiterations | 16 |
| Average Subiterations 0.271186 |  |

Final Convergence Criteria
R 4.063E-6

PPC(p) 0.000023
RPC(p) 0.000109
Object $4.84 \mathrm{E}-10$
Trace(S) 0
Gradient norm 0.000021
Log likelihood-1318.56
Lambda 1E-7

| Observations | Processed |
| :--- | :--- |
| Read | 314 |
| Solved | 313 |
| First | 2 |
| Last | 314 |
| Lagged | 1 |

## Switching Regression Example

The MODEL Procedure


## Switching Regression Example

The MODEL Procedure

| Model Summary |  |
| :--- | :--- |
| Model Variables | 1 |
| Parameters | 9 |
| Equations | 1 |
| Number of Statements12 |  |
| Program Lag Length | 1 |

```
Model
Variab
les starts
Param
eters( sig1(15.474833583(16.330002713)) sig2(19.778335799(15.559141511))
Value(int1(32.822195225(5.5557732586)) b11(0.7395205262(16.643375247)) b13(-
t 15.45585524(-4.844389686)) int2(42.733478901(6.2704528624))
Value) b21(0.7341169857(15.375750849)) b23(-22.51919026(-5.239021591))
) p(25.946057053(3.0452525181))
Equati
ons Starts
```

In short, we can say this is a good model for analysis and non-linear models. While these non-linear models are very good for data analysis and subject research study, we will not propose them for PPNR sensitivity research study.

## Appendix I: Sample SAS Codes Used in this Dissertation

The sample codes for this dissertation are in SAS. The codes can be found in Pace University dissertation document library.

Financial institutions have to make sure that they have enough capital to operate in an adverse economic stress scenario. In PPNR (Pre-Provision Net Revenue Framework), there is provision for how businesses should be prepared for such a scenario. The CLASS (Capital and Loss Assessment under Stress Scenarios) model is a framework for stress testing. There are several issues (collinearity, variable selection, alternative model methodology) that can be resolved with the CLASS model.

In this research, we present a novel approach for PPNR econometrics analysis, or an alternative solution to the CLASS model. After replicating CLASS model, we focus on the systematic econometric study of seven key components of PPNR. We evaluate the parameter estimates of the econometric equations for some PPNR key components of United States financial companies and the 19 companies that were part of the initial CLASS and CCAR (Comprehensive Capital Analysis and Review 2012: Methodology and results for Stress Scenario) model projections. We report our findings based on our econometrics analysis study of the CLASS model. We present an improved alternative - the CLASS-X model - that can be used in a financial Decision Support System (DSS). CLASS-X is an eXtension of CLASS for the seven key PPNR components.


[^0]:    ${ }^{1}$ Details and results of the early European stress tests can be found in European Banking Supervisors (2010) and European Banking Authority (2011)
    ${ }^{2}$ For example, (Kapadia S. M., 2012) describe the RAMSI model developed by the Bank of England and Wong and Hui (2009) (Wong, 2009) describe a model developed at the Hong Kong Monetary Authority to assess liquidity risk.

[^1]:    ${ }^{3}$ The BHCs that participated in CCAR 2012 are Ally Financial Inc., American Express Company, Bank of America Corporation, The Bank of New York Mellon Corporation, BB\&T Corporation, Capital One Financial Corporation, Citigroup Inc., Fifth Third Bancorp, The Goldman Sachs Group, Inc., JPMorgan Chase \& Co., Keycorp, MetLife, Inc., Morgan Stanley, The PNC Financial Services Group, Inc., Regions Financial Corporation, State Street Corporation, SunTrust Banks, Inc., U.S. Bancorp, and Wells Fargo \& Company.

[^2]:    ${ }^{4}$ Given a multivariate time series, the VARMAX procedure estimates the model parameters and generates forecasts associated with vector autoregressive moving-average processes with exogenous regressors (VARMAX) models. VARMAX models are defined in terms of the orders of the autoregressive or moving-average process (or both).
    ${ }^{5}$ BVECM is one example of a VARMAX model.

[^3]:    ${ }^{6}$ CLASS-X is made up of three framework models. CLASS-X Model 1 has similar variables to the CLASS model. However, CLASS-X Model 1 uses a panel regression procedure. CLASS-X Model 2 uses different variables of the CLASS model but same procedure of The CLASS model. And, CLASS-X Model 3 uses different procedure and different variables from The CLASS model. CLASS-X Model 3 uses MLE instead of OLS.

[^4]:    ${ }^{7}$ It is important to mention that CLASS-X has three different models. CLASS-X Model 1 uses the same variables as The CLASS model. But, CLASS-X Model 1 uses different regression procedure (panel regression). CLASS-X Model 2 uses the OLS procedure or method (Ordinary Least Square) but different variables. CLASS-X Model 3 uses different variables, procedures and methodology (Maximum Likehood). These 3 CLASS-X models are our contributions to this research. Appendix B has CLASS specifications and Appendix C and D have CLASS-X specifications.

[^5]:    ${ }^{8}$ FR Y-9C - This report collects basic financial data from a domestic bank holding company (BHC), a savings and loan holding company (SLHC), a U.S intermediate holding company (IHC), and a securities holding company (SHC) on a consolidated basis in the form of a balance sheet, an income statement, and detailed supporting schedules, including a schedule of off balance-sheet items.

[^6]:    ${ }^{9}$ Again this CLASS-X Model 1 uses the same variables as the CLASS model but with a different procedure (proc panel).

[^7]:    ${ }^{10}$ Equation is similar to that of CLASS-X Model 1. However, the variables in the vectors are different than the CLASS model and CLASS-X Model 1.

[^8]:    Figure 20: Net Charge-off rate

