Three Essays on Financial Institutions and Markets

by

Sunghoon Joo

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 3, 2019

Keywords: Pensions, Funded Ratios, Bank Cross-ownership, Network Analysis, Capital Ratio, and Forecasting

Approved by

James Richard Barth, Chair, Lowder Eminent Scholar
Jitka Hillard, Associate Professor of Finance
Kang Bok Lee, Assistant Professor of Business Analytics
Stace Sirmans, Assistant Professor of Finance

Abstract

In chapter 1, given the financial troubles facing state pension plans in recent years, we examine determinants of the ratio of assets to liabilities, or the funded ratio, based on data for 153 pension plans from 2001 to 2014. The focus is on the relationship between both the actual investment return on pension assets and the assumed return used to discount pension liabilities, or the funded ratio. Importantly, only when appropriate empirical techniques are employed to address potential econometric problems do we find that these two factors have the expected relationship with the funded ratio. Surprisingly, we also find the actual and assumed returns are negatively correlated, even though the correlation is quite low. Furthermore, the assumed return is on average higher than the actual return and has a much larger marginal effect on the funded ratio. We therefore show how a relatively high value can be assigned to the assumed return to make a pension plan appear to far healthier than actually is the case.

In chapter 2, we examine the effects of banks' client stock ownership structure on their governance mechanism and their risk-taking as well as the effects of such ownership ties in the banking sector on systemic risk in the financial system. Importantly, we apply a dyadic level of analysis to provide new insights on the relevance of such cross-ownership as effective mutual monitoring channel and as a possible source of interconnectedness between and among financial institutions. Our empirical results indicate that bank-client cross-ownership of bank stocks is negatively associated with the riskiness of BHCs. This means that large external equity holders have the potential to perform an effective monitoring role and mitigate agency problems in the banking sector. We also find that bank-client cross-ownership of bank stocks is positively associated with systemic risk and the effects of such cross-ownership on systemic risk is stronger in times of a financial crisis.

In chapter 3, we propose dimension reduction methods and shrinkage methods to forecast tier 1 common capital ratio (T1CR) of the five biggest bank holding companies (BHCs) in the U.S. in a data-rich environment. Specifically, we employ two dimension reduction methods – the principal component regression (PCR) and the partial least squares regression (PLSR), and three shrinkage methods – the ridge regression, the Least Absolute Shrinkage Selection Operator (LASSO) regression, and the elastic net regression. We apply these methods to in-sample and out-of-sample forecasting exercises for T1CR, an extremely important banking variable and the most accurate indicator of the ability of banks to absorb losses. Our results show that factor-type models, PCR and PLSR, dominate the other alternative models over 1- to 10-quarter ahead forecast horizons, while shrinkage methods tend to outperform the factor-type forecasting models over 11- to 12-quarter ahead forecast horizons. In addition, we find that bank and stress test variables help produce the most accurate forecasts for short-term forecast horizons, while macro variables are useful in forecasting long-term horizons. Finally, we find that only six factors account for much of the variance of our 162 quarterly time series in the full dataset and that the most accurate forecasts of T1CR are obtained with just a few factors. One interpretation of such findings is that there may be only a few important sources that are necessary to accurately forecast banks' capital.

Acknowledgments

First and foremost, I would like to express my sincerest gratitude to my advisor, Dr. James Barth, for his guidance and advice throughout my graduate studies as well as to my advisory committee, Dr. Jitka Hilliard, Dr. Kang Bok Lee, and Dr. Stace Sirmans, for their time, constructive criticisms, and encouragement. I would like to thank Dr. Justin Benefield for his continuous support throughout this process. I would also like to express thanks to all other faculty, staff and fellow graduate students who were always willing to give much needed advice and assistance when called upon. Special thanks to Mikyung Kwon for her love and patience throughout this journey and to all of my friends for being a part of this amazing experience.

Lastly, and most importantly, I would like to thank my parents, Youngkok Joo and Jungsook Kim, and my brother, Ensung Joo, for their relentless support and never-ending belief in me. To my grandfather, I know you would be proud.

I have been very fortunate to have countless people who have shaped me in a different way to help me become who I am today. Thank all of you for your part in my journey.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AM	Alternative Model
AR	Autoregressive
ARC	Annual Required Contribution
BHCs	Bank Holding Companies
BM	Benchmark Model
CAFRs	Comprehensive Annual Financial Reports
CCAR	Comprehensive Capital Analysis and Review
CoVAR	Conditional Value at Risk
CRSP	Center for Research in Security Prices
DFAST	Dodd-Frank Act Stress Tests
DMW	Diebold-Mariano-West
EN	Elastic Net
GMM	Generalized Method of Moments
GSP	Gross State Product
LASSO	Least Absolute Shrinkage Selection Operator
LLPs	Loan Loss Provisions
LLRs	Loan Loss Reserves
LMRQAP	Longitudinal Multiple Regression Quadratic Assignment Procedure
NCOs	Net Charge-Offs
OLS	Ordinary Least Squares
PC	Principal Component
PLS	Partial Least Squares

PUC	Projected Unit Credit
ROA	Return on Assets
RRMSPE	Root Mean Square Prediction Error
RSS	Residual Sum of Squared
RW	Random Walk
SCAP	Supervisory Capital Assessment Program
T1CR	Tier 1 Common Capital Ratio
VaR	Value at Risk

Chapter 1

Another Look at the Determinants of the Financial Conditions of the State Pension Plans

1.1 Introduction

The population of the United States is gradually and steadily aging as life expectancies have been significantly increasing during the past century. A person born in 1900 could have expected to live to age 47, while today the comparable figure is 79. Clearly, a nearly doubling in the life expectancy of individuals is good news. Individuals now have far more time beyond their working years to enjoy a more relaxed and flexible lifestyle. Of course, funds are needed to help ensure that more years spent in retirement are truly enjoyable. The amount of funds available will depend on the savings a person accumulates while working, on the Social Security benefits that a person receives, and on the retirement benefits that a worker receives after retiring.

Focusing on retirement plans, there are two basic types: defined benefit plans and defined contribution plans. The traditional defined benefit plan is designed for longer-service employees and the amount paid to a retiree under such a plan is based on a fairly simple formula that typically takes into account the years of employment and the pay level for the last few years of service. In contrast, a defined contribution plan is designed for a more mobile workforce and the amount paid is based on contributions by the worker and the employer as well as the performance of the investments made with those funds.

Whether it is the employer or the employee that bears the risk associated with the benefits ultimately received depends in large part on which of two types of pension plans in which a worker is enrolled. In the case of a defined benefit plan the risk of the funds based upon contributions and investment earnings being insufficient to provide the benefits promised is borne by the employer.

However, if the employer is a public entity like a state or local government, then it is ultimately the taxpayers of the relevant jurisdiction that cover any shortfalls in the benefits promised. In the case of a defined contribution plan, the risk that the benefits are less than expected is borne by the retiree since it is solely the contributions and the investment earnings of those contributions that determine what a retiree receives. In a few states hybrid plans are available that combine features of both defined benefit plans and defined contribution plans. A major issue faced by most states is how best to fund their commitments to current employees and to retirees.

The purpose of this paper is to examine which factors are important in explaining the funded ratios of state and local pension plans for public employees. Our analysis is initially based on the important study Munnell et al. (2011), who consider such factors as funding discipline, plan governance, plan characteristics, and the fiscal situation of states in explaining funded ratios. However, we extend the analysis to consider additional factors, including investment returns and assumed rates of return as well as the degree of unionization in states. By expanding the analysis, the results will provide additional and important information to assist in deciding whether new or different public policies are needed to better ensure the continued financial solvency of public pension plans throughout the country.

The contribution of our study lies in providing more timely information regarding key factors behind the growing funding shortfalls facing many public pension plans over the period 2001 to 2014. Indeed, as shown in Figure 1.1, the aggregate funded ratio for all the plans has declined to 73 percent from 100 percent over the period. Furthermore, more than half the states have funded ratios that are less than 80 percent (see Figures 2 and 3 as well as Table 1.1 for more detailed information). Among the states, Kentucky and Illinois have the two lowest funded ratios at 46 and 47 percent, respectively. This means that in both cases the present value of plan assets are substantially less than the present or discounted value of plan liabilities (i.e., the amount due to current and future retirees). The results of this study should be of great interest not only to other academic researchers studying pension plans but also to governmental policymakers as they grapple with understanding the reasons for shortfalls in funding for public plans as well as ways to eliminate them over time.

[Figure 1.1, 1.2, and 1.3] & [Table 1.1]

1.2 Current Issues Affecting Public Pension Systems

Pension plans have been undergoing major changes over time, primarily among private plans, with most of them shifting to a defined contribution-type of plan. Barth and Jahera (2015), in a study of the Alabama public pension system, provide a great deal of information on the public plans in each of the states throughout the country. Based on the data in their report, roughly 80 percent of the total membership of private pension plans consisted of members in defined benefit plans in 1975, while the remaining 20 percent consisted of members in defined contribution plans, as shown in Figure 1.4. In 2012, based upon the most recent data available, as also shown in the same figure, the corresponding percentages were almost completely reversed. Specifically, the share of total membership in both types of plans accounted for by defined contribution plans had increased to almost 70 percent, while the share accounted for by defined benefit plans declined to slightly more than 30 percent. This dramatic reversal has certainly helped relieve some of the financial pressure on employers (and the Pension Benefit Guaranty Corporation, PBGC, which guarantees the benefits promised to private-sector workers in defined benefit plans) over the years since far more of the aggregate risk in the private pension sector is now being borne by employees.

[Figure 1.4]

Serious funding challenges remain for the public sector, however. At the state and local level, there were 3,998 public pension systems, of which 227 were administered at the state level, in 2012. The state-administered pension plans account for about 90 percent of the nearly 20 million members of all public pension plans. The vast majority of these pension systems, moreover, are defined benefit plans. The total state and local government defined benefit pension plans at yearend 2013 had $3.7 trillion in assets, but $4.9 trillion in pension obligations, leaving a funding gap of $1.2 trillion, as shown in Figure 1.5.

[Figure 1.5]

The major problem with the public defined benefit plans is their funding status. As may be seen in Figure 1.6, in the aggregate there has been a significant downward trend in the funded ratio in recent years. In 1975, the ratio of pension fund assets to liabilities was 53 percent and then increased to a high of 128 percent in 1999. The ratio thereafter trended downward to a low of 64 percent in 2011. In the following two years the ratio increased and at yearend 2013 was 75 percent. However, during each of the last twelve years the ratio has been below 100 percent and even below 80 percent in each of the past six years. The latter figure is considered by many individuals to be important because in an annual study of pensions by Bloomberg Rankings, 80 percent is considered to be common threshold of sustainability, or what is needed to pay promised benefits.

[Figure 1.6]

As already noted, Figure 1.5 shows the funding gap for the defined benefit plans of state and local governments. As may be seen, the funding gap remained fairly low from 1975 to 1996, when it then turned positive for six years. It then increased thereafter to a high of $1.6 trillion in 2011. By 2013, the funding gap had decreased to $1.2 trillion, which is still higher than in 34 of the 38 years shown in the figure.

Many states have not been able to sustain their annual required contributions (ARC) in the face of other demands on taxpayer dollars. In Alabama alone, the legislature appropriated approximately $1 billion in fiscal year 2014 to meet the ARC. That is in addition to the employee contributions and the investment returns of the Alabama retirement system. There are many reasons for the serious underfunding situation, including an aging population and increases in life expectancy. Other more plan specific and state specific issues include the overall fiscal condition of the state, the financial promises made to retirees, automatic cost of living adjustments, weak investment policies and poor governance. Given these and other factors, many states have been and still are struggling to fund their obligations to current and future retirees.

1.3 Literature Review

The literature regarding public pension plans, and in particular the condition and performance of these plans, is quite extensive, covering many years and appearing in discipline- specific journals focusing on public administration, economics, finance and accounting, among other fields. Generally, we focus on the more recent research on public pensions. However, one early study worthy of mention is by Mitchell and Smith (1994). They rely on survey data to examine determinants of pension funding, including required annual contributions, actual annual contributions and pay levels of public employees. Based on data from the 1980s, they find large differences in the actual contributions made to public plans, with many failing to meet their obligations. State fiscal constraints are found to be an important contributor to the failure to meet their obligations. It is also found that increases in retirement benefits are associated with a reduction in public employee salaries.

One study that provides an excellent literature review is by Yang and Mitchell (2005). In their review of earlier work, they note that most empirical studies are based on single-equation type models, and reach the general conclusion that funded ratios as well as investment performance tend to be related to governance practices and specific investment policies of a pension plan. Yang and Mitchell examine the funding and performance of plans over a ten-year period, considering the relationship between past and future funded ratios. They estimate three empirical models with three dependent variables: the funded ratio, the flow funded ratio and investment performance. These variables are hypothesized to be a function of a set of explanatory variables capturing elements of the specific plan board composition as well as its investment and reporting practices. A finding is that investment performance, as one might suspect, is positively related to the funded ratio. In addition, they find that plan governance is related to both performance and funding level. They offer several recommendations for improving plan performance, including better training and education for board members as well as greater transparency.

In an interesting study of pension funding, Eaton and Nofsinger (2008) examine the relationship between gender and funded ratios. Examining 110 public plans for the years 2002 to 2005, they find that underfunding increased during that time period, with an average funded ratio of only 83 percent. They model the funded ratio using a set of explanatory variables that includes the percent of females and the ratio of active employees to retirees as well as a set of dummy variables to distinguish among the specific plans (i.e., for teachers, law and fire fighters, and other public employees). Interestingly, they conclude that a major determinant of underfunding is when there is a higher share of female participants in a pension plan. Specifically, plans for teachers (with a large proportion of female members) had lower funded ratios. In further analysis, they find that specific asset allocations and actuarial assumptions do not appear to be important in explaining the underfunding issue.

Novy-Marx and Rauh (2009) address the issue of how best to measure the present value of public pension plan liabilities. They conclude that plans typically use discount rates that are "unreasonably" high, in their words. Most plans use an assumed rate of return of 8 percent in determining the present value of future liabilities. Novy-Marx and Rauh examine 116 public pension plans, calculating an estimated liability of $2.98 trillion as of 2008. In an interesting twist, they make a case that given state obligations to retirees, future payments are in essence risk-free and hence the payments should be discounted using a risk-free Treasury security rate. Using such a rate yields a discounted liability of $5.17 trillion, almost double the amount using the higher 8 percent. In a later study, Rauh (2010) examines 115 public pension plans to assess the long-run viability of the plans given current assumptions and practices. His conclusion is rather gloomy in that he argues that taxpayers could be asked to support state pension plans that find themselves in deep financial distress in the future. More pointedly, his analysis indicates that in the absence of major reforms, many plans will simply run out of funds in the next 10 to 20 years. Relatedly, Novy-Marx and Rauh (2011) reaffirm their earlier findings regarding the appropriateness of using a risk-free discount rate.

Munnell et al. (2011) examine 126 public plans that had an average funded ratio of 78 percent in 2009. Their data show substantial variation in funded ratios, with over half being below the 80 percent level that is taken by many to be the minimum desired level for a plan to be in adequate financial condition. Using OLS regressions, they examine factors that help explain funded ratios. They focus on funding discipline, plan governance, plan characteristics and the overall financial health of states. It is noted in their study that the funding situation has worsened significantly since the financial crisis in 2007 to 2008. Of course, the funding shortfall would be even more dire were a risk-free discount rate used, as noted earlier by Novy-Marx and Rauh

(2009). In general, Munnell et al. conclude that plans with low funded ratios tend to be located in states with greater fiscal difficulties. These plans, moreover, experience less discipline in their funding strategy and also provide greater benefits to retirees. The authors point out that at the time of their study a number of states were taking action to improve the funding status of their plans, but as noted earlier the overall situation has not significantly improved.

Biggs (2011) takes a novel approach to valuing pension plan liabilities through the application of option-pricing techniques. For those plans with fully funded ratios, taxpayers are protected, at least as long as this situation holds. But taxpayers in states with less than fully funded ratios may be called upon to contribute funds to cover any shortfalls that occur. He argues that such public plans have essentially a put option whereby taxpayers are in a position of being called upon to fund shortfalls. When an options pricing approach is used, Biggs shows that funded ratios would be substantially below their current levels. He suggests that policy makers must have a reliable approach to assessing the potential liability to taxpayers and the use of the option pricing methodology is one such approach.

Kelly (2014) examines pension funding issues in the context of public choice. The research is based on an examination of 79 public plans in 42 different states. Variables that are included in the study include the median voting age, median voter income, state debt levels, union membership, the percentage of active members and the percentage of retirement beneficiaries to total members. The empirical findings are quite interesting insofar as the level of underfunding is directly related to median voter income. That is, the higher the income, the greater is the underfunding. Similarly, state debt level is found to be positively related to underfunding. The variable with the greatest explanatory power in explaining unfunded liabilities is the percentage of retirees to total state population. The argument made is that retirees have a shorter remaining life expectancy and hence have of an incentive to take action to deal with underfunding.

Mohan and Zhang (2014) address the risk-taking behavior of public pension plans. Like many other studies, they rely upon data from the Public Plans Database available from the Center for Retirement Research at Boston College. For the time period 2001 to 2011, they find that public pension plan managers take on greater risk when their plans are underfunded. This in essence suggests that the unfunded problem leads to what is commonly referred to as "kicking the can" down the road. Mohan and Zhang also find evidence that some plans rely to some degree on such large plans like the California Public Pension Plan (CALPERS) when making their own decisions. Their results suggest, moreover, that as unions demand greater benefits, plans may well take on higher risks in their portfolios with greater underfunding being a likely result. Their policy recommendation is that employers should consider making greater contributions to the pension plans rather than relying on a higher risk investment strategy to achieve adequate funding.

A recent paper by Aggarwal and Goodell (2015) examines factors that explain estimated discount rates, noting that the 8 percent level used by many states over time may well be too high in the current environment, thereby understating the actual funding condition of pension plans. Their study is based on the period 2001 to 2011 and actual estimated rates of return. They find that such estimated rates tend to be positively related to a number of factors, including the level of corruption and income in a state. It is also found that fund size and age are influential factors. (See Healey, Hess and Nicholson (2012) for a comprehensive review of the pension funding issue in the United States.)

One of the most recent studies is by Wang and Peng (2016). They use the change in the funded ratio as their dependent variable in a study of 84 public pension plans. Like most other studies, their data is from the Public Plans Database. Their results echo results from the earlier studies discussed above. As regards policy implications, they suggest that states should consider different investment strategies, increasing their required contribution, increasing the employee contribution rate, and limiting cost of living adjustments.

1.4 Data and Methodology

The analysis performed here utilizes regression analysis to explain the variability in funded ratios. The explanatory variables used in our study are based on earlier research. We also rely in large part on data from the Public Plans Database which has plan-level data from 2001 through 2014 for 153 pension plans. This particular dataset includes information on plans that cover about 90 percent of public pension membership and assets nationwide. In addition to the data obtained from this database, we also obtain data from the Comprehensive Annual Financial Reports (CAFRs) of individual states when necessary.

The general empirical model that is estimated is as follows:

$$\begin{aligned} \textit{Funded ratio}_{i,t} &= \beta_0 + \beta_1 \textit{ARC}_{i,t} + \beta_2 \textit{PUC}_{i,t} + \beta_3 \textit{Actives to Retirees}_{i,t} + \beta_4 \textit{Age}_{i,t} + \beta_5 \textit{Large Plan}_{i,t} \\ &+ \beta_6 \textit{Teachers}_{i,t} + \beta_7 \textit{Debt to GSP}_{i,t} + \beta_8 \textit{Actual Return}_{i,t} + \beta_9 \textit{Assumed Return}_{i,t} + \beta_{10} \textit{Union}_{i,t} \\ &+ \varepsilon_{i,t}. \end{aligned} \tag{1}$$

The variables used in the analysis and their descriptions are given in Table 1.2. We first follow the work of Munnell et al. (2011) by replicating to the degree possible their empirical model. This means including the following variables: the projected unit credit (PUC), the ratio of active employees to retirees (instead of the percentage of board seats occupied by retirees and employees), age of the plan, the plan asset size, whether teachers are members of the plan, and the state level debt to gross state product ratio.

[Table 1.2]

We also include additional explanatory variables, including the actual return of the plan. The expectation is that the greater the level of the return, the higher will be the funded ratio for public pensions. We also include the assumed rate of return of the plan. As Novy-Marx and Rauh (2009) point out, the assumed return plays a crucial role in measuring the present value of public pension plan liabilities. It is therefore expected that this variable will be positively related to the funded ratio. Moreover, consistent with other studies, we include a measure of public union membership. Several studies found that a higher level of union membership is related to a lower funded ratio. This is most notable in Illinois, which has had great difficulty in reforming their public pension system due, in part, to objections by union members.

1.5 Empirical Results

Table 1.3 provides summary statistics for the variables used in this study. The focus of our study is the funded ratio, which ranges from a low of 0.19 to a high of 1.97. This means there are some cases in which state public pension plans have assets well in excess of their liabilities. Union membership averages about 37 percent for all public pension plans. During our sample period 2001 to 2013, the mean and median of the actual return are 7 and 10 percent, respectively. The assumed rate of return used by states to determine the discounted value of their pension liabilities does not have much variation since most states use 8 percent. Turning to other explanatory variables, the ratio of active employees to retirees varies widely, ranging from a low of 0.01 to a high of 1.79.

[Table 1.3]

Table 1.4 provides summary statistics on public pension plans by state for fiscal year 2014. It provides the most recent perspective on the funding status of each state pension plan. California has the largest number of pension plans at 15, followed by Illinois at 8. The average investment return is greater than the average assumed return in most states. Despite the recent favorable investment performance, more than half of the states have funded ratios that are less than 80 percent (see also Figure 1.4).

[Table 1.4]

Table 1.5 provides information on the correlations among the variables used in our study. The funded ratio is positively correlated with *ARC*, *Actives to Retirees*, and *Large Plan*, but negatively correlated with *PUC*, *Age*, *Teachers*, *Debt to GSP*, and *Actual Return*. It is expected that the annual required contribution and the ratio of active members to retirees are positively correlated with the funded ratio of the plan. Plan asset size is also positively correlated with the funded ratio. A possible explanation is that plans with larger assets are more likely to possess sophisticated asset management skills, which may stem from a better pool of investment advisors. Consistent with previous studies, we find the funded ratio is negatively associated with *PUC*, *Age*, *Teachers*, and *Debt to GSP*. *Assumed Return* and *Union* are not significantly correlated with the funded ratio.

[Table 1.5]

Table 1.6 presents the regression results for pooled OLS for the period 2001 to 2013. In Model (1), we basically follow Munnell et al. (2011) and chose our explanatory variables with three additional factors; the actual investment return, the assumed rate of return, and the ratio of union members in a state to total employees in the public sector of each state. As can be seen, we find that the ARC ratio is positive and significantly related to the funded ratio, as one would expect.

That is, states that meet their ARC obligations will of course have greater funded ratios.[1] The ratio of active employees to retirees, the asset size of the plan, and the ratio of union members in a state to total employees in the public sector of each state are also positive and significantly related to the funded ratio. In Munnell et al., they find negative and statistically significant relationships between whether the plan is for teachers and the funded ratio and between whether the plan uses projected unit credit method and the funded ratio. They also find negative relationships between the level of state debt to GSP and the funded ratio. Importantly, our results are consistent with those of Munnell et al.. Indeed, we essentially confirm their findings for the overlapping variables using a panel dataset. Regarding three additional explanatory variables, the actual investment return shows negative and statistically significant association with the funded ratio, a finding that contradicts to our expected sign. We will address this issue in models in Table 1.8 by adding the lagged funded ratio as an explanatory variable. The estimated coefficient on the assumed rate of return indicates positive and statistically significant relationships between the assumed rate of return and the funded ratio. This finding supports the fact that higher assumed return decreases the liability of a pension plan, resulting in an increase in the funded ratio. The ratio of public union members to total public employees in state shows negative and statistically significant association with the funded ratio. This finding contradicts to our expectation that strong union will demand more benefits, resulting in a decrease in the funded ratio.

[Table 1.6]

In Model (3), we add an additional explanatory variable, the proportion of non-state workers to the total population in a state (*NMTP*), other than variables used in Model (1). *NMTP* is included to examine whether the proportion of the population in a state that does not belong to

[1] In the published version of their paper, Munnell et al. (2011) do not include ARC, but do include it an earlier working paper. We also include ARC in our empirical model. See Figure 1.7 for the ARC by state for year 2014.

the state's pension plan has any relationship to the funded ratio. The results shows a positive and statistically significant relationship between *NMTP* and the funded ratio.

In Model (5), we interact the ARC ratio with the proportion of non-state workers to the total population in a state to see whether there are conflicting interests by not being members but nonetheless being taxpayers. The estimated coefficient on the interaction term shows a negative and statistically significant relationship.

In Model (2), (4), and (6), we include year dummies to control for time-specific effects. Most of explanatory variables do not change sign and the level of significance remains. However, the coefficients on *Actual Return* and *Assumed Return* lose their significance and change their sign.

[Table 1.7]

Table 1.7 presents the regression results for individual public pension plan-fixed effects, which control for time-invariant unobservable characteristics of a plan for the period from 2001 to 2013. Model (1) in Table 1.7 corresponds to that in Table 1.6. We lose significance on *PUC* and *Large Plan* and have opposite sign on the coefficient on *Union* once we control for individual plan characteristics. A negative and statistically significant coefficient on *Union* is now consistent with our expectation that strong union in state is negatively associated with the funded ratio. The coefficient on other variables are consistent with the previous finding in Model (1) in Table 1.6.

In Model (3), we add the proportion of non-state workers to the total population in a state. Unlike findings in Table 1.6, we do not find statistical relationships between *NMTP* and the funded ratio after controlling for individual plan characteristics. In Model (5), we interact the ARC ratio with the proportion of non-state workers to the total population in a state. We also do not find statistical association between the interaction of *ARC* × *NMTP* and the funded ratio after controlling for individual plan characteristics.

In Model (2), (4), and (6), we include year dummies to control for time-specific effects. The coefficient on *Actual Return* lose their significance and change their sign to positive after we control for individual plan characteristics and time-specific effects. Most of explanatory variables, however, do not change sign and the level of significance remains.

[Table 1.8]

Table 1.8 presents the regression results for dynamic panel data models. We include the lagged funded ratio throughout all model specifications. The current level of the funded ratio is heavily determined by its past level. Not including the lagged funded ratio will lead to omitted variable bias, making our results unreliable. The coefficients on the lagged funded ratio and the size of plan are positive and statistically significant in all models. Contrary to models in Table 1.7, when using a difference Generalized Method of Moments (GMM) estimator (see Arellano and Bond, 1991) in Table 1.8, there are positive and statistically significant coefficients on the 1-year investment return (*Actual Return*) throughout all models, which is to be expected.[2] Our view is that including the lagged funded ratio captures the marginal contribution of the actual return on the funded ratio. With regard to the assumed rate of return, the higher it is the higher the funded ratio. That is, plans use the assumed rate of return when computing the discounted value of their future obligations. A higher assumed rate leads to lower actuarial liabilities, leading to a higher funded ratio of a plan.

In Model (2), (4), and (6) in which we include year dummies, we find negative and statistically significant coefficients on *Union*. This is consistent with our expectation that strong union in state is negatively associated with the funded ratio. In Model (6), our main variable of

[2] A fixed effects model may suffer from a finite sample bias (see Nickell, 1981) because we include a lagged endogenous variable in the equation. We therefore used a GMM estimator and conducted the standard diagnosis statistics (e.g., second order autocorrelation test AR (2)), which did not indicate any issue on the validity of the instrumentation at the 5% significant level.

interest is the interaction term between the ARC ratio and the proportion of non-state workers to the total population in a state. The estimated coefficient on the interaction term shows a negative and statistically significant relationship. This finding may suggest that there are conflicting interests between non-state workers, mainly state taxpayers, and members of state pension plans.

1.6 Summary and Conclusions

It is well known that public pension plans are struggling due to serious funding issues throughout the United States and many state governors and legislatures are grabbling with how best to meet resolve them. Some states are moving away from the traditional defined benefit plans to either defined contribution plans or some type of hybrid plans. Some, while retaining a defined benefit plan, are increasing the level of employee contributions and raising the age at which a member becomes eligible for benefits. Some states are now even offering employees a choice of the type of plan in which they would like to enroll. The bottom line is that many who have studied the current problems facing public pensions issue believe that the defined benefit plan is simply not sustainable in the long run. Private industries have already come to this realization, and as mentioned earlier, the trend is away from defined benefit plans toward defined contribution plans.

In an effort to better understand the serious funding problems facing public pension plans, we build upon prior research and examine a wide set of explanatory variables that may impact the funded ratio. We confirm the important and earlier work of Munnell et al. (2011) as well as expand on that work by employing a panel dataset, adding new explanatory variables and using appropriated econometric techniques. Importantly, from a policy standpoint, it is time for states to work to address the funding issues. While most states currently do meet their ARC commitments, not all have done so. States face many competing demands upon taxpayer dollars with money needed for a variety of state programs, such as Medicaid, education, prison reform, among others.

Unfortunately, pension funding does not always enjoy the same priority for funding as these programs. Yet, it is evident that this issue will not disappear in the near term and policymakers should continue to explore ways in which to insure appropriate benefits for current and future retirees in a manner that is sustainable for the long run.

1.7 References

Aggarwal, R., & Goodell, J. W. (2015). Determinants of expected returns at public defined benefit pension plans. *Federal Reserve Bank of Cleveland Working Paper*.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277-297.

Barth, J. R., & Jahera Jr., J. S. (2015). Alabama's public pensions: Building a stable financial foundation for the years ahead. Research report for the Alabama policy institute, Birmingham, AL.

BIGGS, A. G. (2011). An Options Pricing Method for Calculating the Market Price of Public Sector Pension Liabilities. *Public Budgeting & Finance*, *31*(3), 94-118.

Eaton, T. V., & Nofsinger, J. R. (2008). Funding levels and gender in public pension plans. *Public Budgeting & Finance*, *28*(3), 108-128.

Healey, T. J., Hess, C., & Nicholson, K. (2012). Underfunded public pensions in the United States. *Harvard Kennedy School M-RCBG Faculty Working Paper*.

Kelley, D. G. (2014). The political economy of unfunded public pension liabilities. *Public Choice*, *158*(1-2), 21-38.

Mitchell, O. S., & Smith, R. S. (1991). Pension funding in the public sector. *The Review of Economics and Statistics*, *76*(2), 278-290.

Mohan, N., & Zhang, T. (2014). An analysis of risk-taking behavior for public defined benefit pension plans. *Journal of Banking & Finance*, *40*, 403-419.

Munnell, A. H., Aubry, J. P., & Quinby, L. (2011). Public pension funding in practice. *Journal of Pension Economics & Finance*, *10*(2), 247-268.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417-1426.

Novy-Marx, R., & Rauh, J. D. (2009). The liabilities and risks of state-sponsored pension plans. *Journal of Economic Perspectives*, *23*(4), 191-210.

Novy-Marx, R., & Rauh, J. (2011). Public pension promises: how big are they and what are they worth?. *The Journal of Finance*, *66*(4), 1211-1249.

Rauh, J. D. (2010). Are state public pensions sustainable? Why the federal government should worry about state pension liabilities. *National Tax Journal*, *63*(3), 585-602.

Wang, Q., & Peng, J. (2016). An empirical analysis of state and local public pension plan funded ratio change, 2001-2009. *The American Review of Public Administration*, *46*(1), 75-91.

Yang T., & Mitchell, O. S. (2008). Public sector pension governance, funding and performance: A longitudinal appraisal, Chapter 8 in *Pension Fund Governance: A Global Perspective on Financial Regulation*, Edited by John Evans, Michael Orszag and John Piggot.

Table 1.1
Funded Ratio (%) by State, 2001-2014

State	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Alabama	101	96	92	90	84	82	79	77	73	70	67	66	66	67
Alaska	98	72	69	66	63	73	73	74	60	58	58	54	51	59
Arizona	121	109	101	93	87	84	80	80	78	74	71	67	66	60
Arkansas	101	96	90	86	83	82	87	87	77	74	71	70	74	78
California	108	98	91	88	87	88	90	89	83	80	77	74	74	77
Colorado	99	92	84	81	82	83	83	78	78	75	70	71	70	66
Connecticut	86	81	77	74	73	72	74	75	66	65	65	61	62	62
Delaware	112	110	107	103	102	102	104	103	99	96	94	91	91	92
District of Columbia	-	-	-	-	-	101	106	104	106	113	105	102	100	101
Florida	118	115	114	112	107	106	106	105	88	88	87	86	85	87
Georgia	103	102	101	99	98	95	94	91	88	83	80	78	76	80
Hawaii	91	84	76	72	69	65	67	69	65	61	59	59	60	61
Idaho	97	85	84	92	95	96	106	93	74	79	90	85	85	94
Illinois	82	73	68	70	69	68	70	64	59	54	51	47	47	47
Indiana	74	71	74	72	70	71	72	73	67	65	62	60	63	65
Iowa	97	93	89	86	87	89	89	89	83	81	79	77	77	80
Kansas	88	85	78	75	70	69	69	71	59	64	62	59	60	58
Kentucky	116	108	99	89	81	72	70	66	60	56	52	48	46	46
Louisiana	89	83	76	73	75	78	81	79	69	66	66	64	67	70
Maine	91	96	92	90	92	92	94	93	85	81	86	83	83	88
Maryland	99	95	93	92	88	82	80	78	65	64	65	64	65	68
Massachusetts	80	78	69	72	72	72	75	74	63	68	70	65	61	63
Michigan	96	90	85	82	78	83	84	81	77	73	68	64	64	64
Minnesota	101	98	93	91	88	86	84	81	75	78	77	72	71	73
Mississippi	88	83	79	75	72	73	74	73	67	64	62	58	58	61
Missouri	92	89	82	81	81	81	83	83	77	75	77	75	75	77
Montana	-	94	87	82	80	83	86	85	75	70	66	63	74	70
Nebraska	87	95	91	87	86	87	90	91	87	82	80	77	77	83
Nevada	82	81	79	76	74	73	75	74	71	70	70	71	70	73
New Hampshire	85	82	75	71	60	61	67	68	58	58	57	56	57	61
New Jersey	109	101	93	87	82	78	76	73	67	71	68	66	64	63
New Mexico	99	95	89	84	81	80	82	82	76	72	67	63	66	69
New York	112	104	94	89	87	84	84	85	83	75	73	72	73	83

State	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
North Carolina	106	105	104	104	104	103	103	102	99	98	97	97	97	97
North Dakota	103	98	92	87	83	82	86	87	81	72	68	63	60	63
Ohio	95	84	82	80	79	81	85	75	69	70	66	66	70	73
Oklahoma	75	73	72	68	67	66	68	69	64	63	77	75	76	82
Oregon	98	107	91	97	96	104	110	112	80	86	87	82	91	96
Pennsylvania	103	100	94	88	84	82	86	84	78	75	71	68	67	58
Rhode Island	98	92	83	76	71	70	73	77	73	61	72	70	70	71
South Carolina	91	89	87	84	79	77	77	74	72	70	70	68	66	64
South Dakota	96	97	97	98	97	97	97	97	92	96	96	93	100	93
Tennessee	95	95	96	96	96	94	93	91	88	90	91	92	106	106
Texas	101	94	92	90	88	89	89	85	85	84	82	81	78	75
Utah	102	92	94	90	91	94	93	84	83	80	78	75	81	87
Vermont	91	93	94	94	94	92	93	87	72	74	72	70	69	69
Virginia	105	99	93	89	83	83	84	86	79	74	73	71	75	78
Washington	182	161	145	135	124	124	126	125	120	115	113	114	106	98
West Virginia	53	47	46	51	54	59	74	67	61	61	66	65	69	75
Wisconsin	117	106	108	108	111	113	115	99	106	102	98	95	97	99
Wyoming	103	92	92	96	95	94	94	79	88	85	82	79	78	79
Average Funded Ratio	100	94	89	86	84	84	85	83	77	75	74	71	71	73

Note: Table 1.1 shows the aggregate funded ratio of state and local pension plans. Analysis is based on annual data from 2001-2014. The years shown in this table indicate the fiscal year end of the comprehensive annual financial report for the plan.
Source: Boston College's Center for Retirement Research.

Table 1.2
Variable Definitions

Variable	Definition	Source
Funded Ratio	Ratio of actuarial assets to actuarial liabilities.	Boston College's Center for Retirement Research
ARC	Ratio of actual contribution to required contribution of a pension plan.	Boston College's Center for Retirement Research
PUC	Projected unit credit method.	Boston College's Center for Retirement Research
Actives to Retirees	Ratio of active employees to retirees.	Boston College's Center for Retirement Research
Age	Age of a pension plan.	Boston College's Center for Retirement Research
Large Plan	A plan in the top third in terms of assets. Large Plan takes a value 1 if a plan is included in the top third of our sample in terms of assets, 0 otherwise.	Boston College's Center for Retirement Research
Teachers	A plan includes teachers. Teachers takes a value 1 if a plan includes teachers, 0 otherwise.	Boston College's Center for Retirement Research
Debt to GSP	Ratio of total state debt to gross state product (GSP).	Gross State Product (GSP), Bureau of Economic Analysis and U.S. State Debt, U.S. Census Bureau.
Actual Return	1 year investment return of a pension plan.	Boston College's Center for Retirement Research.
Assumed Return	Assumed investment return.	Boston College's Center for Retirement Research
Union	Ratio of public union members to total public employees in state.	http://www.unionstats.com provides private and public sector union membership, coverage, and density estimates compiled from the Current Population Survey
NMTP	Ratio of non-member tax payers to total population in state.	U.S. Census Bureau.

Table 1.3
Descriptive Statistics

	N	Mean	Std. Dev.	Minimum	Median	Maximum
Funded Ratio	2,021	0.82	0.19	0.19	0.82	1.97
ARC	2,061	0.94	0.53	0.00	1.00	17.28
PUC	2,100	0.08	0.27	0.00	0.00	1.00
Active to Retirees	2,018	2.47	5.76	0.01*	1.79	179.73
Age	2,100	61.87	19.61	1.00	63.00	119.00
Large Plan	2,100	0.32	0.47	0.00	0.00	1.00
Teachers	2,100	0.25	0.44	0.00	0.00	1.00
Debt to GSP	1,924	0.07	0.03	0.02	0.06	0.20
Actual Return	2,008	0.07	0.12	-0.31	0.10	0.31
Assumed Return	1,942	0.08	0.00	0.06	0.08	0.09
Union	2,100	0.37	0.19	0.03	0.38	0.72
NMTP	2,019	0.61	0.03	0.52	0.61	0.71

*This unusually low number is from the Minneapolis Employees Retirement Fund (MERF). MERF was closed to new members on July 1, 1978, and only 43 active members remain in the plan.

Table 1.4
Descriptive Statistics for Public Pension Plans by State (FY 2014)

State	Number of Pension Plans	Avg. Assumed Return (%)	Avg. Actual Return (%)	Avg. Return (2001-2014) (%)	Avg. Actuarial Assets ($millions)	Total Actuarial Assets ($millions)	Avg. Actuarial Accrued Liabilities ($millions)	Total Actuarial Liability ($millions)	Avg. Funded Level ($millions)	Total Funded Level ($millions)	Avg. Funded Ratio (%)	Avg. Retirees to Actives (%)	Avg. ARC Ratio (%)
AL	2	8.00	12.08	5.75	15,471	30,942	22,988	45,976	7,517	15,035	67	60	100
AK	2	8.00	18.51	6.70	5,751	11,503	9,583	19,166	3,832	7,663	59	166	105
AZ	4	7.50	15.26	4.86	10,300	41,199	14,959	59,834	4,659	18,635	60	63	99
AR	2	7.75	19.34	6.96	10,135	20,270	13,087	26,174	2,952	5,904	78	61	92
CA	15	7.50	14.77	6.89	43,712	655,682	58,275	874,122	14,563	218,441	77	83	96
CO	5	7.50	5.57	7.00	12,854	64,272	20,762	103,811	7,908	39,539	66	55	139
CT	3	8.00	14.09	5.80	9,320	27,960	18,002	54,006	8,682	26,046	62	78	100
DE	1	7.20	21.90	8.09	8,067	8,067	8,740	8,740	673	673	92	69	100
DC	2	6.50	8.18	5.56	2,964	5,927	2,924	5,848	-40	-80	101	59	100
FL	1	7.65	17.40	6.15	138,621	138,621	160,131	160,131	21,509	21,509	87	78	105
GA	2	7.50	17.23	6.58	37,677	75,353	46,407	92,814	8,731	17,461	80	57	100
HI	1	7.75	17.80	6.27	13,642	13,642	22,220	22,220	8,578	8,578	61	64	93
ID	1	7.50	17.20	6.60	13,833	13,833	14,737	14,737	903	903	94	62	96
IL	8	7.50	11.89	6.56	15,991	127,926	34,624	276,994	18,634	149,068	47	75	67
IN	2	6.75	13.73	5.84	12,092	24,185	19,162	38,324	7,070	14,140	65	62	98
IA	2	7.50	17.04	7.46	14,258	28,515	17,323	34,645	3,065	6,130	80	66	100
KS	1	8.00	18.40	6.90	14,390	14,390	24,828	24,828	10,437	10,437	58	58	79
KY	3	7.75	16.40	6.31	9,070	27,211	18,538	55,613	9,467	28,402	46	73	75
LA	5	7.75	15.59	7.50	6,654	33,271	10,830	54,151	4,176	20,880	70	95	97
ME	2	7.25	16.70	5.86	6,411	12,821	7,516	15,032	1,105	2,210	88	81	100
MD	2	7.65	14.37	5.27	20,307	40,615	29,471	58,942	9,164	18,327	68	73	74
MA	3	8.00	17.13	9.16	22,261	44,521	35,711	71,421	13,450	26,900	63	66	86
MI	3	8.00	12.53	6.30	19,376	58,127	31,458	94,374	12,082	36,247	64	114	102
MN	7	8.00	18.55	6.73	7,538	52,765	9,920	69,438	2,382	16,674	73	68	96

State	Number of Pension Plans	Avg. Assumed Return (%)	Avg. Actual Return (%)	Avg. Return (2001-2014) (%)	Avg. Actuarial Assets ($millions)	Total Actuarial Assets ($millions)	Avg. Actuarial Accrued Liabilities ($millions)	Total Actuarial Liability ($millions)	Avg. Funded Level ($millions)	Total Funded Level ($millions)	Avg. Funded Ratio (%)	Avg. Retirees to Actives (%)	Avg. ARC Ratio (%)
MS	1	8.00	18.60	6.31	22,570	22,570	37,015	37,015	14,445	14,445	61	58	100
MO	6	8.00	15.69	7.13	8,698	52,189	10,819	64,915	2,121	12,726	77	70	102
MT	2	7.75	17.17	6.05	3,997	7,993	5,684	11,369	1,688	3,375	70	75	97
NE	1	8.00	18.00	10.06	8,622	8,622	10,426	10,426	1,804	1,804	83	52	100
NV	2	8.00	17.60	7.71	4,478	8,955	6,266	12,532	1,788	3,576	73	54	93
NH	1	7.75	17.60	6.19	6,701	6,701	11,045	11,045	4,345	4,345	61	64	100
NJ	3	7.90	16.72	5.65	28,023	84,068	45,818	137,453	17,795	53,384	63	65	48
NM	2	7.75	16.06	6.79	12,099	24,198	17,378	34,756	5,279	10,558	69	69	88
NY	7	7.00	16.29	7.22	60,728	425,098	68,432	479,025	7,704	53,927	83	74	100
NC	2	7.25	15.67	6.22	41,931	83,862	43,672	87,343	1,741	3,481	97	55	102
ND	2	8.00	16.46	5.88	1,918	3,836	3,039	6,078	1,121	2,241	63	53	81
OH	2	7.75	11.76	7.18	41,714	166,858	55,386	221,543	13,671	54,685	73	69	97
OK	3	7.50	18.46	7.47	7,405	22,215	10,178	30,534	2,773	8,320	82	64	122
OR	1	7.75	16.60	6.93	60,014	60,014	62,594	62,594	2,580	2,580	96	80	100
PA	4	7.50	10.68	6.76	29,795	89,384	48,357	145,070	18,562	55,686	58	94	98
RI	2	7.50	15.12	7.14	3,766	7,532	6,068	12,137	2,302	4,604	71	85	100
SC	2	7.50	15.29	6.32	14,862	29,724	24,427	48,855	9,566	19,131	64	70	100
SD	1	7.25	18.90	9.05	9,887	9,887	10,608	10,608	720	720	93	63	122
TN*	2	7.50	16.65	5.69	19,624*	39,249*	20,193*	40,387*	569*	1,138*	106*	62	100
TX	8	8.00	10.68	6.99	23,459	187,672	29,481	235,851	6,022	48,179	75	46	85
UT	2	7.50	7.52	7.16	11,998	23,996	13,702	27,403	1,704	3,407	87	65	100
VT	2	8.28	6.70	7.60	1,588	3,176	2,349	4,697	760	1,521	69	77	119
VA	2	7.50	15.95	6.47	9,187	18,373	12,232	24,465	3,046	6,091	78	61	88
WA	4	7.80	19.04	7.31	12,402	49,608	12,880	51,519	478	1,911	98	22	98
WV	2	7.50	17.90	7.12	5,945	11,891	8,185	16,371	2,240	4,480	75	82	105
WI	2	8.25	5.06	7.24	47,079	94,158	47,164	94,328	85	170	99	62	100
WY	1	7.75	4.70	6.08	6,672	6,672	8,437	8,437	1,765	1,765	79	65	71

Notes: Actuarial value of assets refers to the value of pension plan investments and other property used by the actuary for the purpose of an actuarial valuation (sometimes referred to as valuation assets). Actuaries often select an asset valuation method that smooths the effects of short-term volatility in the market value of assets. Actuarial accrued liability is computed differently under different funding methods. The Actuarial Accrued Liability generally represents the portion of the Present Value of Fully Projected Benefits attributable to service credit earned (or accrued) as of the valuation date. (Source: Office of the State Actuary).

* TN: We use 2013 Boston College's Center for Retirement Research Database to compute average (or total) actuarial assets, liabilities, and funded ratio (or level) for Tennessee Consolidated Retirement System. Boston College's Center for Retirement Research Database covers two public pension plans of Tennessee, Tennessee Political Subdivisions Retirement Plan and Tennessee State and Teachers' Retirement Plan. We cannot obtain data on actuarial assets and liabilities of FY 2014 for the two pension plans, either from Boston College's Center for Retirement Research or 2014 Comprehensive Annual Financial Report (CAFR) of Tennessee Consolidated Retirement System.

Table 1.5

Pearson Correlation Matrix

Variable	*Funded Ratio*	*ARC*	*PUC*	*Active to Retirees*	*Age*	*Large Plan*	*Teachers*	*Debt to GSP*	*Actual Return*	*Assumed Return*	*Union*	*NMTP*
Funded Ratio	1.0000											
ARC	0.1354*** (0.0000)	1.0000										
PUC	-0.1643*** (0.0000)	-0.0225 (0.3078)	1.0000									
Active to Retiree	0.4040*** (0.0000)	0.0304 (0.1738)	-0.0378* (0.0899)	1.0000								
Age	-0.4036*** (0.0000)	-0.0407* (0.0646)	-0.0120 (0.5820)	-0.2774*** (0.0000)	1.0000							
Large Plan	0.1124*** (0.0000)	-0.0637*** (0.0038)	-0.0148 (0.4985)	-0.0536** (0.0160)	0.1817*** (0.0000)	1.0000						
Teachers	-0.1633*** (0.0000)	-0.0342 (0.1201)	0.0508** (0.0200)	-0.0022 (0.9197)	0.2766*** (0.0000)	0.2251*** (0.0000)	1.0000					
Debt to GSP	-0.2663*** (0.0000)	-0.0105 (0.6469)	0.0437* (0.0555)	-0.0829*** (0.0003)	0.1849*** (0.0000)	-0.0224 (0.3260)	0.0757*** (0.0009)	1.0000				
Actual Return	-0.1306*** (0.0000)	-0.0862*** (0.0001)	-0.0172 (0.4408)	-0.0550** (0.0146)	0.0522** (0.0192)	-0.0256 (0.2513)	-0.0092 (0.6814)	0.0183 (0.4280)	1.0000			
Assumed Return	-0.0176 (0.4418)	-0.0672*** (0.0031)	0.1852*** (0.0000)	0.0289 (0.2061)	0.1332*** (0.0000)	-0.0197 (0.3853)	0.0773*** (0.0006)	0.0698*** (0.0029)	-0.0925*** (0.0001)	1.0000		
Union	-0.0093 (0.6772)	-0.0250 (0.2561)	-0.0019 (0.9310)	-0.0016 (0.9439)	0.3510*** (0.0000)	0.1346*** (0.0000)	0.0467** (0.0322)	0.4708*** (0.0000)	-0.0081 (0.7162)	0.1502*** (0.0000)	1.0000	
NMTP	0.0499** (0.0258)	0.0031 (0.8885)	0.0139 (0.5329)	0.0755*** (0.0007)	0.0946*** (0.0000)	-0.2342*** (0.0000)	0.0686*** (0.0021)	0.0624*** (0.0065)	0.0218 (0.3326)	-0.0726*** (0.0012)	0.2585*** (0.0000)	1.0000

Note: Table 1.5 shows Pearson correlation matrix between the variables used in the analysis over the period, 2001-2013. *Funded Ratio* is ratio of actuarial assets to actuarial liabilities of a pension plan. *ARC* is ratio of actual contribution to required contribution of a pension plan. *PUC* is projected unit credit method. *Active to Retirees* is ratio of active employees to retirees of a pension plan. *Age* is age of a pension plan. *Large Plan* is a plan in the top third in terms of asset (*Large Plan* takes a value 1 if a plan is included in the top third of our sample in terms of assets, 0 otherwise). *Teachers* is a plan includes teachers (*Teachers* takes a value 1 if a plan includes teachers, 0 otherwise). *Debt to GSP* is ratio of total state debt to gross state product (GSP). *Actual Return* is 1-year investment return of a pension plan. *Assumed Return* is Assumed investment return of a pension plan. *Union* is ratio of public union members to total public employees in state. *NMTP* is the proportion of non-state workers to the total population in state. p-values in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 1.6
Public Pension Plans, Pooled OLS Regression, 2001-2013 (1)

VARIABLE	(1) **Funded Ratio** **Pooled OLS**	(2) **Funded Ratio** **Pooled OLS**	(3) **Funded Ratio** **Pooled OLS**	(4) **Funded Ratio** **Pooled OLS**	(5) **Funded Ratio** **Pooled OLS**	(6) **Funded Ratio** **Pooled OLS**
ARC	0.0389***	0.0280***	0.0391***	0.0280***	0.7898**	0.5429**
	(4.4977)	(4.3855)	(4.3848)	(4.2729)	(2.4538)	(2.0745)
PUC	-0.0926***	-0.0974***	-0.0950***	-0.1007***	-0.0955***	-0.1009***
	(-6.3197)	(-7.0157)	(-6.5352)	(-7.3514)	(-6.5745)	(-7.3785)
Active To Retiree	0.0093***	0.0088***	0.0090***	0.0085***	0.0091***	0.0085***
	(3.7309)	(3.6872)	(3.7227)	(3.6756)	(3.8237)	(3.7470)
Age	-0.0034***	-0.0027***	-0.0035***	-0.0028***	-0.0035***	-0.0028***
	(-12.5993)	(-10.5245)	(-12.9311)	(-11.0590)	(-13.0025)	(-11.1072)
Large Plan	0.0772***	0.0715***	0.0863***	0.0830***	0.0864***	0.0831***
	(10.8784)	(10.8291)	(11.8216)	(12.2402)	(11.8268)	(12.2593)
Teachers	-0.0385***	-0.0472***	-0.0411***	-0.0506***	-0.0409***	-0.0504***
	(-4.0469)	(-5.2019)	(-4.3748)	(-5.6790)	(-4.3805)	(-5.6724)
Debt to GSP	-1.5518***	-1.2093***	-1.4873***	-1.1199***	-1.4911***	-1.1250***
	(-13.6705)	(-11.8463)	(-13.3799)	(-11.4091)	(-13.4209)	(-11.4547)
Actual Return	-0.1000***	0.0504	-0.1033***	0.0479	-0.1049***	0.0420
	(-3.4305)	(1.0515)	(-3.5444)	(1.0013)	(-3.6020)	(0.8742)
Assumed Return	2.3691***	-1.0949	2.6637***	-0.7496	2.6777***	-0.7120
	(2.8783)	(-1.3854)	(3.2096)	(-0.9463)	(3.2040)	(-0.8952)
Union	0.2314***	0.1980***	0.2028***	0.1613***	0.2039***	0.1624***
	(10.3402)	(9.5321)	(9.1110)	(7.9152)	(9.1241)	(7.9370)
NMTP			0.5337***	0.6716***	1.6797***	1.4561***
			(4.0405)	(5.4038)	(3.2958)	(3.4727)
*ARC * NMTP*					-1.2165**	-0.8343**
					(-2.3548)	(-1.9783)
Constant	0.8063***	1.1708***	0.4707***	0.7542***	-0.2388	0.2656
	(12.0474)	(17.6347)	(4.4708)	(7.4456)	(-0.7348)	(0.9877)
Year dummies	NO	YES	NO	YES	NO	YES
Joint test (F-test) for year dummies	-	F(12, 1817) = 23.67 Prob. > F = .000	-	F(12, 1816) = 24.58 Prob. > F = .000	-	F(12, 1816) = 24.25 Prob. > F = .000
Observations	1,840	1,840	1,840	1,840	1,840	1,840
R-squared	0.4125	0.4976	0.4166	0.5039	0.4195	0.5053

Table 1.7
Public Pension Plans, Fixed Effects Regression, 2001-2013 (2)

VARIABLE	(1) **Funded Ratio Fixed Effects**	(2) **Funded Ratio Fixed Effects**	(3) **Funded Ratio Fixed Effects**	(4) **Funded Ratio Fixed Effects**	(5) **Funded Ratio Fixed Effects**	(6) **Funded Ratio Fixed Effects**
ARC	0.0150**	0.0132**	0.0143**	0.0129**	0.0461	0.0370
	(2.1046)	(2.0722)	(2.0698)	(2.0632)	(0.1863)	(0.1550)
PUC	-0.0093	-0.0129	-0.0149	-0.0168	-0.0150	-0.0169
	(-0.4263)	(-0.5976)	(-0.6689)	(-0.7649)	(-0.6724)	(-0.7672)
Active To Retiree	0.0041***	0.0039***	0.0041***	0.0039***	0.0041***	0.0039***
	(4.3024)	(4.0870)	(4.2792)	(4.0896)	(4.2613)	(4.0695)
Age	-0.0181***	-0.0219***	-0.0178***	-0.0216***	-0.0178***	-0.0216***
	(-14.3307)	(-16.2357)	(-13.9231)	(-15.1924)	(-13.8379)	(-15.0662)
Large Plan	0.0302	0.0336	0.0279	0.0317	0.0279	0.0317
	(1.4167)	(1.5134)	(1.2831)	(1.4099)	(1.2814)	(1.4074)
Teachers	-	-	-	-	-	-
Debt to GSP	-1.2726***	-1.0042**	-1.1177***	-0.9607**	-1.1172***	-0.9601**
	(-3.1211)	(-2.2730)	(-2.6307)	(-2.1687)	(-2.6257)	(-2.1629)
Actual Return	-0.0521***	0.0092	-0.0461***	0.0094	-0.0462***	0.0092
	(-4.3148)	(0.5192)	(-3.5746)	(0.5344)	(-3.6079)	(0.5253)
Assumed Return	2.9867*	2.9945*	2.8135*	2.6429	2.8098*	2.6396
	(1.9164)	(1.8039)	(1.7904)	(1.5168)	(1.7884)	(1.5129)
Union	-0.2285**	-0.2523**	-0.2045**	-0.2347**	-0.2051**	-0.2350**
	(-2.3034)	(-2.4918)	(-2.0654)	(-2.2819)	(-2.0796)	(-2.2893)
NMTP			-1.7899	-1.4268	-1.7432	-1.3938
			(-1.4514)	(-0.8511)	(-1.4586)	(-0.8593)
*ARC * NMTP*					-0.0514	-0.0389
					(-0.1286)	(-0.1008)
Constant	1.8464***	2.0977***	2.9052***	2.9586***	2.8764***	2.9380***
	(11.3394)	(12.3463)	(3.9420)	(2.9022)	(3.9877)	(2.9687)
Year dummies	NO	YES	NO	YES	NO	YES
Joint test (F-test) for year dummies	-	F(11, 147) = 27.46 Prob. > F = .000	-	F(11, 147) = 27.40 Prob. > F = .000	-	F(11, 147) = 27.15 Prob. > F = .000
Hausman test	$\chi^2(9) = 382.22$ Prob.$> \chi^2 = .000$	$\chi^2(12) = 71.05$ Prob.$> \chi^2 = .000$	$\chi^2(9) = 389.84$ Prob.$> \chi^2 = .000$	$\chi^2(12) = 73.99$ Prob.$> \chi^2 = .000$	$\chi^2(10) = 388.42$ Prob.$> \chi^2 = .000$	$\chi^2(12) = 70.11$ Prob.$> \chi^2 = .000$
Observations	1,840	1,840	1,840	1,840	1,840	1,840
R-squared	0.1751	0.1633	0.1628	0.1560	0.1628	0.1560

Table 1.8
Public Pension Plans, Dynamic Panel Data Model, 2001-2013 (3)

VARIABLE	(1) **Funded Ratio Difference GMM**	(2) **Funded Ratio Difference GMM**	(3) **Funded Ratio Difference GMM**	(4) **Funded Ratio Difference GMM**	(5) **Funded Ratio Difference GMM**	(6) **Funded Ratio Difference GMM**
Funded Ratio $_{t-1}$	0.9313***	0.8922***	0.9518***	0.8830***	0.9461***	0.8781***
	(12.4510)	(17.4603)	(13.0512)	(18.2295)	(13.0710)	(18.2509)
ARC	0.0049	0.0062	0.0081	0.0061	0.1805	0.2389***
	(0.6677)	(1.1564)	(1.0797)	(1.1413)	(1.3200)	(2.9153)
PUC	0.0043	-0.0024	0.0057	-0.0025	0.0052	-0.0027
	(0.2076)	(-0.2011)	(0.2911)	(-0.2137)	(0.2657)	(-0.2274)
Active To Retiree	-0.0022	-0.0013*	-0.0023*	-0.0012*	-0.0022*	-0.0011*
	(-1.6064)	(-1.8129)	(-1.7379)	(-1.7566)	(-1.6738)	(-1.7025)
Age	0.0037*	0.0019	0.0040**	0.0016	0.0039**	0.0017
	(1.9549)	(1.3056)	(2.1464)	(1.1354)	(2.1119)	(1.1754)
Large Plan	0.0358***	0.0266***	0.0365***	0.0265***	0.0354***	0.0257***
	(3.4180)	(3.1291)	(3.6097)	(3.1238)	(3.4676)	(2.9969)
Teachers						
Debt to GSP	-1.1152***	-0.0312	-1.4509***	-0.0305	-1.4380***	-0.0347
	(-3.2398)	(-0.1284)	(-4.0652)	(-0.1270)	(-4.0546)	(-0.1467)
Actual Return	0.1561***	0.1705***	0.1531***	0.1691***	0.1516***	0.1663***
	(6.9982)	(7.6599)	(7.1169)	(7.5949)	(7.0073)	(7.6536)
Assumed Return	6.8674***	5.6412***	5.9640***	5.6491***	6.0132***	5.7657***
	(5.1508)	(3.9993)	(4.0099)	(4.0134)	(4.0566)	(4.1695)
Union	-0.0477	-0.0922**	-0.0584	-0.0944**	-0.0613	-0.0947**
	(-0.6622)	(-2.0712)	(-0.8125)	(-2.0907)	(-0.8516)	(-2.1163)
NMTP			2.4221***	0.6306	2.6239***	0.9192
			(2.9025)	(0.8621)	(3.1222)	(1.2284)
*ARC * NMTP*					-0.2783	-0.3752***
					(-1.2628)	(-2.8456)
Year dummies	NO	YES	NO	YES	NO	YES
Joint test (χ^2)	-	$\chi^2(10) = 187.49$	-	$\chi^2(10) = 168.45$	-	$\chi^2(10) = 170.44$
for year dummies		$\text{Prob.} > \chi^2 = .000$		$\text{Prob.} > \chi^2 = .000$		$\text{Prob.} > \chi^2 = .000$
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AR(2)	0.771	0.947	0.747	0.948	0.774	0.898
Sargan test	0.000***	0.257	0.000***	0.252	0.000***	0.257
Hansen test	0.000***	0.426	0.000***	0.416	0.000***	0.425
Instrument	t-2	t-2	t-2	t-2	t-2	t-2
Observations	1,565	1,565	1,565	1,565	1,565	1,565

Figure 1.1
Change in Aggregate Funded Ratio, 2001-2014

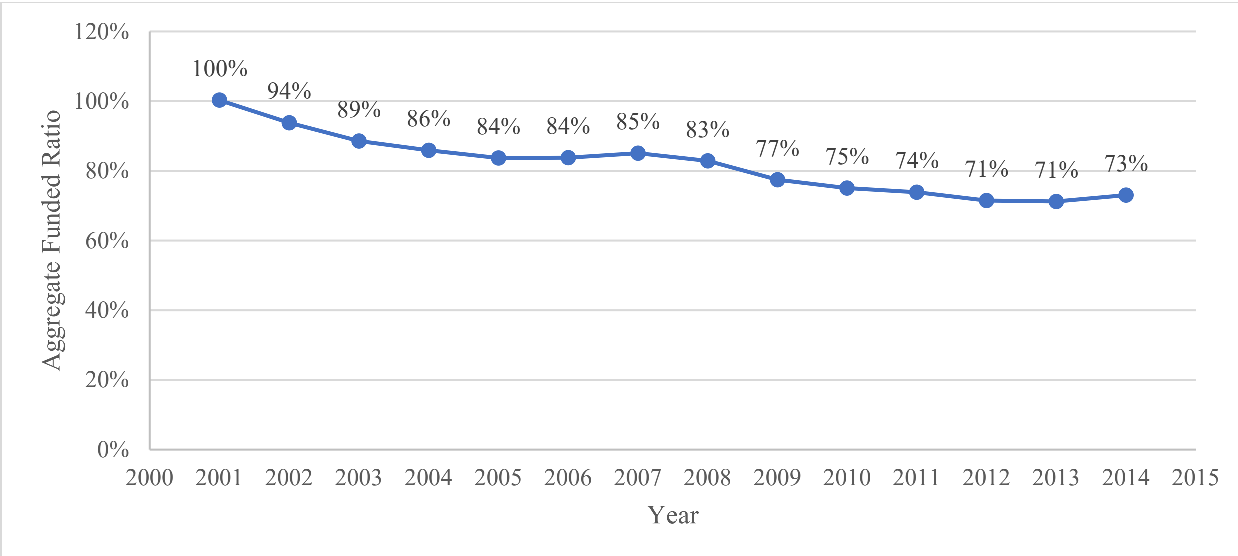


Figure 1.2
Funded Ratio by State, FY 2014

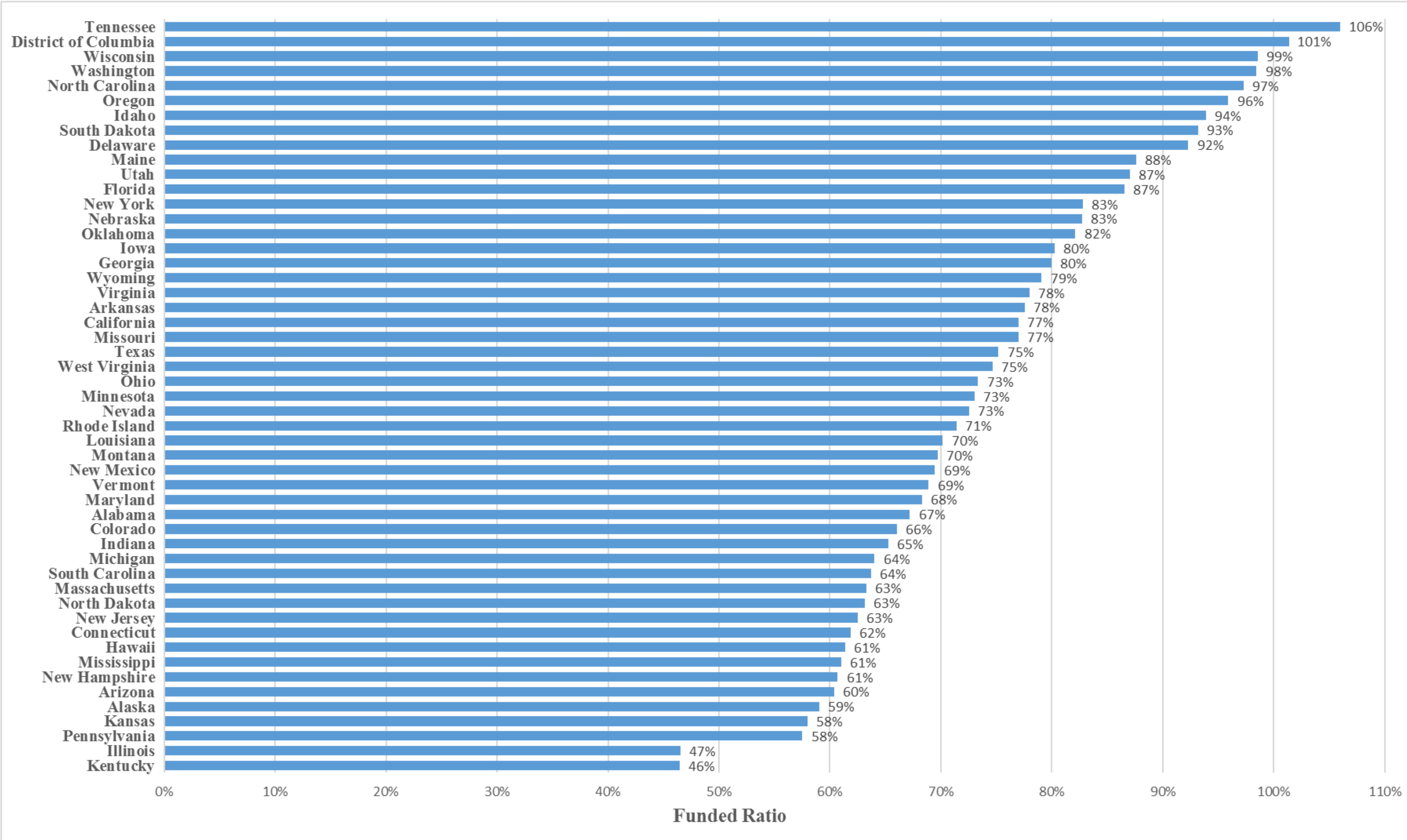
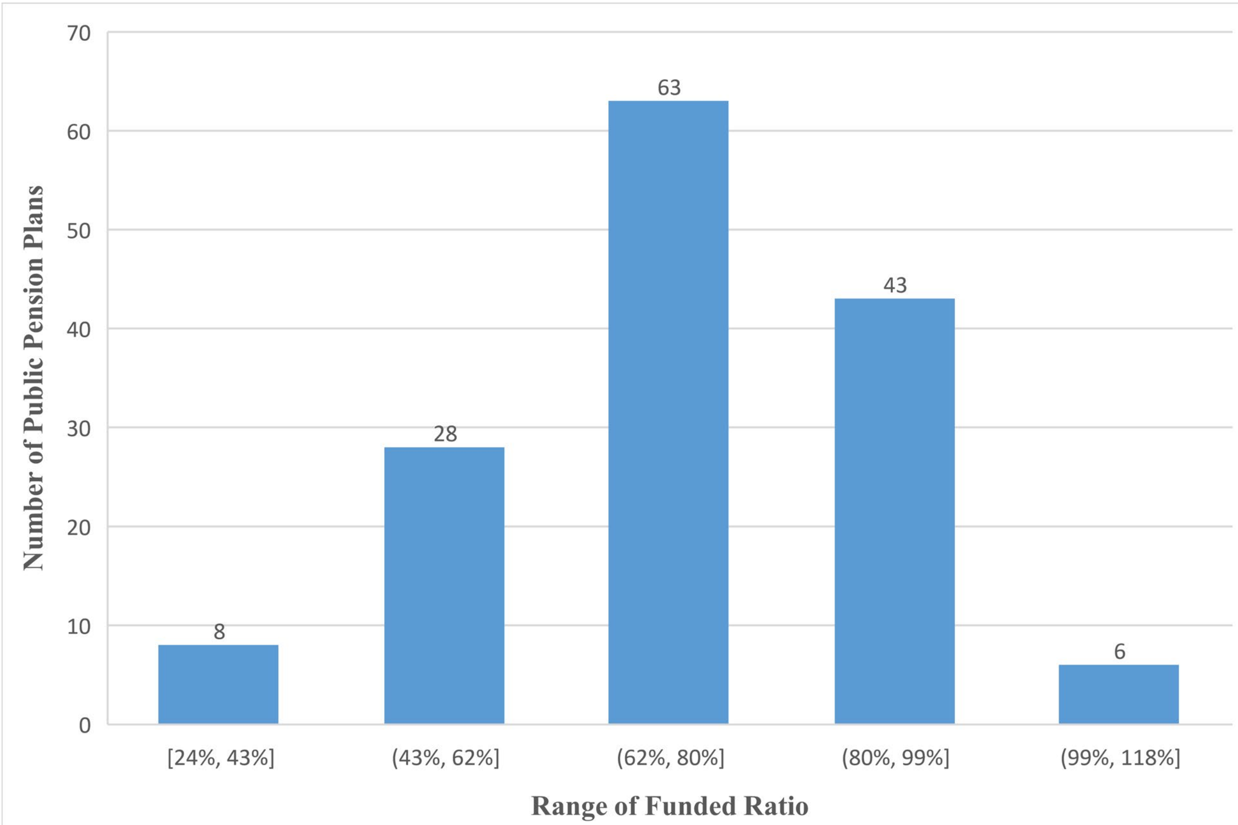
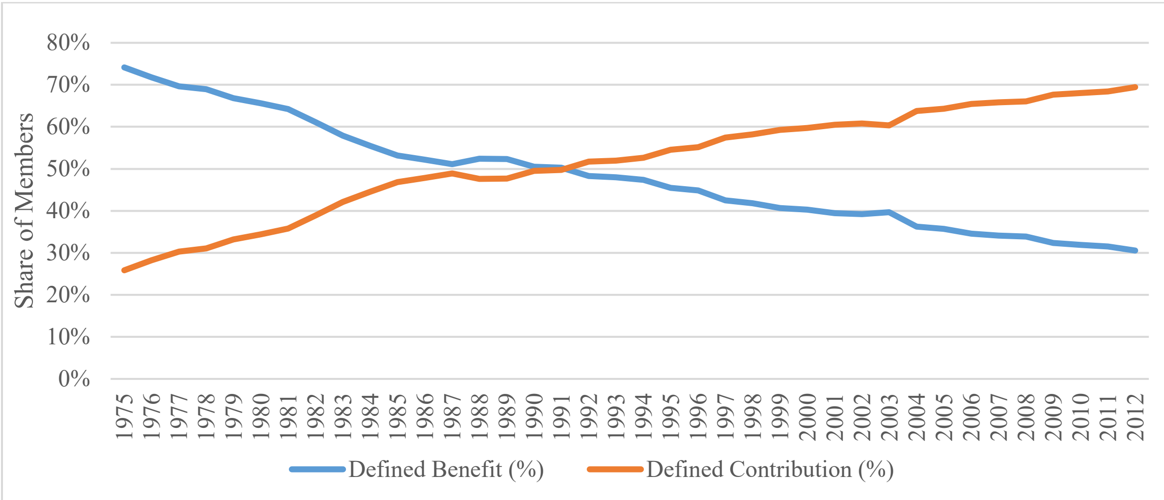


Figure 1.3
Distribution of Funded Ratio for Public Pension Plans, 2014



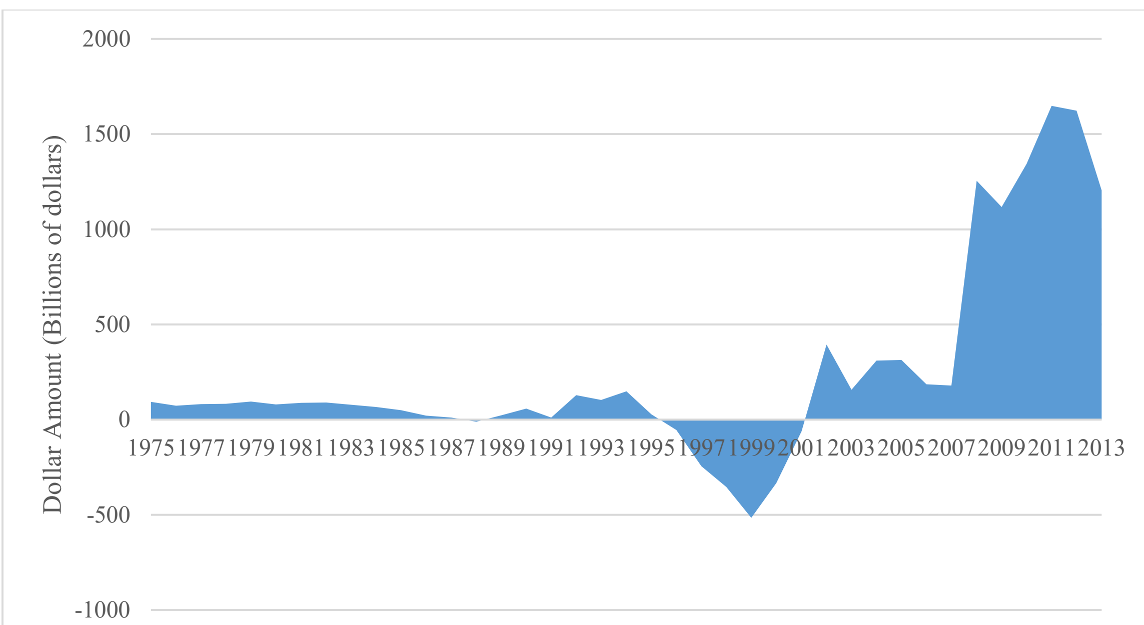
Note: Fig. 2 shows distribution of funded ratio for state and local pension plans in 2014. The year 2014 shown in this table indicates the fiscal year end of the comprehensive annual financial report for the plan. Source: Boston College's Center for Retirement Research.

Figure 1.4
Private Retirement Plans: Defined Contribution Plans Overtake Defined Benefit Plans



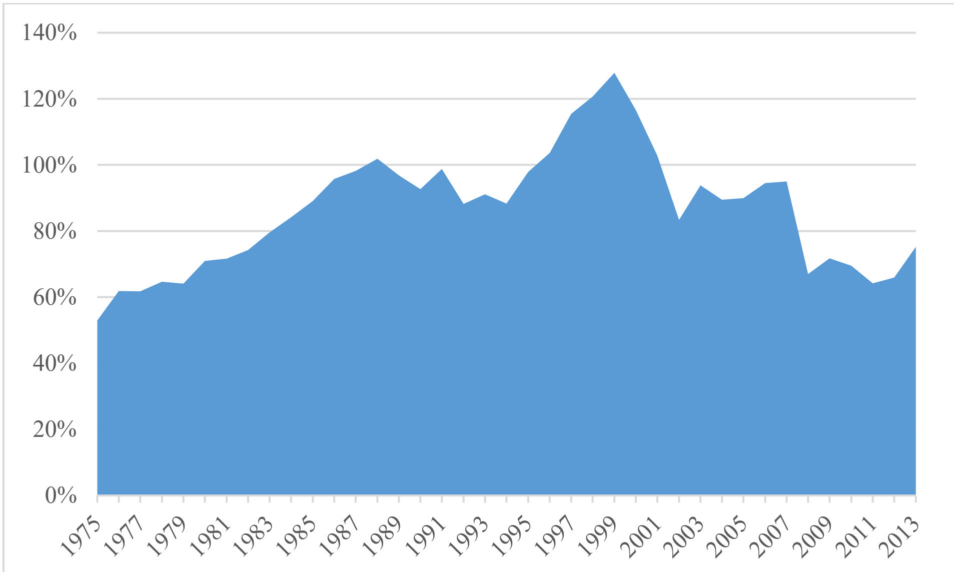
Source: Barth and Jahera (2015), Private Pension Plan Bulletin Historical Tables and Graphs, U.S. Department of Labor, September 2014.

Figure 1.5
Defined Benefit Plans for State and Local Governments: Funding Gap



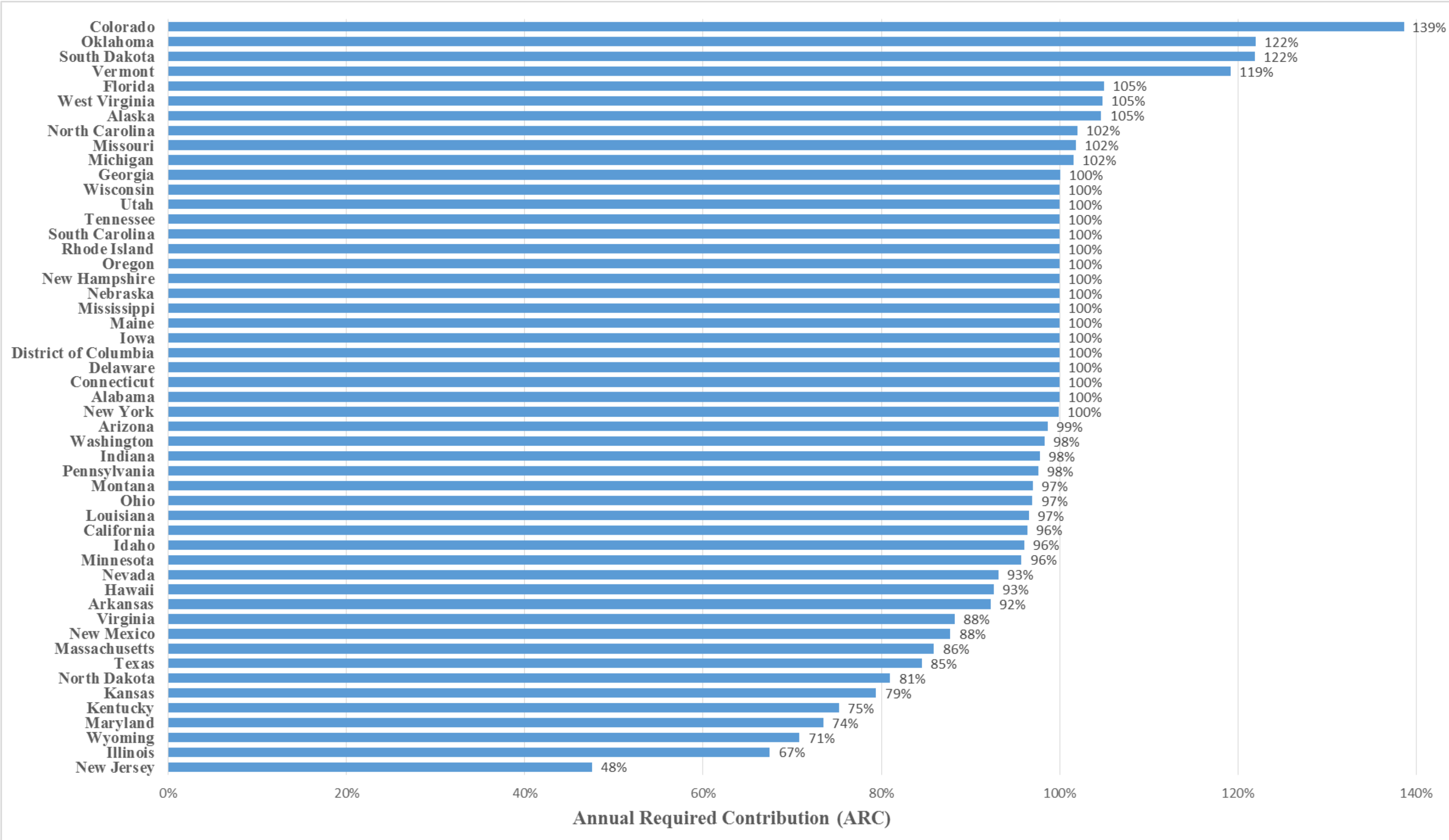
Source: Barth and Jahera (2015), Financial Accounts of the United States, Federal Reserve Board, September 18, 2014.

Figure 1.6
Defined Benefit Plans for State and Local Governments: Funded ratio



Source: Barth and Jahera (2015), Financial Accounts of the United States, Federal Reserve Board, September 18, 2014.

Figure 1.7
Annual Required Contribution (ARC) by State, FY 2014



Chapter 2

The Effects of Banks' Cross-Ownership on Bank Governance, Risk-Taking, and Systemic Risk in the Financial System: Evidence from Banks' Client Stock Ownership Structure

2.1 Introduction

In the banking sector, the body of literature linking banks' ownership structure and risk-taking (or risk exposure) has attracted a great deal of attention (Boyd and Hakenes, 2008; Iannotta et al., 2007; Iannotta et al., 2013; Laeven and Levine, 2009; Saunders et al., 1990). A majority of studies in this literature have focused on the effects of banks' ownership structure, mainly ownership concentration and the nature of owners[3], on banks' governance and risk-taking. Using a sample of 181 large European banks over the period 1999–2004, Iannotta et al. (2007) show that a concentrated ownership structure improves loan quality and decreases asset risk and insolvency risk. Laeven and Levine (2009) show that banks owned by shareholders with large cash flow rights tend to take more risk and that ownership structure and regulations jointly shape banks' risk-taking. Iannotta et al. (2013) examine the impact of government ownership on bank risk and find that government-owned banks have lower default risk. Overall, these studies show that ownership structure of individual banks alters owners' risk-taking behavior through either the changing standard risk-shifting incentives or interacting with certain bank regulatory policies.

Unlike these studies on banks' ownership structure on risk-taking behavior at the individual bank level, our study focus on the ownership ties of the clients of banks in 537 bank holding companies (BHCs) in the U.S. for the period, 2007–2015. Applying a dyadic level of analysis (a pair of entities as a unit of analysis), we aim to provide new insights on the relevance of the bank

[3] The nature of owners is mainly classified into three groups: privately owned stock banks (POBs), mutual banks (MBs), and government-owned banks (GOBs).

ownership ties of the clients of banks in reducing the risking taking behavior of banks and as a possible source of herding behavior of those clients that may contribute to systemic risk in the banking sector. More specifically, we examine bank-client ownership ties among financial institutions as a type of ownership structure that may serve as an effective mutual monitoring mechanism. We then turn to examine how such ownership interconnectedness among financial institutions by bank clients is related to the stability of the financial system. To the best of our knowledge, no researchers have examined such a connection between the ownership structure of bank stocks by bank clients and individual bank risk taking behavior as well as systemic risk in the banking system.

We label such client ownership ties among BHCs as "cross-ownership". Table 2.1 shows the matrix of cross-ownership among the major U.S. BHCs as of the end of 2015. As Table 2.1 illustrates, it is not uncommon for client shares of some BHCs to also be client shares of other BHCs. Notice that the cross-ownership matrix in Table 2.1 has a directionality that goes from the rows to the columns. For example, JPMorgan Chase (the first row) holds 1.70% of common shares for its clients of Bank of America as of the end of 2015 and Bank of America (the second row) holds 1.57% of common shares of JPMorgan Chase for its clients as of the end of 2015.

[Table 2.1]

One may note that the percentage of cross-ownership in Table 2.1 accounts for only small fraction of a BHC's shares outstanding. Nevertheless, such seemingly small percentages can translate into significant dollar amounts. Table 2.2 presents the dollar amount of the five largest BHCs' holdings for its client's common shares outstanding of the other 536 BHCs in the sample for the period, 2007–2015. JPMorgan Chase, Bank of America, Wells Fargo, Citigroup, and Goldman Sachs are the five largest bank holding companies, and each of them holds \$13, \$13, \$6,

$5, and $14 billions of equity stakes in the other 536 BHCs for its clients as of the end of 2007, respectively. We compare these equity stakes with total equity capital in Panel A and with tangible equity capital in Panel B. Tangible equity capital includes core capital elements[4] and therefore plays a critical role in assessing the viability of financial institutions. In the third column of each BHC, we present how much a BHC's ownership stakes held for its clients account for total equity capital in Panel A and for tangible equity capital in Panel B, in percentage. As can be seen, these percentages are not negligible and the difference in these percentages between Panel A and Panel B is notable, especially in 2007, for all the five largest BHCs. Overall, Table 2.2 illustrates that total ownership stakes held for the banks' clients among BHCs are not negligible in dollar amount.

[Table 2.2]

The ownership structure of economic entities is often characterized by a complex network of interdependent owners (Dietzenbacher and Temurshoev, 2008). Cross-ownership among BHCs by the clients of these banks may be a potential source that contributes to the complexity and the interdependency in the financial system, yet we have been unable to find research on the effects of such cross-ownership on bank risk-taking behavior and systemic risk. Given the fact that a BHC's ownership stakes on behave of its clients can account for a large fraction of its own tangible equity capital, cross-ownership among BHCs can be a possible overlooked factor in explaining systemic interconnectedness in the financial system. Specifically, if the clients of the banks have information not available to other owners of bank stocks and they decide all at once to sell their shares, sending the price of the stocks plunging, this may create a panic as to the solvency of banks. This, in turn, can lead to uninsured deposit runs and the inability of banks to continue their funding with repurchase agreements.

[4] See Federal Register/Vol. 78, No. 198/Friday, October 11, 2013/Rules and Regulations, for the components of tangible equity capital.

The recent 2007–2009 financial crisis has drawn considerable scholarly attention on systemic risk arising from systemic interconnectedness among financial institutions (Allen and Babus, 2008; Allen and Gale, 2000; Cai et al., 2018; Houston et al., 2015). Indeed, a high degree of interdependency originates from two channels (Allen and Babus, 2008): 1) a direct connection through mutual exposures in the interbank market, or 2) an indirect connection through holding similar portfolios. The former example is Freixas et al. (2000) and Silva et al. (2016). Freixas et al. (2000) model systemic risk in an interbank market. Similarly, Silva et al. (2016) study the Brazilian financial network and measure interrelatedness among financial institutions using the most representative financial instruments[5] traded in interbank market. The latter example is Houston et al. (2015) and Cai et al. (2018). Houston et al. (2015) use relationship ties among board members of banks as a source of interconnectedness and show that connected banks partner more often in the syndicated loan market. Likewise, Cai et al. (2018) identify a major source of systemic risk for the U.S. banks as a similarity in their holdings of syndicated loan portfolios.

In our study, a high degree of interrelatedness originates from both direct and indirect connections.[6] The direct ownership connections between BHCs through their clients' bank stock holdings can be readily obtained from our sample data. Not easily identified, however, is a hidden network of indirect relations arising from cross-ownership through the bank clients' stock holdings. Figure 2.1 shows a client stock ownership network among the major BHCs in our sample and illustrates that the major BHCs are closely interconnected through client holding shares of one another. Given the sheer size of BHCs in the overall financial system, such linkages through bank client cross-ownership of shares across BHCs in financial networks creates a complex web of an ownership network that may contribute to systemic risk.

[5] These financial instruments include interbank deposits, repos with federal securities, on-lending, credit assignment and loans.
[6] In our study, this direct connection is through mutual exposures not in the interbank market, but in the stock market.

[Figure 2.1]

The main contribution of this study is that we relate two topics examined in isolation of each other in earlier literature. The first topic is the effects of banks' client stock ownership structure on their governance mechanism and their risk-taking and the second topic is the effects of such ownership ties in the banking sector on systemic risk in the financial system. Importantly, we apply a dyadic level of analysis. This enables us to provide new insights on the relevance of such cross-ownership as effective mutual monitoring channel and as a possible source of interconnectedness between and among financial institutions.

The rest of the paper is organized as follows. In Section 2.2, we describe the theoretical background and discuss the hypotheses. In Section 2.3, we explain the data, variables, and methodology. In Section 2.4, we discuss the empirical results. In Section 2.5, the conclusions are presented.

2.2 Theoretical Background and Hypotheses

The primary source of profits for most banking firms comes from the collection and investment of depositors' funds in such a way that banks earn the interest margin by charging lower interest on deposits and higher interest on loans (Walter, 1991). The major assets in which banks invest depositors' funds are loans. Banks can improve assets quality through the enhanced monitoring system of their loan portfolio (Goetz et al., 2016). In our context, cross-shareholdings among BHCs by bank clients may provide a more direct form of mutual monitoring and potentially align the incentives of one BHC with those of the other BHCs. Indeed, the extent to which bank-client cross-ownership of bank stocks provides an effective monitoring mechanism will depend on how large a stake a BHC client owns (Di Donato and Tiscini, 2009). Therefore, bank stock cross-ownership by the banks' clients may impose additional monitoring on BHCs' risk-taking behavior.

If the bank clients have information not otherwise available in the marketplace, their sale of bank stocks in large amounts may set off a chain reaction that adversely affects the performance of banks and thereby impose additional discipline on banks. Therefore, our hypothesis is:

H.1.: Bank-client cross-ownership of bank stocks is negatively associated with the riskiness of BHCs.

The concern that arises from strong interconnectedness among banks by bank clients through stock ownership is that such a situation may lead to losses rapidly being spread across financial institutions due to the clients suddenly selling their shares and thereby triggering a financial crisis, and threatening the financial system as a whole. This issue of interconnectedness has become particularly relevant and important in the aftermath of the recent financial crisis (Houston et al., 2015). Although there exist both costs and benefits of strong interconnectedness across financial institutions, Hattori and Suda (2007) suggest that the costs (contagion effects) are likely to outweigh the benefits (risk-sharing effects) in times of financial crisis. In addition, Gai and Kapadia (2010) show that "*financial systems exhibit a robust-yet-fragile tendency*". Financial systems are robust in such a way that the probability that contagion events occur may be low, yet fragile since the effects can be extremely widespread when such events occur. If more BHCs are intertwined through the holding of common shares of one another by their clients, such cross-ownership may contribute to greater systemic risk, and more so in crisis periods than normal times. Therefore, we postulate the second hypothesis:

H.2.: Bank-client cross-ownership of bank stocks is positively associated with systemic risk and the effects of such cross-ownership on the systemic risk would be stronger in times of a financial crisis.

2.3 Data, Variables, and Methodology

2.3.1 Data

We compile data from several sources: BankScope, Bloomberg, COMPUSTAT, CRSP, Federal Reserve Board's H.15 statistical release, Federal Reserve Bank of St. Louis, and Thomson Reuters CDA/Spectrum Institutional (13f) Holdings database. Our two main sources for BHCs' cross-ownership data are the BankScope and the Thomson Reuters CDA/Spectrum Institutional (13f) Holdings. We collect information on quarterly accounting data from COMPUSTAT and on the daily equity data from CRSP. We obtain a set of macro-economy state variables from Bloomberg, Federal Reserve Board's H.15 statistical release, and Federal Reserve Bank of St. Louis.

Our primary data comprises a panel data of 537 BHCs in the U.S. for the period 2007–2015. We apply several screens to obtain the final sample of 537 BHCs from the BankScope database. We start with 2,279 U.S. BHCs obtained as of June 25, 2016 from the BankScope database. We disregard BHCs for which we have no client ownership linkage, as of the end of 2015, with any other BHCs included in our initial sample. In this process, a total of 1,717 BHCs are eliminated and a total of 562 BHCs remain in our sample. Among these 562 BHCs, there are 25 financial institutions classified as BHCs by the BankScope, but not matched with "*Bank Holding Company Name List*" available at Federal Reserve Bank of Chicago, therefore eliminated from our sample. This sample selection process yields a total of 537 BHCs in our final sample. *Appendix 1* provides a list of bank holding companies included in our final sample.

2.3.2 Variables

2.3.2.1 Dependent Variables

In our study, we examine the effects of bank-client cross-ownership of bank stocks among BHCs on their risk-taking and systemic risk across the whole network of BHCs. Specifically, we test for the relevance of the monitoring channel using three measures of loan quality: loan loss reserves, loan loss provisions, and net charge-offs, all expressed as a fraction of gross loans. All three measures are the unconditional risk proxies and are considered to be negatively related to loan quality. Following Adrian and Brunnermeier (2016), we also measure the conditional risk proxy, *the conditional value at risk – CoVaR*, to examine the effects of bank-client cross-ownership by bank clients among BHCs on the correlation of the risk exposure across the entire network of BHCs in the U.S.

2.3.2.1.1 Loan Loss Reserves

Following Billings et al. (1996) and Dinger and Von Hagen (2009), we use the ratio of loan loss reserves (LLRs) to gross loans as a proxy for banks' risk-taking. The federal banking regulators such as Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency, and the Federal Reserve require all banks to include an account named LLRs, also known as allowance for loan losses, in their financial statement (Walter, 1991). LLRs reflect banks' perceptions on expected loan losses and play a critical role in being a signal of important changes to come in banks' loan charge-offs decisions, earnings and dividend payments (Docking et al., 1997). Therefore, the reserve for loan loss account plays an important role in preserving a bank's solvency by absorbing current and expected future credit losses in outstanding loans.

2.3.2.1.2 Loan Loss Provisions

Following Altunbas et al. (2007), we use the ratio of loan loss provisions (LLPs) to gross loans to measure banks' risk exposure. LLPs are banks' main accrual and a key accounting variable that not only influences the volatility and cyclicality of bank earnings, but also reflects loan portfolios' risk attributes of banks (Bushman and Williams, 2012). Laeven and Majnoni (2003) show that bankers on average maintain too little provisions during good times and are then forced to increase them during economic downturns. This behavior, in turn, magnifies losses and inevitably increases banks' risk exposure (Laeven and Majnoni, 2003). Thus, holding appropriate level of LLPs plays an important role in maintaining their stability. In general, the higher level of the ratio of LLPs to gross loans indicates greater risk-taking of banks.

2.3.2.1.3 Net Charge-Offs

To measure the riskiness of banks, we also use the ratio of net charge-offs (NCOs) to gross loans. In banking literature, this ratio has been widely used as a proxy for banks' risk exposure (Billings et al., 1996; Chava and Purnanandam, 2011; Deng and Elyasiani, 2008; Dinger and Von Hagen, 2009). Banks with large unpaid loans must recognize losses on a significant portion of these loans, reducing net earnings and ultimately capital. Thus, a high ratio of NCOs to gross loans indicates the deterioration of the quality of banks' loan portfolios and unavoidably increases banks' risk exposure (Laeven and Majnoni, 2003).

2.3.2.1.4 Systemic Risk Measure – CoVaR

The value at risk (VaR) is widely used standard benchmark of risk measure by a financial institution. $VaR_{q,t}^{i}$, for example, represents the maximum loss of a financial institution i for a given time horizon t at the $q\%$ – confidence level. Statistically, VaR is the critical value of the probability distribution at the certain quantile:

$$\Pr\left(X_t^i \leq VaR_{q,t}^i\right) = q\%, \tag{2.1}$$

where X_t^i is the return losses on market equity of institution i for which $VaR_{q,t}^i$ is defined for a given time horizon t. VaR, however, is merely a benchmark for relative judgements on the risk of an individual institution relative to another (Duffie and Pan, 1997). Thus, it does not necessarily reflect the correlation of the risk exposure across financial institutions (Adrian and Brunnermeier, 2016).

Systemic risk measure, *CoVaR*, recently developed by Adrian and Brunnermeier (2016) takes into account this shortfall of the *VaR* and well captures tail co-movement of return losses that can arise from contagious, financial distress across institutions. With the prefix "*Co*", *CoVaR* indicates conditional value at risk:

$$\Pr\left(X_t^j | C(X_t^i) \leq CoVaR_{q,t}^{j|C(X_t^i)}\right) = q\%, \tag{2.2}$$

where $CoVaR_{q,t}^{j|C(X_t^i)}$ is defined as the *VaR* of the whole financial system *j* conditional on a particular event $C(X_t^i)$ of institution *i* for a given time horizon *t* at the *q%* – confidence level. Similar to the statistical interpretation of *VaR*, *CoVaR* is the critical value of the conditional probability distribution at the certain quantile.

In our study, we use Δ*CoVaR* as our main systemic risk measure. One can calculate Δ*CoVaR* by taking the difference between the *CoVaR* conditional on the distress of an institution at the *q%* - quantile and the *CoVaR* conditional on the normal, or median, state of that institution at the *50%* - quantile. Specifically, we use a time-varying systemic risk measure, $\Delta CoVaR_{q,t}^{system|i}$, which captures the time variation of tail-dependency of return losses on market equity across the whole network of financial system conditional on the distress of a particular institution *i*:

$$\Delta CoVaR_{q,t}^{system|i} = CoVaR_{q,t}^{system|X_t^i = VaR_{q,t}^i} - CoVaR_{q,t}^{system|X_t^i = VaR_{50,t}^i}. \tag{2.3}$$

A more detailed discussion about the estimation procedure is relegated to Section 2.3.3.2.

2.3.2.2 Independent Variable

Our main independent variable is bank-client cross-ownership of bank stocks among BHCs. We use the BankScope and the Thomson Reuters CDA/Spectrum Institutional (13f) Holdings database to identify such cross-ownership among BHCs. Using voting shares held directly and indirectly at the dyadic level (pairs of entities), we measure cross-ownership between BHCs as the sum of the direct and indirect percentages of ownership by bank clients between BHC i and BHC j. To be more specific, we measure cross-ownership as follows:

$$\text{Cross-ownership by bank clients between BHC } i \text{ and BHC } j$$

$$= 100 \times \left[\left(DIRECT_{ij} + INDIRECT_{ij}\right) + \left(DIRECT_{ji} + INDIRECT_{ji}\right)\right], \qquad (2.4)$$

where $DIRECT_{ij}$ is the ratio of total direct ownership by bank client of BHC i in BHC j, and $INDIRECT_{ij}$ is the ratio of total indirect ownership by bank client of BHC i in BHC j, and vice versa. Figure 2.2 illustrates how the BankScope calculates the total ownership by bank client of BHC i in BHC j if there is an indirect ownership by bank client linkage through BHC k.

[Figure 2.2]

Apparently, there are infinite situations which involve 3 or more companies in the example above. In some cases, the BankScope describes that its information source indicates that bank clients of entity i have a total stake in entity j without specifying the path through which the ownership is held. In this case, we use total ownership as it is recorded in the BankScope.

2.3.2.3 Control Variables

We control for the determinants of banks' risk-taking that are well documented in the literature. We identify the total of six control variables as follows: i) log of total assets, ii) deposits to total assets, iii) net loans to total assets, iv) non-interest income to total assets, v) equity to total assets, and vi) return on total assets. Like the measure of bank-client cross-ownership, the control variables are measured at the dyadic level. Hence, control variables in our study are the sum of the control variables of each pair of BHCs.

2.3.2.3.1 Log of Total Assets

Following Chong (1991), Brunnermeier et al. (2012), and Goetz et al. (2016), we use the natural log of total assets as a proxy for the size of BHCs. The literature presents mixed results regarding the effects of banks' size on banks' risk-taking. Extensive literature on banks' size and risk shows that bigger banks tend to take on greater risk since they expect government bailouts in times of a crisis (Chong, 1991). A recent study by Goetz et al. (2016), however, discusses a positive effect of banks' size on banks' stability since bigger banks are likely to become more diversified. Indeed, Beck et al. (2013) find a negative association between banks' risk, measured as log of Z-score, and banks' size, measured as log of total assets.

2.3.2.3.2 Deposits to Total Assets

We use the ratio of total customer deposits to total assets to account for the effects of funding structure on banks' risk-taking. Iannotta et al. (2007) show that relatively smaller and better capitalized mutual banks are funded with a higher percentage of retail deposit and have better loans quality than privately owned banks. Focusing on the defaults of the U.S. banks during the recent global financial crisis, Bologna (2011) examines whether any specific funding structure contributes to explain banks' fragility and likelihood of failure. In this study, Bologna (2011) also supports the notion that banks that strongly depend on retail insured deposits are less vulnerable to failure during the global financial crisis. Indeed, core retail deposits are considered to be more stable than other short-term funding sources (Vazquez and Federico, 2015).

2.3.2.3.3 Loans to Total Assets

We include the ratio of net loans to total assets to control for the effects of banks' business models on banks' risk exposure (Beck et al., 2013; Saghi-Zedek, 2016; Saghi-Zedek and Tarazi, 2015). Loans are usually considered to be more stable income sources than those from non-traditional intermediation activities (Iannotta et al., 2007). Therefore, a higher share of loans relative to total assets are expected to be negatively related to banks' risk exposure. Using Z-score as a measure of banks' risk, Saghi-Zedek and Tarazi (2015) and Saghi-Zedek (2016) find that the ratio of net loans to total assets is negatively related to Z-score. Beck et al. (2013), however, find no supporting evidence on such negative association.

2.3.2.3.4 Non-Interest Income to Total Assets

To control for the effects of diversification on the risk of an individual bank, we use the ratio of non-interest income to total assets. Non-interest income originates from non-traditional, fee-based activities such as trading, securitization, investment banking, advisory, brokerage, venture capital, and non-hedging derivatives (Brunnermeier et al., 2012). To improve profit margins and diversify risk, banks increasingly depend on these non-traditional income sources. Prior empirical findings show mixed evidence on the impact of a rise in such fee-based business on banks' risk-taking. Stiroh (2004) finds that non-interest income is related to an increase in the volatility of bank returns and DeYoung and Roland (2001) show that non-traditional activities are associated with an increase in revenue and earnings volatility. Contrary to these findings, however, Demirgüç-Kunt and Huizinga (2010) show a negative association between fee-income generating activities and banks' risk exposure.

2.3.2.3.5 Equity to Total Assets

To control for the effects of bank capitalization on banks' risk-taking, we include the ratio of book value of equity to total assets. Equity capital is not only a source of loanable funds, but also protects banks from credit and liquidity risks by playing a critical role in being a cushion for loan losses in economic downturns (Hughes and Mester, 1998). Therefore, an increase in equity capital reduces the probability of banks' failure. Moreover, equity capital represents banks' own stake on their risk management. This, in turn, provides an incentive to banks to allocate additional resources to manage risk. As such, higher level of capitalization is negatively associated with banks' risk exposure. Using the ratio of equity to total assets as a proxy for banks' risk-taking, Berger et al.

(2010) find a negative association between bank capitalization and banks' risk-taking. Laeven and Levine (2008) point out that banks with higher capitalization have fewer incentives to take excessive risks, but find no relationship between bank capitalization and banks' risk exposure.

2.3.2.3.6 Return on Total Assets

Following Anginer et al. (2014), we use return on total assets (ROA) to control for the effects of banks' profitability on banks' risk-taking. We measure return on total assets as net income divided by total assets. A majority of studies show that increased competition reduces banks' franchise values and induces them to take more risk (Hellmann et al., 2000; Keeley, 1990; Matutes and Vives, 2000). The recent study by Jiang et al. (2017) also find that intense levels of competition substantially heighten banks' risk-taking and suggest that this positive relationship is driven by reduced banks' profit margins. Boyd and De Nicolo (2005), however, acknowledge that there exists the same kind of mechanism that have opposite effects. Banks operating in the competitive pressures charge lower rates and this decrease in interest rates, in turn, provides their borrowers with an incentive to choose safer investments, implying a negative association between banks' profitability and risk-taking (Boyd and De Nicolo, 2005; Martinez-Miera and Repullo, 2010).

2.3.3 Methodology

2.3.3.1 Longitudinal Multiple Regression Quadratic Assignment Procedure (LMRQAP)

We apply the longitudinal version of multiple regression quadratic assignment procedure (LMRQAP) (Borgatti and Cross, 2003; Krackhardt, 1988). LMRQAP is a certain type of permutation test for a data set structured in a square matrix form among *n* objects. It has been widely used to test models in network research (Borgatti and Cross, 2003; Gibbons and Olk, 2003; Krackhardt, 1988; Sorenson and Stuart, 2001).

The LMRQAP approach is specifically designed to address the structural autocorrelation problem which arises from modeling network-related dependence among observations. Researchers have well recognized that such structural autocorrelation problem limits reasonable interpretations of statistical tests (Laumann et al., 1977; Laumann and Pappi, 1976). It is important to note that the unit of analysis in our study is pairs of BHCs: all of the variables are dyadic (pairs of entities) and doubly indexed (e.g., the variable X_{ij} refers to the way in which entity *i* is related to entity *j*). Therefore, observations in our data are inevitably subject to the structural autocorrelation problem. Table 2.3 is an example of network data structure drawn from our sample BHCs. We transform the cross-ownership matrix shown in Table 2.1 in such a way that the unit of analysis becomes pairs of BHCs.

[Table 2.3]

As Table 2.3 shows, the same BHCs repeatedly appear and form a cluster in the transformed data, resulting in error terms in standard ordinary least square (OLS) regressions to be correlated across observations. Indeed, when a moderate extent of structural autocorrelation presents in dyadic data, it is not uncommon that the standard OLS approach biases the regression coefficients to such a degree that the incorrect rejection rates of a true null hypothesis (type I errors rates of t-statistics) exceed 50% (Dekker et al., 2007; Krackhardt, 1988).

In LMRQAP regressions, however, standard errors are estimated by using permutations of the dataset (Simpson, 2001). Only the dependent variable is permuted and the same permutations are executed for the rows as for the columns to preserve any dependence among elements of the same rows or columns. This permuted data set of the dependent variable is then merged back with the independent variables. This process, therefore, generates a random data set with the same row–column interdependence of observations as there is in the original data set (Dekker et al., 2007).

In the permuted random data set, there is no statistical association between the dependent and the independent variables under the null hypothesis. If one observes statistical association between the dependent and independent variable in such randomly permuted data set, this association is a random association drawn from the same underlying distribution as that of the original data set (Dekker et al., 2007). In our study, we repeat such permutations of the data 1,000 times and generate empirical sampling distribution under the null hypothesis.[7] We, then, compare actual coefficients obtained from the original data set with those drawn from the empirical sampling distribution to test the statistical significance of the coefficients. The p-values of the coefficients can be obtained from the relative frequency of the values of the statistic that are larger than or equal to the observed values (Dekker et al., 2007; Krackhardt, 1988; Simpson, 2001).

2.3.3.2 Estimation Procedure of Δ***CoVaR***

Following Adrian and Brunnermeier (2016), we use the conditional quantile regression on weekly data and estimate the time-varying features of the systemic risk measure. The conditional quantile models appeal not only for their simplicity, but also for their inherent robustness to outliers in the response variable (Koenker and Hallock, 2001). With only the relevant information that determines quantiles of the response variable, one can utilize quantile regression to directly model the conditional VaR (Chernozhukov and Umantsev, 2001). Unlike most commonly used parametric models, the conditional quantile models are semi-parametric in nature and impose no strong assumptions about the distribution function of the underlying error term. These aspects provide the conditional quantile models with considerable flexibility (Chernozhukov and Umantsev, 2001).

The estimation of $\Delta CoVaR_{q,t}^{i}$ involves five steps:

[7] In practice, reference sampling distribution can be approximated with relatively small random sample (1,000 or 10,000) from the set of all n! permutations (Jackson and Somers, 1989; Mantel, 1967; Pitman, 1937).

In the first step, we project return losses of financial institutions on a vector of lagged state variables M_{t-1}:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i, \tag{2.5}$$

where X_t^i is weekly return losses on market equity of institution i, α_q^i is the constant, M_{t-1} is a vector of lagged state variables which capture variation in tail risk not directly associated with the financial system risk exposure, and $\varepsilon_{q,t}^i$ is an error term.

In the second step, we calculate the weekly *99% VaR* for each institution, using the predicted values from Eq. (2.5):

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}, \tag{2.6}$$

where $\hat{\alpha}_q^i$ and $\hat{\gamma}_q^i$ are the coefficient estimates from Eq. (2.5).

In the third step, we project return losses of the financial system on a vector of lagged state variables and on financial institutions' loss variable:

$$X_t^{system|i} = \alpha_q^{system|i} + \gamma_q^{system|i} M_{t-1} + \beta_q^{system|i} X_t^i + \varepsilon_{q,t}^{system|i}, \tag{2.7}$$

where $X_t^{system|i}$ is weekly return losses on market equity of the financial system, $\alpha_q^{system|i}$ is the constant, M_{t-1} is a vector of lagged state variables, X_t^i is return losses on market equity of institution i, and $\varepsilon_{q,t}^{system|i}$ is an error term. Following Adrian and Brunnermeier (2016), we use the sample of the publicly traded U.S. financial institutions to compute the financial system losses for which we take average market equity losses, weighted by lagged market equity. $\beta_q^{system|i}$ captures the contribution of the return losses on market equity of each institution to the overall losses of financial system.

In the fourth step, we compute the weekly *99% CoVaR* for each institution, using the predicted values from Eq. (2.7):

$$CoVaR_{q,t}^{system|i} = \hat{\alpha}_q^{system|i} + \hat{\gamma}_q^{system|i} M_{t-1} + \hat{\beta}_q^{system|i} VaR_{q,t}^{i}. \quad (2.8)$$

where $\hat{\alpha}_q^{system|i}$, $\hat{\gamma}_q^{system|i}$, and $\hat{\beta}_q^{system|i}$ are the coefficient estimates from Eq. (2.7) and $VaR_{q,t}^{i}$ is the weekly *99% VaR* estimates from Eq. (2.6).

In the final step, we calculate $\Delta CoVaR_{q,t}^{system|i}$ by subtracting the *CoVaR* at the *50%* - quantile from the *CoVaR* at the *99%* - quantile:

$$\Delta CoVaR_{q,t}^{system|i} = CoVaR_{q,t}^{system|i} - CoVaR_{50,t}^{system|i}, \quad (2.9)$$

or

$$\Delta CoVaR_{q,t}^{system|i} = \hat{\beta}_q^{system|i} (VaR_{q,t}^{i} - VaR_{50,t}^{i}). \quad (2.10)$$

From the steps above, we estimate a panel of weekly $\Delta CoVaR_{q,t}^{system|i}$ for each BHC in our sample. We then compute a yearly panel of $\Delta CoVaR_{q,t}^{system|i}$ by averaging the weekly observations within each year. Note that the Δ*CoVaR* is expressed in percentage loss rates, with higher values indicating greater contribution to the systemic risk. Table 2.4 shows summary statistics for state variables and Table 2.5 provides the estimates of our yearly conditional Δ*CoVaR* measures obtained from quantile regressions. Summary statistics for state variables are based on the weekly data for the period 2007-2015 and those for estimated risk measures are calculated on the universe of financial institutions for the same sample period.

[Table 2.4 and Table 2.5]

2.4 Empirical Results

In this section, we analyze whether bank-client cross-ownership of bank stocks is associated with loan quality of BHCs and systemic risk across financial institutions. Table 2.6 presents the LMRQAP results for pairs of BHCs using proxies for BHCs' risk exposure (columns 1–3) and systemic risk measures (columns 4–5). Throughout all models, we control for other factors affecting banks' risk-taking that are well documented in the literature: i) log of total assets, ii) deposits to total assets, iii) net loans to total assets, iv) non-interest income to total assets, v) equity to total assets, and vi) return on total assets.

[Table 2.6]

Model (1), (2), and (3) provide the results when we use LLRs, LLPs, and NCOs as proxies for loan quality of BHCs. The results provide clear support for *Hypothesis 1*. The negative and statistically significant coefficients on cross-ownership in models (1)–(3) are consistent with the monitoring hypothesis that large external equity holders perform an effective monitoring role and mitigate agency problem (*LLRs*: coefficient = −.1237 with p – value < 0.05, *LLPs*: coefficient = −.0767 with p – value < 0.05, and *NCOs*: coefficient = −.0708 with p – value < 0.10). Note that *LLRs*, *LLPs*, and *NCOs* are all expressed as a fraction of gross loans. Therefore, the lower these ratios indicate the better loan quality.

In model (4) and (5), we test whether interconnectedness among BHCs through client holdings of common shares of one another is related to greater systemic risk across the whole network of financial system. Model (4) provides the results using the 99 percent $\Delta CoVaR$ as our systemic risk measure. Consistent with *Hypothesis 2*, an increase in cross-ownership across BHCs is positively associated with an increase in $\Delta CoVaR$ at the 99 percent quantile (coefficient = .0019, p – value < 0.10). This result holds, in model (5), for the 95 percent $\Delta CoVaR$ (coefficient = .0013, p – value < 0.10). Our findings from the last two models of Table 2.6 suggest that cross-ownership by bank clients across BHCs can contribute to making them vulnerable to adverse movements in stock prices of other BHCs.

[Table 2.7]

We now turn to the LMRQAP results in Table 2.7 for the sub-period, 2008–2010 (columns

1 and 2) and 2011–2015 (columns 3 and 4), using both the 99 and the 95 percent $\Delta CoVaR$ as our systemic risk measures. As demonstrated by the recent financial crisis, strong interdependencies across financial institutions have created an environment that shocks to the financial system are amplified through feedback responses (Gai and Kapadia, 2010). In such environment, the degree to which BHCs are connected through bank-client cross-ownership of bank shares would matter more so in crisis period than normal times and therefore would be associated with greater systemic risk. Consistent with our expectation, our findings show the positive and statistically significant coefficients on cross-ownership only for the sub-period 2008–2010 ($\Delta CoVaR_{95}$: coefficient = .0014 with p – value < 0.05 and $\Delta CoVaR_{95}$: coefficient = .0009 with p – value < 0.05).

[Table 2.8]

In Table 2.8, we estimate the same models as those in Table 2.5 with cross-sectional data for each year, 2008–2015. Using the 99 percent $\Delta CoVaR$ as our systemic risk measure, we further analyze whether cross-ownership by bank clients is associated with greater systemic risk in times of crisis. Not surprisingly, we confirm that our results regarding the relationship between cross-ownership and systemic risk are mostly driven by sub-samples from the recent financial crisis periods.[8] In models (1)–(4) of Table 2.8, the estimated coefficients on cross-ownership are the positive and statistically significant only from the year 2008 to 2011. After these years, we do not find the statistical association between our cross-ownership measure and systemic risk. Overall, these results are also consistent with the notion that the degree to which BHCs are connected through cross-ownership would matter more so in a crisis period than normal times.

Of course, bankers are interested in their clients purchasing ever more shares of bank stocks, given that such behavior contributes to ever-higher stock prices. But bankers also are well

[8] We find consistent results when we use the 95 percent $\Delta CoVaR$ as our systemic risk measure.

aware that when their clients sell shares this can lead to declines in the stock prices of banks, and thereby potentially trigger still further declines in those prices. Bankers are therefore always doing their best to report good news about the performance of their banks to mitigate any tendency for their stock prices to decline. The clients of banks who own stocks in the banks are also interested in seeing bank stock prices only increasing. However, the history of banking indicates that there are crises in the banking sector now and then so that bank stock prices can plummet also now and then. For this reason, the clients of banks are always on the alert to avoid holding onto bank stocks when they detect troubles arising within the banking sector. Bank clients that own stocks in banks are therefore a potentially good monitoring source to prevent excess risk-taking behavior by banks. At the same time, to the extent that such clients detect trouble brewing in the banking sector, they can be a potential source that contributes to systemic risk. Our quantitative analysis builds upon this qualitative analysis, and thereby provides evidence about the role of cross-ownership in affecting the riskiness of banks, both individually and collectively.

2.5 Conclusions

In this paper, we have examined the effects of banks' client stock ownership structure on their governance mechanism and their risk-taking as well as the effects of such ownership ties in the banking sector on systemic risk in the financial system. Importantly, we applied a dyadic level of analysis to provide new insights on the relevance of such cross-ownership as effective mutual monitoring channel and as a possible source of interconnectedness between and among financial institutions.

Our empirical results provide clear support for the hypothesis that bank-client cross-ownership of bank stocks is negatively associated with the riskiness of BHCs. In particular, the negative and statistically significant coefficients on cross-ownership in our three models are consistent with the monitoring hypothesis that large external equity holders perform an effective monitoring role and mitigate agency problems.

We also test the hypothesis that bank-client cross-ownership of bank stocks is positively associated with systemic risk and the effects of such cross-ownership on the systemic risk would be stronger in times of a financial crisis. Once again, our empirical results confirm this hypothesis. In particular, an increase in cross-ownership across BHCs is positively associated with an increase in systemic risk in the banking sector. When examining whether cross-ownership by bank clients is associated with greater systemic risk in times of crisis, not surprisingly, we find that the relationship between cross-ownership and systemic risk is mostly driven by sub-samples from the recent financial crisis periods. Overall, these results are also consistent with the notion that the degree to which BHCs are connected through cross-ownership matters more in a crisis period than normal times.

2.6 References

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*. *106*(7), 1705-1741.

Allen, F., & Babus, A. (2009). Networks in finance. In *The network challenge: Strategy, profit, and risk in an interlinked world*, edited by Paul R. Kleindorfer and Yoram (Jerry) Wind, 367-382. Upper Saddle River, NJ: Wharton School Publishing.

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, *108*(1), 1-33.

Altunbas, Y., Carbo, S., Gardener, E. P., & Molyneux, P. (2007). Examining the relationships between capital, risk and efficiency in European banking. *European Financial Management*, *13*(1), 49-70.

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk?. *Journal of Financial Intermediation*, *23*(1), 1-26.

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, *22*(2), 218-244.

Berger, A. N., Hasan, I., & Zhou, M. (2010). The effects of focus versus diversification on bank performance: Evidence from Chinese banks. *Journal of Banking & Finance*, *34*(7), 1417-1435.

Gonzalez-Hermosillo, B., & Billings, R. (1996). Banking system fragility: Likelihood versus timing of failure: An application to the Mexican financial crisis. IMF Working Paper 96/412.

Black, H. A., Collins, M. C., Robinson, B. L., & Schweitzer, R. L. (1997). Changes in market perception of riskiness: The case of too-big-to-fail. *Journal of Financial Research*, *20*(3), 389-406.

Bologna, P. (2011). Is there a role for funding in explaining recent U.S. banks' failures? IMF Working Paper 11/180.

Borgatti, S. P., & Cross, R. (2003). A relational view of information seeking and learning in social networks. *Management Science*, *49*(4), 432-445.

Boyd, J. H., & De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance*, *60*(3), 1329-1343.

Boyd, J. H., & Hakenes, H. (2008). Looting and gambling in banking crises. University of Minnesota, Minneapolis, MN.

Brewer, E. (1995). The impact of deposit insurance on S&L shareholders' risk/return trade-offs. *Journal of Financial Services Research*, *9*(1), 65-89.

Brunnermeier, M.K., Dong, G.N., Palia, D., 2012. Banks' non-interest income and systemic risk. Working Paper, Princeton University.

Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *Journal of Accounting and Economics*, *54*(1), 1-18.

Cai, J., Eidam, F., Saunders, A., & Steffen, S. (2018). Syndication, interconnectedness, and systemic risk. *Journal of Financial Stability*, *34*, 105-120.

Chava, S., & Purnanandam, A. (2011). The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics*, *99*(1), 116-135.

Chen, A. H., Cornett, M. M., Mazumdar, S. C., & Tehranian, H. (1994). Stock price to the passage of the Federal Deposit Insurance Corporation Improvement Act of 1991. Working Paper, Southern Methodist University.

Chernozhukov, V., & Umantsev, L. (2001). Conditional value-at-risk: Aspects of modeling and estimation. *Empirical Economics*, *26*(1), 271-292.

Chong, B. S. (1991). The effects of interstate banking on commercial banks' risk and profitability. *The Review of Economics and Statistics*, 78-84.

Dekker, D., Krackhardt, D., & Snijders, T. A. (2007). Sensitivity of MRQAP tests to collinearity and autocorrelation conditions. *Psychometrika*, *72*(4), 563-581.

Demirgüç-Kunt, A., & Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics*, *98*(3), 626-650.

Deng, S., & Elyasiani, E. (2008). Geographic diversification, bank holding company value, and risk. *Journal of Money, Credit and Banking*, *40*(6), 1217-1238.

DeYoung, R., & Roland, K. P. (2001). Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model. *Journal of Financial Intermediation*, *10*(1), 54-84.

Di Donato, F., & Tiscini, R. (2009). Cross ownership and interlocking directorates between banks and listed firms: an empirical analysis of the effects on debt leverage and cost of debt in the Italian case. *Corporate Ownership & Control*, *6*(3), 473-481.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401-419.

Dietzenbacher, E., & Temurshoev, U. (2008). Ownership relations in the presence of cross-shareholding. *Journal of Economics*, *95*(3), 189-212.

Dinger, V., & Von Hagen, J. (2009). Does interbank borrowing reduce bank risk?. *Journal of Money, Credit and Banking*, *41*(2-3), 491-506.

Docking, D. S., Hirschey, M., & Jones, E. (1997). Information and contagion effects of bank loan-loss reserve announcements. *Journal of Financial Economics*, *43*(2), 219-239.

Duffie, D., & Pan, J. (1997). An overview of value at risk. *Journal of Derivatives*, *4*(3), 7-49.

Freixas, X., Parigi, B. M., & Rochet, J. C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit & Banking*, *32*(3), 611-611.

Gai, P., & Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *466*(2120), 2401-2423.

Gibbons, D., & Olk, P. M. (2003). Individual and structural origins of friendship and social position among professionals. *Journal of Personality and Social Psychology*, *84*(2), 340.

Goetz, M. R., Laeven, L., & Levine, R. (2016). Does the geographic expansion of banks reduce risk?. *Journal of Financial Economics*, *120*(2), 346-362.

Goodhart, C., Hartmann, P., Llewellyn, D. T., Rojas-Suarez, L., & Weisbrod, S. (2013). Financial regulation: Why, how, and where now? Routledge, London.

Hattori, M., & Suda, Y. (2007, December). Developments in a cross-border bank exposure network. In *proceedings of a CGFS workshop held at the Bank for International Settlements*.

Hellmann, T. F., Murdock, K. C., & Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough?. *American Economic Review*, *90*(1), 147-165.

Houston, J. F., Lee, J., & Suntheim, F. (2018). Social networks in the global banking sector. *Journal of Accounting and Economics*, *65*(2-3), 237-269.

Hughes, J. P., & Mester, L. J. (1998). Bank capitalization and cost: Evidence of scale economies in risk management and signaling. *Review of Economics and Statistics*, *80*(2), 314-325.

Iannotta, G., Nocera, G., & Sironi, A. (2007). Ownership structure, risk and performance in the European banking industry. *Journal of Banking & Finance*, *31*(7), 2127-2149.

Iannotta, G., Nocera, G., & Sironi, A. (2013). The impact of government ownership on bank risk. *Journal of Financial Intermediation*, *22*(2), 152-176.

Jackson, D. A., & Somers, K. M. (1989). Are probability estimates from the permutation model of Mantel's test stable?. *Canadian Journal of Zoology*, *67*(3), 766-769.

Jiang, L., Levine, R., & Lin, C. (2017). Does competition affect bank risk? National Bureau of Economic Research.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American Economic Review*, *80*(5), 1183-1200.

Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, *15*(4), 143-156.

Krackhardt, D. (1988). Predicting with networks: Nonparametric multiple regression analysis of dyadic data. *Social Networks*, *10*(4), 359-381.

Laeven, L., & Levine, R. (2007). Complex ownership structures and corporate valuations. *The Review of Financial Studies*, *21*(2), 579-604.

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, *93*(2), 259-275.

Laeven, L., & Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late?. *Journal of Financial Intermediation*, *12*(2), 178-197.

Laumann, E. O., Marsden, P. V., & Galaskiewicz, J. (1977). Community-elite influence structures: Extension of a network approach. *American Journal of Sociology*, *83*(3), 594-631.

Laumann, E. O., & Pappi, F. U. (1976). *Networks of collective action: A perspective on community influence systems*. Academic, New York.

Mantel, N. (1967). The detection of disease clustering and a generalized regression approach. *Cancer research*, *27*(2), 209-220.

Martinez-Miera, D., & Repullo, R. (2010). Does competition reduce the risk of bank failure?. *The Review of Financial Studies*, *23*(10), 3638-3664.

Matutes, C., & Vives, X. (2000). Imperfect competition, risk taking, and regulation in banking. *European Economic Review*, *44*(1), 1-34.

O'hara, M., & Shaw, W. (1990). Deposit insurance and wealth effects: the value of being “too big to fail”. *The Journal of Finance*, *45*(5), 1587-1600.

Peltzman, S. (1970). Capital investment in commercial banking and its relationship to portfolio regulation. *Journal of Political Economy*, *78*(1), 1-26.

Pitman, E. J. (1937). Significance tests which may be applied to samples from any populations. *Supplement to the Journal of the Royal Statistical Society*, *4*(1), 119-130.

Saghi-Zedek, N. (2016). Product diversification and bank performance: does ownership structure matter?. *Journal of Banking & Finance*, *71*, 154-167.

Saghi-Zedek, N., & Tarazi, A. (2015). Excess control rights, financial crisis and bank profitability and risk. *Journal of Banking & Finance*, *55*, 361-379.

Santos, J. A. (2001). Bank capital regulation in contemporary banking theory: A review of the literature. *Financial Markets, Institutions & Instruments*, *10*(2), 41-84.

Saunders, A., Strock, E., & Travlos, N. G. (1990). Ownership structure, deregulation, and bank risk taking. *The Journal of Finance*, *45*(2), 643-654.

Shleifer, A., & Vishny, R. W. (1986). Large shareholders and corporate control. *Journal of Political Economy*, *94*(3), 461-488.

Silva, T. C., Guerra, S. M., Tabak, B. M., & de Castro Miranda, R. C. (2016). Financial networks, bank efficiency and risk-taking. *Journal of Financial Stability*, *25*, 247-257.

Simpson, W. (2001). QAP: The quadratic assignment procedure. In *North American STATA users' group meeting*, *March*.

Sorenson, O., & Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, *106*(6), 1546-1588.

Stiroh, K. J. (2004). Diversification in banking: Is noninterest income the answer?. *Journal of Money, Credit, and Banking*, *36*(5), 853-882.

Vazquez, F., & Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of Banking & Finance*, *61*, 1-14.

Walter, J.R., 1991. Loan loss reserves. *Federal Reserve Bank of Richmond Economic Review*, *77* (July/August 1991), 20–28.

Table 2.1
The Matrix of Cross-ownership between the Major U.S. BHCs as of the End of 2015

	JPMorgan Chase	Bank of America	Wells Fargo	Citi Group	Goldman Sachs	Prudential	State Street	Bank of NY Mellon
JPMorgan Chase	.	1.70 %	1.97 %	1.55 %	1.22 %	1.58 %	0.66 %	0.44 %
Bank of America	1.57 %	.	1.03 %	1.04 %	0.97 %	0.78 %	0.69 %	0.50 %
Wells Fargo	0.65 %	0.61 %	.	0.38 %	0.94 %	0.47 %	0.21 %	0.28 %
Citi Group	0.10 %	1.20 %	0.00 %	.	2.49 %	0.12 %	0.00 %	0.00 %
Goldman Sachs	0.57 %	0.63 %	0.30 %	0.52 %	.	1.37 %	0.20 %	0.47 %
Prudential	0.42 %	0.42 %	0.30 %	0.64 %	0.60 %	.	0.18 %	0.15 %
State Street	4.18 %	3.98 %	3.69 %	4.07 %	4.76 %	4.03 %	.	4.28 %
Bank of NY Mellon	1.28 %	1.06 %	0.96 %	1.31 %	0.85 %	1.66 %	1.03 %	.

Note: Table 2.1 shows the matrix of cross-ownership between the major U.S. BHCs, in percentages as of the end of 2015. This matrix has a directionality that goes from the rows to the columns. For example, JPMorgan Chase (the first row) owns 1.70% of common shares of Bank of America as of the end of 2015 and Bank of America (the second row) owns 1.57% of common shares of JPMorgan Chase as of the end of 2015.

Table 2.2

Total Equity Holdings of Five Largest Bank Holding Companies in the Other 536 Bank Holding Companies

	JPMorgan Chase			Bank of America			Wells Fargo			Citigroup			Goldman Sachs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A	Total ownership ($ mil)	Total equity ($ mil)	%	Total ownership ($ mil)	Total Equity ($ mil)	%	Total ownership ($ mil)	Total equity ($ mil)	%	Total ownership ($ mil)	Total equity ($ mil)	%	Total ownership ($ mil)	Total equity ($ mil)	%
2015	27,222	247,573	11.0	8,855	256,176	3.5	3,021	193,891	1.6	5,525	223,092	2.5	11,203	87,187	12.8
2014	22,938	231,727	9.9	8,901	243,471	3.7	6,065	185,262	3.3	6,556	211,696	3.1	12,055	83,201	14.5
2013	22,508	211,178	10.7	8,448	232,685	3.6	5,821	171,008	3.4	7,073	206,133	3.4	11,615	78,793	14.7
2012	17,005	204,069	8.3	5,762	236,956	2.4	3,856	158,911	2.4	7,159	190,997	3.7	8,857	76,224	11.6
2011	11,384	183,573	6.2	3,637	230,101	1.6	2,711	141,687	1.9	3,893	179,573	2.2	6,110	71,829	8.5
2010	16,321	176,106	9.3	4,555	228,248	2.0	5,113	127,889	4.0	2,234	165,789	1.3	8,995	78,228	11.5
2009	11,045	165,365	6.7	9,859	231,444	4.3	3,587	114,359	3.1	1,123	154,973	0.7	8,223	71,674	11.5
2008	7,193	166,884	4.3	7,173	177,052	4.1	3,439	99,084	3.5	2,352	144,022	1.6	7,440	66,012	11.3
2007	13,122	123,221	10.6	13,381	146,803	9.1	6,342	47,628	13.3	4,707	113,447	4.1	13,768	50,065	27.5
Panel B	Total ownership ($ mil)	Tangible Equity ($ mil)	%	Total ownership ($ mil)	Tangible Equity ($ mil)	%	Total ownership ($ mil)	Tangible Equity ($ mil)	%	Total ownership ($ mil)	Tangible Equity ($ mil)	%	Total ownership ($ mil)	Tangible Equity ($ mil)	%
2015	27,222	199,233	13.7	8,855	182,647	4.8	3,021	165,195	1.8	5,525	197,022	2.8	11,203	83,039	13.5
2014	22,938	182,888	12.5	8,901	169,082	5.3	6,065	155,125	3.9	6,556	183,538	3.6	12,055	79,041	15.3
2013	22,508	161,479	13.9	8,448	157,267	5.4	5,821	139,599	4.2	7,073	176,068	4.0	11,615	74,417	15.6
2012	17,005	153,659	11.1	5,762	160,296	3.6	3,856	126,007	3.1	7,159	159,627	4.5	8,857	71,125	12.5
2011	11,384	132,178	8.6	3,637	152,113	2.4	2,711	107,622	2.5	3,893	147,560	2.6	6,110	66,361	9.2
2010	16,321	123,213	13.2	4,555	144,464	3.2	5,113	92,354	5.5	2,234	132,133	1.7	8,995	72,706	12.4
2009	11,045	112,387	9.8	9,859	133,104	7.4	3,587	76,619	4.7	1,123	120,867	0.9	8,223	66,754	12.3
2008	7,193	113,276	6.3	7,173	86,583	8.3	3,439	60,942	5.6	2,352	102,731	2.3	7,440	60,812	12.2
2007	13,122	71,852	18.3	13,381	58,977	22.7	6,342	33,768	18.8	4,707	58,087	8.1	13,768	44,973	30.6

Note: Table 2.2 presents the dollar amount of total equity stakes of five largest bank holding companies (in terms of total assets) in the other 536 bank holding companies in the sample for the period, 2007-2015. The five largest bank holding companies are JPMorgan Chase, Bank of America, Wells Fargo, Citigroup, and Goldman Sachs. The first column of each bank holding company indicates the dollar amount of total equity holdings in the other 536 bank holdings companies in the sample. The second column of each bank holding company presents total equity in Panel A and tangible equity capital in Panel B. The third column shows the percentage of total equity holdings to total equity in Panel A and the percentage of total equity holdings to tangible equity capital in Panel B. We use the Thomson Reuters CDA/Spectrum Institutional (13f) Holdings database to calculate the total ownership stakes. We obtain the information on total equity from the Bloomberg. All calculations are as of the end of each year.

Table 2.3
Transformation of Bank Holding Company Data into Network Data

Pair of BHCs	Row BHC	Column BHC	Row Number (i)	Column Number (j)	Sum of Cross-ownership (Pair of BHCs)
X_{12}	JP Morgan	Bank of America	1	2	3.27 %
X_{13}	JP Morgan	Wells Fargo	1	3	2.55 %
X_{14}	JP Morgan	Citi Group	1	4	1.65 %
X_{15}	JP Morgan	Goldman Sachs	1	5	1.79 %
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
X_{23}	Wells Fargo	Citi Group	2	3	$\vdots$
X_{24}	Wells Fargo	Goldman Sachs	2	4	$\vdots$
X_{25}	Wells Fargo	Morgan Stanley	2	5	$\vdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Note: Table 2.2 presents an example of network data structure drawn from our sample BHCs. We transform the cross-ownership matrix shown in Table 2.1 in such a way that the unit of analysis becomes pairs of BHCs. Therefore, all of the variables are dyadic (pairs of entities) and doubly indexed (e.g., the variable X_{ij} refers to the way in which entity *i* is related to entity *j*).

Table 2.4
State Variable Summary Statistics

	Mean	Std. Dev.	Min.	Max.
Three-month yield change	-1.09	10.61	-98	59
Term spread change	0.54	14.10	-87	86
TED spread	53.65	58.70	10	458
Credit spread change	0.35	12.10	-60	75
Market return	0.10	2.65	-13.85	13.83
Real estate excess return	-0.04	4.39	-30.60	27.12
Equity Volatility	1.17	0.79	0.33	5.12

Note: Table 2.4 presents summary statistics for state variables. A set of state variables are three-month yield change, term spread change, TED spread, credit spread change, market return, real estate excess return, and equity volatility. Three-month yield change is the change in the three-month yield obtained from the Federal Reserve Board's H.15 release. Term spread change is measured by the change in the spread between the ten-year Treasury rate and the three-month Treasury bill rate obtained from the Federal Reserve Board's H.15 release and the Federal Reserve Bank of St. Louis, respectively. TED spread is defined as the difference between the three-month LIBOR rate and the three-month secondary market Treasury bill rate obtained from the Federal Reserve Bank of St. Louis. Credit spread change is the credit spread between Moody's *Baa*-rated bonds and the ten-year Treasury rate from the Federal Reserve Board's H.15 release. Market return is the weekly market return computed from the S&P500. Real estate excess return is calculated in excess of the market financial sector return by using Dow Jones U.S. Real Estate Index return as real estate sector return. We obtain Dow Jones U.S. Real Estate Index from the Bloomberg. Equity volatility is the 22-day rolling standard deviation calculated with the daily CRSP equity market return.

Table 2.5
Summary Statistics for Estimated Risk Measures

	Mean	Std. Dev.	Observations
X_t^i	−0.226	3.944	11,736
$VaR_{95,t}^i$	7.862	4.932	11,736
$CoVaR_{95,t}^i$	6.625	2.479	11,736
$\Delta CoVaR_{95,t}^i$	1.941	1.495	11,736
$VaR_{99,t}^i$	12.512	7.383	11,736
$CoVaR_{99,t}^i$	10.210	3.138	11,736
$\Delta CoVaR_{99,t}^i$	3.260	2.367	11,736

Note: Table 2.5 shows summary statistics for the market equity losses and 95 and 99 percent risk measures of the 1,590 financial institutions for weekly data from the period 2007–2015. X_t^i denotes the weekly market equity losses. We obtain $VaR_{95,t}^i$ and $VaR_{99,t}^i$, the individual institution risk measures, by estimating 95 and 99 percent quantile regressions of returns on the one-week lag of the state variables and by calculating the predicted value of the regression. We compute $\Delta CoVaR_{95,t}^i$ ($\Delta CoVaR_{99,t}^i$) by taking the difference between $CoVaR_{95,t}^i$ ($CoVaR_{99,t}^i$) and $CoVaR_{95,t}^{i|median}$ ($CoVaR_{99,t}^{i|median}$), where $CoVaR_{q,t}^i$ is the predicted value from a q% quantile regression of the financial system equity losses on the financial institution equity losses and on the lagged state variables. All measures are expressed in weekly percentage returns.

Table 2.6
QAP Regression, 2008-2015
(Iteration 1,000)

Model	(1)	(2)	(3)	(4)	(5)
Dependent Variable	LLRs	LLPs	NCOs	$\Delta CoVaR_{99}$	$\Delta CoVaR_{95}$
Independent Variable					
Own	**-.1237****	**-.0767****	**-.0708***	**.0019***	**.0013***
(p–value)	**(4.1 Pct.)**	**(2.2 Pct.)**	**(9.8 Pct.)**	**(94.3 Pct.)**	**(92.5 Pct.)**
Control Variables					
Ln(Assets)	.0645***	.1071***	.0968***	.0049***	.0041***
(p–value)	(99.3 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)
Deposits	.0106***	-.0083*	.0013**	.0001	.0001**
(p–value)	(100 Pct.)	(91.7 Pct.)	(96.6 Pct.)	(84.7 Pct.)	(95.7 Pct.)
Loans	-.0050	.0064***	.0012**	-.0001	.0001
(p–value)	(46.1 Pct.)	(99.1 Pct.)	(97.9 Pct.)	(31.5 Pct.)	(73.0 Pct.)
NII	.0748***	.1013***	.0979***	.0003	.0002
(p–value)	(99.5 Pct.)	(99.4 Pct.)	(100 Pct.)	(82.9 Pct.)	(84.2 Pct.)
Equity/Assets	.0181**	-.0042	.0158**	-.0002	-.0001
(p–value)	(95.5 Pct.)	(75.6 Pct.)	(96.7 Pct.)	(39.0 Pct.)	(55.2 Pct.)
ROA	-.3738***	-.7872***	-.6087***	.0019***	.0012***
(p–value)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(100 Pct.)	(100 Pct.)
Constant	.4911***	-.3106***	-1.4923***	-.1014	-.1028***
(p–value)	(0.2 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)
Obs.	605,635	594,627	574,441	611,869	611,869

Note: LLRs, LLPs, and NCOs are loan loss reserves, loan loss provisions, and net charge-offs, all expressed as a fraction of by gross loans. $\Delta CoVaR$ is systemic risk measure which captures tail co-movement of return losses that can arise from contagious, financial distress across financial institutions. We calculate $\Delta CoVaR_{99}$ ($\Delta CoVaR_{95}$) by taking the difference between the $CoVaR$ conditional on the distress of an institution at the *99%* - quantile (at the *95%* - quantile) and the $CoVaR$ conditional on the normal, or median, state of that institution at the *50%* - quantile. Own is cross-ownership between two bank holdings companies. Ln(Assets) is natural log of total assets. Deposits is total customer deposits divided by total assets. Loans is net loans divided by total assets. Non-interest income (NII) is total non-interest operating income divided by total assets. Equity/Assets is total equity divided by total assets. Return on assets (ROA) is return on average assets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. p-values are in parenthesis.

Table 2.7
$\Delta CoVaR$ QAP Regression for the Sub-Period 2008-2010 and 2011-2015
(Iteration 1,000)

Model	(1)	(2)	(3)	(4)
Sample Period	2008-2010		2011-2015	
Dependent Variable	$\Delta CoVaR_{99}$	$\Delta CoVaR_{95}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{95}$
Independent Variable				
Own	**.0014****	**.0009****	.0015	.0010
(p–value)	**(96.9 Pct.)**	**(95.2 Pct.)**	(86.4 Pct.)	(84.0 Pct.)
Control Variables				
Ln(Assets)	.0069***	.0059***	.0048***	.0039***
(p–value)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)
Deposits	.0001	.0001**	.0001**	.0001**
(p–value)	(86.4 Pct.)	(95.4 Pct.)	(95.0 Pct.)	(98.9 Pct.)
Loans	.0002	.0002**	-.0001*	.0001
(p–value)	(86.8 Pct.)	(95.7 Pct.)	(5.8 Pct.)	(28.9 Pct.)
NII	.0003	.0001	.0002	.0002
(p–value)	(82.8 Pct.)	(70.9 Pct.)	(75.9 Pct.)	(83.6 Pct.)
Equity/Assets	-.0001	.0001	.0001	.0001
(p–value)	(53.1 Pct.)	(69.4 Pct.)	(56.3 Pct.)	(68.9 Pct.)
ROA	.0043***	.0032***	.0015***	.0008***
(p–value)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)
Constant	-.1901***	-.1790***	-.1132***	-.1102***
(p–value)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)
Obs.	167,079	167,079	444,790	444,790

Note: $\Delta CoVaR$ is systemic risk measure which captures tail co-movement of return losses that can arise from contagious, financial distress across financial institutions. We calculate $\Delta CoVaR_{99}$ ($\Delta CoVaR_{95}$) by taking the difference between the *CoVaR* conditional on the distress of an institution at the *99%* - quantile (at the *95%* - quantile) and the *CoVaR* conditional on the normal, or median, state of that institution at the *50%* - quantile. Own is cross-ownership between two bank holdings companies. Ln(Assets) is natural log of total assets. Deposits is total customer deposits divided by total assets. Loans is net loans divided by total assets. Non-interest income (NII) is total non-interest operating income divided by total assets. Equity/Assets is total equity divided by total assets. Return on assets (ROA) is return on average assets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. p-values are in parenthesis.

Table 2.8

$\Delta CoVaR_{99}$ QAP Regression for Each Year 2008-2015

(Iteration 1,000)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	2008	2009	2010	2011	2012	2013	2014	2015
Dependent Variable	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$	$\Delta CoVaR_{99}$
Independent Variable								
Own	**.0010****	**.0017****	**.0013****	**.0010***	.0018	.0013	.0018	.0019
(*p*–value)	**(94.4 Pct.)**	**(98.6 Pct.)**	**(97.0 Pct.)**	**(92.3 Pct.)**	(84.8 Pct.)	(72.4 Pct.)	(81.5 Pct.)	(80.1 Pct.)
Control Variables								
Ln(Assets)	.0082***	.0075***	.0055***	.0064***	.0048***	.0044***	.0043***	.0052***
(*p*–value)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)
Deposits	.0001	.0001	.0001*	.0002**	.0002**	.0002**	.0001*	.0001*
(*p*–value)	(64.4 Pct.)	(53.0 Pct.)	(94.4 Pct.)	(98.5 Pct.)	(98.6 Pct.)	(96.1 Pct.)	(92.2 Pct.)	(91.7 Pct.)
Loans	.0002*	.0002*	.0001	-.0001	-.0001	-.0001*	-.0001*	-.0001
(*p*–value)	(94.7 Pct.)	(97.1 Pct.)	(36.8 Pct.)	(11.9 Pct.)	(12.6 Pct.)	(6.7 Pct.)	(9.2 Pct.)	(12.0 Pct.)
NII	.0012	.0010	-.0004	.0001	.0001	.0004	.0002	.0002
(*p*–value)	(78.0 Pct.)	(84.6 Pct.)	(23.3 Pct.)	(53.9 Pct.)	(67.6 Pct.)	(87.4 Pct.)	(73.3 Pct.)	(75.8 Pct.)
Equity/Assets	-.0007**	.0003	.0005**	.0001	.0001	.0001	.0001	-.0001
(*p*–value)	(2.2 Pct.)	(83.3 Pct.)	(98.0 Pct.)	(67.8 Pct.)	(64.3 Pct.)	(55.4 Pct.)	(61.1 Pct.)	(47.5 Pct.)
ROA	.0061***	.0042***	.0029***	.0031***	.0030***	.0015*	.0014*	.0021*
(*p*–value)	(99.1 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(100 Pct.)	(92.3 Pct.)	(92.8 Pct.)	(94.8 Pct.)
Constant	-.2318***	-.2208***	-.1525***	-.1724***	-.1304***	-.1138***	-.1087***	-.1374***
(*p*–value)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)	(0.0 Pct.)
Obs.	44,253	46,971	75,855	83,845	85,905	88,410	94,395	92,235

Note: $\Delta CoVaR$ is systemic risk measure which captures tail co-movement of return losses that can arise from contagious, financial distress across financial institutions. We calculate $\Delta CoVaR_{99}$ by taking the difference between the *CoVaR* conditional on the distress of an institution at the *99%* - quantile and the *CoVaR* conditional on the normal, or median, state of that institution at the *50%* - quantile. Own is cross-ownership between two bank holdings companies. Ln(Assets) is natural log of total assets. Deposits is total customer deposits divided by total assets. Loans is net loans divided by total assets. Non-interest income (NII) is total non-interest operating income divided by total assets. Equity/Assets is total equity divided by total assets. Return on assets (ROA) is return on average assets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. *p*-values are in parenthesis.

Figure 2.1
Major U.S. BHCs

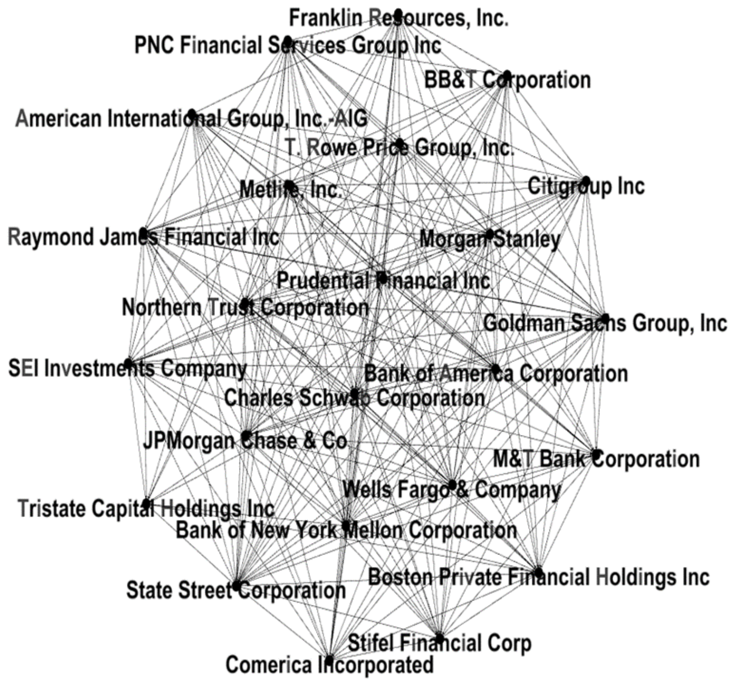
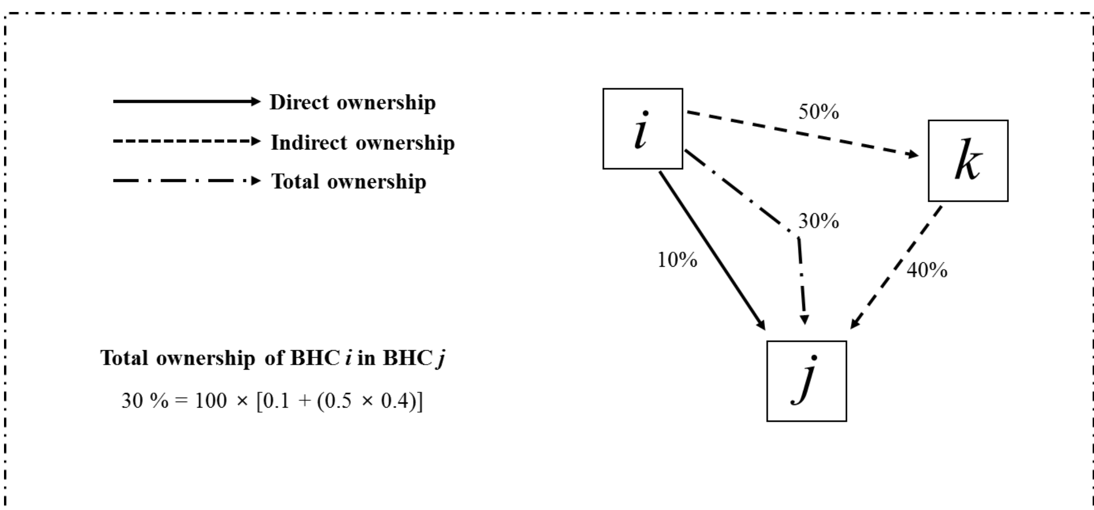


Figure 2.2
An Illustration of Total Ownership Calculation When There Is An Indirect Ownership Linkage



Source: Bankscope

Appendix 1

List of 537 Bank Holding Companies

RSSD	NAME	RSSD	NAME
2784920	1st Constitution Bancorp	1469800	Bay Bancorp Inc
1199602	1st Source Corporation	1074156	BB&T Corporation
1075500	Abigail Adams National Bancorp, Inc.	2961879	BBCN Bancorp, Inc
3109904	Access National Corporation	1078529	BBVA Compass Bancshares Inc
1117464	ACNB Corporation	3170539	BCB Bancorp, Inc.
1246926	Albany Bancshares, Inc.	3832015	Bear State Financial Inc
2067007	Alerus Financial Corporation	2333663	Berkshire Hills Bancorp Inc
1247419	Allegheny Valley Bancorp, Inc.	2469227	BFC Financial Corporation
3744239	Allegiance Bancshares Inc	1020340	BMO Bankcorp Inc
1562859	Ally Financial Inc	1245415	BMO Financial Corp
1107205	Amarillo National Bancorp, Inc.	3141650	BNC Bancorp
1208661	AMCORE Financial, Inc.	3814310	BofI Holding Inc
3008753	American Bank, Pennsylvania	1883693	BOK Financial Corporation
1275216	American Express Company	1248078	Boston Private Financial Holdings Inc
1083635	American Gateway Financial Corporation	1416523	Bridge Bancorp, Inc
1562176	American International Group, Inc.-AIG	3260841	Broadway Financial Corporation
1076691	American National Bankshares Inc.	2631510	Brookline Bancorp Inc
2312837	American River Bankshares	3793684	Brooklyn Federal Bancorp, Inc
1082067	Ameris Bancorp	1140994	Bryn Mawr Bank Corporation
1117316	AmeriServ Financial, Inc	3929791	BSB Bancorp Inc
1202258	Ames National Corporation	2183493	C&F Financial Corporation
1048812	Arrow Financial Corp.	4558901	C1 Financial, Inc.
1095674	Arvest Bank Group, Inc.	1100037	Cadence Financial Corporation
1199563	Associated Banc-Corp.	2907381	California First National Bancorp
2504128	Astoria Financial Corporation	1130249	Camden National Corporation
3555686	Atlantic Capital Bancshares Inc	4160939	Capital Bank Financial Corp
3840029	Atlantic Coast Financial Corporation	1085509	Capital City Bank Group, Inc.
1129533	Auburn National Bancorporation, Inc.	2277860	Capital One Financial Corporation
1108350	Austin Bancorp, Inc	4226910	Capitol Federal Financial Inc
1379552	BAC North America Holding Company	2682996	Cardinal Financial Corporation
1199769	Bana Holding Corporation	2943473	Carolina Bank Holdings, Inc.
3153130	Banc of California Inc	2507790	Carolina Financial Corporation
1133286	BancFirst Corporation	2531245	Carver Bancorp, Inc
3554250	Bancorp of New Jersey, Inc.	1848003	Cascade Bancorp
2858951	Bancorp, Inc., The	1098648	Cass Information Systems, Inc.
1097614	Bancorpsouth, Inc.	1843080	Cathay General Bancorp Inc
1101735	Bancshares, Inc.	3135190	Cecil Bancorp, Inc.
1025608	BancWest Corporation	2868129	CenterState Banks, Inc
3149021	Bank Capital Corporation	2746049	Central Bancorp, Inc., Massachusetts
1208009	Bank First National Corp	1025662	Central Bancorporation
1245620	Bank Leumi Le-Israel Corporation	1250295	Central Bancshares, Inc., Minnesota
2929374	Bank Mutual Corporation	3828577	Central Federal Corporation
1073757	Bank of America Corporation	1022764	Central Pacific Financial Corp.
1030040	Bank of Commerce Holdings	2935405	Central Valley Community Bancorp
1025309	Bank of Hawaii Corporation	1111088	Century Bancorp, Inc.
3590388	Bank of Marin Bancorp	1026632	Charles Schwab Corporation
3587146	Bank of New York Mellon Corporation	4459839	Charter Financial Corporation
2297701	Bank of South Carolina Corporation	1201934	Chemical Financial Corporation
3217032	Bank of The James Financial Group, Inc.	1133594	Chemung Financial Corporation
1097089	Bank Of The Ozarks Inc	3434633	Chicopee Bancorp Inc
3035928	BankFinancial Corporation	1036967	CIT Group, Inc
3104570	Bankshares, Inc., The	3375370	Citicorp
4028712	BankUnited, Inc	1951350	Citigroup Inc
2126977	Banner Corporation	1143623	Citizens & Northern Corporation
3434624	Banorte USA Corporation	3823929	Citizens Community Bancorp, Inc.
1115385	Bar Harbor Bankshares	1132449	Citizens Financial Group Inc.
2938451	Barclays Delaware Holdings LLC	2750952	Citizens First Corporation
2914521	Barclays Group US Inc.	1083475	Citizens Holding Company

RSSD	NAME	RSSD	NAME
3127104	Citizens South Banking Corporation	1070345	Fifth Third Bancorp
1076262	City Holding Company	1032464	Financial Institutions, Inc
1246533	Civista Bancshares, Inc	1056134	First Altus Bancorp, Inc.
3762457	CM Florida Holdings Inc	1250101	First American Financial Corporation
1022924	CMC Holding (Delaware) Inc.	2744894	First BanCorp
1118340	CNB Financial Corporation	1133932	First Bancorp, Inc (The)
1083671	Coastal Bankshares, Inc.	1076431	First Bancorp, North Carolina
1060328	CoBiz Financial Inc	2385493	First Bancshares, Inc., The
1142475	Codorus Valley Bancorp, Inc.	2971261	First Banctrust Corporation
2078816	Columbia Banking System, Inc	1203602	First Busey Corporation
1029259	Comerica Holdings Incorporated	1247428	First Business Financial Services, Inc.
1199844	Comerica Incorporated	1075612	First Citizens BancShares
1049341	Commerce Bancshares, Inc.	1142130	First Citizens of Paris, Inc.
1125843	Community Banc-corp Of Sheboygan, Inc.	2374787	First Commercial Bancshares, Inc.
1048867	Community Bank System, Inc.	1071306	First Commonwealth Financial Corp.
3687046	Community Bankers Trust Corporation	1478017	First Community Bancshares, Inc
1140659	Community First Bancshares, Inc., Tennessee	2337401	First Community Corporation, South Carolina
1099766	Community First Financial Group, Inc.	1132896	First Community Financial Corporation
1070644	Community Trust Bancorp, Inc	3447585	First Community Financial Partners Inc
2626299	Community West Bancshares	3407598	First Connecticut Bancorp, Inc
1133473	CommunityOne Bancorp	3316917	First Defiance Financial Corp
2524788	County Bancorp, Inc.	3852107	First Federal of Northern Michigan Bancorp, Inc
3903661	CrossFirst Holdings LLC	1071276	First Financial Bancorp
1126149	Crosstown Holding Company	1102312	First Financial Bankshares, Inc
1486517	CTBC Capital Corp	1208595	First Financial Corporation
1102367	Cullen/Frost Bankers, Inc	3843628	First Financial Northwest
4284536	Customers Bancorp Inc	3842658	First Foundation Inc
1029222	CVB Financial Corp	1057252	First Gothenburg Bancshares, Inc.
3221217	DCB Financial Corporation	1094640	First Horizon National Corporation
2390031	Delavan Bancshares, Inc.	1134564	First Independence Corporation
2834115	Delta Trust and Banking Corporation	3393178	First Internet Bancorp
2487650	Dime Community Bancshares, Inc	1123670	First Interstate Bancsystem, Inc
2894230	Discount Bancorp	1118265	First Keystone Corporation
3846375	Discover Financial Services	1208559	First Merchants Corporation
1117455	DNB Financial Corporation	1206760	First Mid-illinois Bancshares, Inc.
2184164	Doral Financial Corporation	1208184	First Midwest Bancorp, Inc
2652104	Eagle Bancorp, Inc.	1137529	First National Bank, Indiana
3023466	East Asia Holding Company	1020902	First National of Nebraska, Inc.
2734233	East West Bancorp, Inc	3485541	First NBC Bank Holding Company
2626691	Eastern Virginia Bankshares, Inc.	2648693	First Niagara Financial Group, Inc
1480944	Emclaire Financial Corp	2880626	First Northern Community Bancorp
2089036	Emigrant Bancorp, Inc	1205633	First of Huron Corp.
3695957	ENB Financial Corp	1048894	First of Long Island Corporation (The)
2427665	Entegra Financial Corp.	1062528	First Pioneer Bank Corp.
2461016	Enterprise Bancorp Inc	3908929	First Savings Financial Group, Inc
2303910	Enterprise Financial Services Corp	2521509	First South Bancorp Inc
3180547	Equity Bancshares Inc	2161165	First Star Bancorp, Inc.
3854268	ESSA Bancorp Inc	1098880	First Union Financial Corporation
1401190	Evans Bancorp, Inc.	1132672	First United Corporation
3838857	EverBank Financial Corp	1070336	First West Virginia Bancorp Inc
1054550	F&M Bankshares, Inc.	1070804	FirstMerit Corporation
1053357	Farm and Home Insurance Agency, Inc.	3852022	Flagstar Bancorp Inc
1095638	Farmers Bancshares, Inc., Kentucky	3557626	Florida Bank Group, Inc
1098732	Farmers Capital Bank Corporation	2393274	Flushing Financial Corporation
1071191	Farmers National Banc Corp	1143230	FNB Corporation
1076600	Fauquier Bankshares, Inc.	3846601	Fox Chase Bancorp Inc
3944628	FCB Financial Holdings, Inc	3637582	Franklin Financial Network, Inc
1891979	Feo Investments, Inc.	1118238	Franklin Financial Services Corporation
2527024	FGH Bancorp, Inc.	1246216	Franklin Resources, Inc.
2330288	Fidelity Bancorporation	1117129	Fulton Financial Corporation
1081118	Fidelity Southern Corporation	1098620	German American Bancorp

RSSD	NAME	RSSD	NAME
2839781	Gideon Enterprises L.P.	3030307	Landmark Bancorp, Inc.
2003975	Glacier Bancorp, Inc	2759900	LCNB Corp.
2001328	Glen Burnie Bancorp	1031588	Learner Financial Corporation
2380443	Goldman Sachs Group, Inc	3101784	Liberty Bancshares, Inc, Arkansas
2339133	Great Southern Bancorp, Inc	3884863	Live Oak Bancshares, Inc.
3136825	Greater Sacramento Bancorp	1491306	M&P Community Bancshares, Inc.
3474835	Green Bancorp Inc	1037003	M&T Bank Corporation
2728607	Greene County Bancorp, Inc	2634696	Macatawa Bank Corporation
3828607	Greenville Federal	1123933	Mackinac Financial Corporation
3254952	Guaranty Bancorp	2067959	Mainline Bancorp, Inc.
1096952	Guaranty Capital Corporation	1209109	MainSource Financial Group, Inc
4415424	Hamilton Bancorp Inc	3805279	Malvern Bancorp, Inc
3228702	Hampden Bancorp, Inc	2514239	Marathon Banking Corp
3012554	Hampton Roads Bankshares, Inc	1250437	Market Street Bancshares, Inc.
1086533	Hancock Holding Company	3832583	Marlin Business Services Corp
2900261	Hanmi Financial Corporation	1123193	Marquette Financial Companies
2861492	Harleysville Savings Financial Corporation	1090987	MB Financial Inc
2038409	Hawthorn Bancshares Inc	2907822	MBT Financial Corporation
1208120	Heartland Bancorp Inc	1071342	Mccreary Bancshares Inc.
1206546	Heartland Financial USA, Inc.	2395326	Mechanics Financial Corporation
1427079	Herget Financial Corp.	3882739	Mercantil Commercebank Florida Bancorp
1143717	Heritage Capital Corporation	2608763	Mercantile Bank Corporation
2634874	Heritage Commerce Corp	1023239	Merchants Bancshares Inc.
2166124	Heritage Financial Corporation, Washington	1128769	Merchants Financial Group, Inc.
2253529	Heritage Oaks Bancorp	2390013	Meta Financial Group, Inc
1472220	High Point Bank Corporation	2945824	Metlife, Inc.
1245291	Hills Bancorporation	3637984	Metropolitan Bancgroup Inc
3838727	Hilltop Holdings Inc	1944204	Mid Penn Bancorp, Inc
2500719	HMN Financial Inc	2176413	Middleburg Financial Corporation
2170868	Hocking Valley Bancshares, Inc.	1398740	Middlefield Banc Corp.
3851191	Home Bancorp Inc	1086654	MidSouth Bancorp, Inc
1491409	Home Bancshares, Inc.	1245228	MidWestOne Financial Group, Inc
3843507	Homestreet Inc	3435386	Monarch Financial Holdings Inc
2648367	Hometown Bancshares, Inc.	1123661	Montana Community Banks, Inc.
4366003	Hometrust Bancshares, Inc	2162966	Morgan Stanley
3832556	HopFed Bancorp, Inc	3599318	MSB Financial Corp
1209136	Horizon Bancorp	1378434	MUFG Americas Holdings Corporation
2872407	HSBC North America Inc	3175794	MutualFirst Financial Inc
1020201	HSBC USA Inc.	3719965	National Americas Holdings LLC
1109601	Huntington Bancshares Inc	3973888	National Bank Holding Corporation
1832851	IBC Subsidiary Corporation	1139925	National Bankshares, Inc.
2291914	Iberiabank Corporation	2173092	NB Holdings Corporation
1363690	INB Financial Corporation	1139279	NBT Bancorp, Inc.
1136803	Independent Bank Corp.	1022661	New Galveston Company
1201925	Independent Bank Corporation	2132932	New York Community Bancorp, Inc
3140288	Independent Bank Group, Inc.	3103603	Nicolet Bankshares, Inc.
2112439	Industry Bancshares, Inc.	2834076	North Central Bancorp
1122075	Inter-mountain Bancorp., Inc.	2324111	Northeast Bancorp
1104231	International Bancshares Corporation	2514136	Northeast Indiana Bancorp, Inc
4090054	Investar Holding Corporation	1210589	Northern States Financial Corporation
1245385	Iowa First Bancshares Corp	1199611	Northern Trust Corporation
1832132	JPMorgan Equity Holdings, Inc	3025385	Northrim Bancorp, Inc.
1039502	JPMorgan Chase & Co	2582827	Northway Financial, Inc
1117512	Juniata Valley Financial Corporation	4122722	Northwest Bancshares Inc
3099443	Kearny Financial Corp.	2237118	Northwest Indiana Bancorp
3824494	Kentucky First Federal Bancorp	2365356	Norwood Financial Corp
1068025	KeyCorp	2445098	Oak Park River Forest Bankshares, Inc.
2721112	Lake Michigan Financial Corporation	3726440	Oak Valley Bancorp
3575750	Lake Sunapee Bank Group	3848285	Ocean Shore Holding Co
1404799	Lakeland Bancorp, Inc	2609975	OceanFirst Financial Corp
1208906	Lakeland Financial Corporation, Indiana	2490575	OFG Bancorp

RSSD	NAME	RSSD	NAME
2873039	Ohio Legacy Corp.	3180060	Riverview Bancorp Inc
2012436	Ohio Valley Banc Corp	2324429	Royal Bancshares of Pennsylvania, Inc.
1085527	Old Florida Bancshares Inc	2718167	RSNB Bancorp
3200221	Old Line Bancshares, Inc	1071397	S & T Bancorp, Inc.
1098303	Old National Bancorp	2693273	Salisbury Bancorp, Inc.
1076673	Old Point Financial Corporation	1248304	Sandy Spring Bancorp, Inc.
1206911	Old Second Bancorp, Inc	2847115	Santander BanCorp
3251661	Optimumbank Holdings, Inc.	3981856	Santander Holdings USA, Inc
2692892	Oritani Financial Corp	1071454	SB Financial Group, Inc
1248153	Orrstown Financial Services, Inc	4183527	SBM Financial Inc
1249383	Oxford Bank	1085013	Seacoast Banking Corporation of Florida
2762973	Pacific Continental Corporation	1135374	Security Bancorp Of Tennessee, Inc.
2869733	Pacific Mercantile Bancorp	1274974	SEI Investments Company
3489594	Pacific Premier Bancorp Inc	3207659	Select Bancorp Inc
2875332	PacWest Bancorp	3635319	ServisFirst Bancshares, Inc.
3021800	Paragon Commercial Corporation	3831465	Severn Bancorp Inc
1142336	Park National Corporation	1055137	Shamrock Bancshares, Inc.
3347292	Parke Bancorp Inc	2429838	Shore Bancshares, Inc.
2596776	Pathfinder Bancorp Inc	3306815	SI Financial Group Inc
3390430	Patriot Bancshares Inc	2976396	Sierra Bancorp
2840479	Patriot National Bancorp, Inc.	3695667	Silvergate Capital Corporation
3836488	PB (USA) Holdings Inc	1094828	Simmons First National Corporation
3120972	PDS Bancorp, Inc	2532402	Sinopac Bancorp
2651590	Peapack-Gladstone Financial Corporation	3065970	Siuslaw Financial Group, Inc.
2621986	Pedcor Bancorp	1133437	South State Corp
1117688	Penns Woods Bancorp, Inc	2794778	Southcoast Financial Corporation
1823587	Peoples Bancorp Inc. of Bullitt County	1248939	Southern Bancorp, Inc.
1070578	Peoples Bancorp Inc., Ohio	2849799	Southern First Bancshares, Inc.
2818245	Peoples Bancorp of North Carolina, Inc	1207824	Southern Michigan Bancorp, Inc
1974443	Peoples Bancorporation, Inc., South Carolina	3266227	Southern Missouri Bancorp, Inc.
1133174	Peoples Financial Corporation	1245068	Southside Bancshares, Inc
1139541	Peoples Financial Services Corp.	1062621	Southwest Bancorp, Inc
2700368	Peoples Service Company	4036324	State Bank Financial Corporation
3650152	People's United Financial, Inc	1111435	State Street Corporation
2748995	People's Utah Bancorp	1124828	Sterling Bancorp Inc
2925657	Pinnacle Financial Partners, Inc.	1486665	Steuben Trust Corporation
3098576	Plumas Bancorp	2290560	Stewardship Financial Corporation
1839823	PNB Holding Co.	3063622	Stifel Financial Corp
1469314	PNC Bancorp, Inc.	1249730	Stock Yard Bancorp Inc
1069778	PNC Financial Services Group Inc	2327541	Suburban Illinois Bancorp, Inc.
4303969	Poage Bankshares Inc	1130865	Suffolk Bancorp
2006118	Popular International Bank, Inc	2618388	Summit Bancorp, Inc.
2138466	Popular North America, Inc	1247679	Summit Financial Group, Inc.
1129382	Popular, Inc	1139242	Sun Bancorp, Inc
1249712	Porter Bancorp, Inc.	1077120	SunTrust Bank Holding Company
2007647	Premier Financial Bancorp, Inc.	1131787	SunTrust Banks, Inc.
2700500	Primebank	2461463	Sussex Bancorp
1839319	Privatebancorp, Inc.	1031449	SVB Financial Group
1109599	Prosperity Bancshares, Inc	4504654	Synchrony Financial
3632493	Provident Financial Holdings, Inc	1078846	Synovus Financial Corp
3133637	Provident Financial Services, Inc.	3045084	T. Rowe Price Group, Inc.
3091924	Prudential Financial Inc	3609682	Talmer Bancorp Inc
2321419	Psb Holdings, Inc.	2816906	Taunus Corporation
2125813	QCR Holdings, Inc.	2389941	TCF Financial Corporation
3815157	Raymond James Financial Inc	3954681	Territorial Bancorp Inc
2891006	Regent Bancorp, Inc.	2706735	Texas Capital Bancshares, Inc
3242838	Regions Financial Corporation	1076105	The Bank of Southside Virginia
1098844	Renasant Corporatio	2149622	The National Bank of Indianapolis
1097025	Republic Bancorp Inc.	2621548	Timberland Bancorp, Inc.
1398807	Republic First Bancorp, Inc.	2367921	Tompkins Financial Corp
2466981	River Valley Bancorp	1030170	TriCo Bancshares

RSSD	NAME	RSSD	NAME
3475074	Tristate Capital Holdings Inc	3292253	Vision Bancshares, Inc.
3233126	Triumph Bancorp, Inc	1136139	Vist Financial Corp.
1048513	TrustCo Bank Corp of NY	3065617	Washington Federal Inc
1079562	Trustmark Corporation	1115349	Washington Trust Bancorp, Inc.
3395668	Two River Bancorp	3922466	WashingtonFirst Bankshares Inc
2099464	UBC Holding Company, Inc.	4523431	Waterstone Financial, Inc
3219577	UBT Bancshares, Inc.	3271203	Wayne Savings Bancshares Inc
1049828	UMB Financial Corporation	1145476	Webster Financial Corp
2747644	Umpqua Holdings Corporation	1120754	Wells Fargo & Company
1971693	Union Bankshares Corporation	2250313	Wells Fargo Financial Services, LLC
1114940	Union Bankshares, Inc	1070448	WesBanco, Inc
1071502	United Bancorp, Inc	1210066	West Bancorporation, Inc.
1136009	United Bancshares, Inc.	1206667	West Shore Bank
2291727	United Bankers' Bancorporation, Inc	1025541	Westamerica Bancorporation
1076217	United Bankshares, Inc.	4472249	Westbury Bancorp, Inc.
1249347	United Community Banks, Inc	2349815	Western Alliance Bancorporation
3831250	United Community Financial Corp	3866382	Westfield Financial, Inc
3015975	United Security Bancshares	2741679	WFC Holdings Corporation
1086168	United Security Bancshares, Inc.	1136175	Wheatland Bankshares, Inc.
2181426	Unity Bancorp, Inc	3940714	Wilmington Trust Corporation
1116609	Univest Corporation of Pennsylvania	3248513	Wilshire Bancorp, Inc.
1132092	US Bancorp	2260406	Wintrust Financial Corporation
2307280	Utrecht-America Holdings, Inc	3844269	WSFS Financial Corporation
2693385	Valley Community Bancshares, Inc.	2140115	WVS Financial Corp.
1048773	Valley National Bancorp	3012554	Xenith Bankshares Inc
3027709	Vantagesouth Bancshares Inc	3432965	Yadkin Financial Corporation
2626646	VIB Corp	1027004	Zions Bancorporation
3251027	Village Bank and Trust Financial Corp		

Note: RSSD is Federal Reserve System unique identifier.

Chapter 3

Forecasting the Tier 1 Common Capital Ratio of the Five Biggest Banks

3.1 Introduction

In recent years, bank stress tests have become an indispensable part of the financial regulation used by a bank regulatory agency to conduct macroprudential regulation and supervision (Greenlaw et al., 2012; Hanson et al., 2011; Hirtle et al., 2016). Since the success of the Supervisory Capital Assessment Program in 2009 – the first formal bank supervisory stress tests – spawned a new paradigm of bank regulation and supervision, there has been an increasing pressure on financial institutions subject to the stress tests to improve the accuracy of their forecasts for the key variables that ultimately determine whether they have sufficient capital to absorb losses and support operations during adverse economic conditions.

Forecasts of significant losses under a hypothetical set of stressful economic scenarios can trigger remedial supervisory actions such as restrictions on dividend payouts and share repurchases, therefore affecting a bank's capital plan. Moreover, the estimated losses resulting from these tests are subtracted from a bank's capital to determine the financial buffer that a bank has to insulate itself from shocks and losses. Since it is costly for banks to hold excess capital, accurate predictions of bank losses and revenues enable banks to assess whether they will satisfy, for instance, the minimum required tier 1 common regulatory capital ratio (Covas et al., 2014). Therefore, banks which succeed in increasing the accuracy of their forecasts for such an important variable are more likely to operate efficiently and therefore remain profitable on an ongoing basis.

The consequences of inaccurate forecasts may extend beyond financial institutions to customers and affect the economy more generally. Any higher capital requirements may encourage banks to shift lending away from certain assets classes, limiting available credit to certain types of borrowers. Suppose that an assets class is particularly projected to be severely deteriorated under stressful economic scenarios, financial institutions would be required to hold more capital against that assets class (e.g., consumer, commercial and industrial, residential real estate, etc.) so that their planned capital is approved by the supervisory authority. This can affect credit availability in certain sectors, with meaningful impact on growth and job creation in the economy.

The purpose of this paper is to obtain the most accurate forecasts of the tier 1 common capital ratio (T1CR) for the five biggest bank holding companies (BHCs)[9] over the period 1996–2016. T1CR is the preferred capital ratio used by bank regulatory authorities to evaluate the capital adequacy of U.S. banking institutions and is the most accurate measure of a bank's ability to absorb losses (Covas et al., 2014). Moreover, in order for a bank to be able to pass the stress test, its projected T1CR must stay above 5% throughout the forecasting horizons under a regulatory determined "*severely adverse*" macroeconomic scenario. Clearly, if one is able to identify a variety of predictive models and predictor variables that produce the accurate forecasts of the key variables, such as T1CR, of banks, such models and predictors may help provide the supervisory authorities with useful early warning indicators of future banking problems and thereby lessen, if not eliminate, the need for future bailouts.

The rest of the paper is organized as follows. Section 3.2 provides an overview of bank stress tests in the United States. In Section 3.3, we describe the data used in the analysis. Section 3.4 outlines our forecasting methods. Section 3.5 contains the main estimation results; we evaluate both in-sample and out-of-sample forecasting ability of our alternative models. Especially, we

[9] The 5 BHCs include JPMorgan Chase & Co., Bank of America, Wells Fargo & Company, Citigroup Inc., and U.S. Bancorp. We exclude Goldman Sachs Group, Inc. and Morgan Stanley that have only recently become bank holding companies. Even though total consolidated assets of these two BHCs are greater than U.S. Bancorp, the relatively limited time span of data available significantly limits our analysis.

compare out-of-sample forecasting ability of our alternative models with that of a benchmark random walk model. Section 3.6 concludes.

3.2 An Overview of U.S. Bank Stress Tests

Banking regulators adopted supervisory stress testing during the global financial crisis of 2007–2009 and have used it as part of their large financial institution supervision process. In the U.S., the Supervisory Capital Assessment Program (SCAP) was the first formal bank supervisory stress test conducted during 2009 to assess the capital adequacy of the largest bank holding companies (BHCs). In 2010, the Dodd-Frank Act mandated an annual assessment by the Federal Reserve of BHCs with $50 billion or more in total consolidated assets, as well as smaller BHCs and nonbank financial institutions regulated by the Federal Reserve. This annual assessment includes two related programs: the Comprehensive Capital Analysis and Review (CCAR) and the Dodd-Frank Act Stress Tests (DFAST). A key objective of these stress tests is to evaluate whether the participating institutions will be able to maintain – over a specified forecast horizon – banks' regulatory capital ratios above a specified minimum threshold to meet obligations to creditors and counterparties in the case of a severe deterioration in economic conditions.

In late 2010, the Federal Reserve – acting in part in response to the statute – initiated the CCAR exercise and has conducted it annually for financial institutions with $50 billion or more in total consolidated assets. In addition to running a company-run stress test, financial institutions with $50 billion or more in total consolidated assets must submit their internal data to the Federal Reserve which will then conduct its own supervisory tests in which the Federal Reserve evaluates banks' capital adequacy, their capital planning process, and their planned capital distributions, such as dividend payments and share repurchases. The results are published annually.

DFAST is a complementary exercise to CCAR. DFAST is a forward-looking quantitative evaluation of the effect of a hypothetical set of stressful economic scenarios developed by the Federal Reserve on a bank's capital. Under the Dodd-Frank Act, all BHCs and insured depository institutions with total consolidated assets of $10 billion or more are required to evaluate and report their capital position under baseline, adverse, and severely adverse economic scenarios on annual basis. BHCs with assets greater than $50 billion have several additional regulatory requirements that the mid-sized financial institutions (total consolidated assets between $10 and $50 billion) do not. They must conduct two company-run DFASTs each year. In contrast, the mid-sized financial institutions are required to conduct one company-run DFAST each year.

CCAR and DFAST are two different exercises that apply to different size financial institutions. For CCAR, the Federal Reserve takes into account BHCs' proposed capital action plans to see whether they would be able to maintain – over a specified forecast horizon – banks' regulatory capital ratios above a specified minimum threshold if stressful conditions emerged and the BHCs implemented their proposed capital action plans. On the other hand, for DFAST, the Federal Reserve uses a standardized set of capital action assumptions that are specified in its DFAST regulations. Therefore, DFAST is less detailed and less tailored to a specific BHC (Barth and Miller, 2017).

3.3 Data

To construct bank-level time series, we mainly use the Consolidated Financial Statements for Bank Holding Companies (the Federal Reserve Y-9C form) and rely on Compustat and the Center for Research in Security Prices (CRSP) to supplement some of bank-level time series, such as tobin's q, stock beta, and price-earnings ratio, for the five biggest BHCs (in terms of total assets) in the U.S., covering the period from 1996:Q1 to 2016:Q4. We also use 19 stress test variables provided by the Federal Reserve for the CCAR and the DFAST. Bank-level and stress test variables are first differenced to avoid issues that are associated with nonstationarity in the data (Stock and Watson, 2002). Finally, we obtain 117 macroeconomic variables from the Federal Reserve Economic Data (FRED) database, each of these variables transformed to stationary with the transformations listed in McCracken and Ng (2016).

Table 3.1 presents the five BHCs included in the sample. These five BHCs are JPMorgan Chase & Co., Bank of America, Wells Fargo & Company, Citigroup Inc., and U.S. Bancorp. We exclude Goldman Sachs Group, Inc. and Morgan Stanley that have only recently become bank holding companies. Even though total consolidated assets of these two BHCs are greater than U.S. Bancorp as shown in *Appendix 2*, the relatively limited time span of data available significantly limits our analysis.[10] All of these five BHCs have reported total consolidated assets of more than $50 billion as of December 31, 2016, a size-cutoff that is consistent with the stress-testing requirements mandated by the 2010 Dodd-Frank financial-overhaul law. Indeed, total assets of U.S. Bancorp, the smallest BHC included in the sample, is greater than $400 billion.

[Table 3.1]

In this study, we consider three different sets of predictors, that is, bank-level predictors (*N*=29), stress test predictors (*N*=16), and macroeconomic predictors (*N*=117) as well as the combinations of these three sets. Therefore, the combination of all three groups yields the maximum number of predictors, *N*=162. Note that our sample expands from 1996:Q1 to 2016:Q4, total of 84 quarterly observations (T =84). Therefore, combining predictors of bank-level or stress test groups with those of macroeconomic group creates a situation in which $T < N$. In this setting,

---

[10] I present the top 50 BHCs in the U.S. in terms of total assets in *Appendix 2*. It is worth noting that total assets of Mutual of Omaha Insurance Company (50th BHC in terms of total assets) account for only 1.5% of total assets of JPMorgan Chase & Co. (1st BHC in terms of total assets) as of December 31, 2016.

the standard ordinary least squares (OLS) forecaster will be poorly behaved or nonexistent (Huber, 1973). We propose forecasting methods that address this problem in Section 3.4.

[Table 3.2]

Table 3.2 presents data descriptions on our target variable and bank-level predictor variables as well as summary statistics for these variables. In terms of the target variable for bank capital, tier 1 common capital ratio (T1CR) is the preferred capital ratio used by bank regulatory authorities to evaluate the capital adequacy of U.S. banking institutions. We measure tier 1 common equity as follows (Covas et al., 2014): Tier 1 capital − Perpetual preferred stock + Nonqualifying perpetual preferred stock − Qualifying class A minority interests − Qualifying restricted core capital − Qualifying mandatory convertible preferred security. Then, we divide tier 1 common equity by risk-weighted assets to calculate the tier 1 common capital ratio (T1CR). The mean of T1CR over the entire sample period is 8.8%, with the standard deviation of 1.6%. *Appendix 3* contains the entire summary statistics for the bank-specific, supervisory stress tests, and macroeconomic predictor variables used in the empirical analysis. These summary statistics are reported before predictor variables are transformed to stationary.

[Figure 3.1]

Figure 3.1 presents the aggregate T1CR for the 5 biggest BHCs in the U.S. as well as the individual T1CR for these financial institutions. Shaded area indicates the most recent recession which began in December 2007 and ended in June 2009. As shown in Figure 3.1.a, the aggregate T1CR stayed around 8% before the 2007-2009 global financial crisis. It, however, dropped dangerously below 5% by the end of the first quarter of 2009. This decrease in the aggregate T1CR is mainly driven by three BHCs, that is, Bank of America (BAC), Wells Fargo & Company (WFC), and Citigroup Inc. (CITI). Among the five BHCs, Citigroup Inc. suffered the most because of severe subprime mortgage related losses during this period, whereas JPMorgan Chase & Co. experienced much less losses. By January 2008, the subprime losses for Citigroup Inc. and JPMorgan Chase & Co. were $18 billion and $1.3 billion, respectively (Erkens et al., 2012).

Since the end of the first quarter of 2009, T1CR has increased dramatically by the end of the fourth quarter of 2016. The substantially enhanced resilience of the banking sector since the end of the most recent recession was primarily due to the issuance of common equity and increased retained earnings, actions that the ''stressed'' financial institutions undertook partly in response to restrictions, imposed by the Federal Reserve and based on the outcomes of the stress tests, on dividend payouts and share repurchases (Covas et al., 2014).

3.4 Forecasting Methods

We investigate a wide range of forecasting methods applied in the previous forecasting literature. These methods include univariate benchmarks such as the random walk (RW) model and the autoregressive (AR) model [11], and some more advanced techniques for forecasting high-dimensional data sets. In our settings in which the number of predictors is more than that of observations, the standard ordinary least squares (OLS) forecaster will be poorly behaved or nonexistent (Huber, 1973). Furthermore, the classical regression analysis assumes that there is no linear relationship among independent variables, a property that is likely to be violated in our setting in which some predictor variables are highly correlated. We suggest five methods to solve such problems: We propose two dimension reduction methods – the principal component regression (PCR) and the partial least squares regression (PLSR), and three shrinkage (or regularization) methods – the ridge regression, the LASSO regression, and the elastic net regression.

[11] In this paper, we do not report the results using the AR model as a benchmark since the RW model outperforms the AR model over most of the out-of-sample forecast horizons.

Dimension reduction methods work in two steps. First, a relatively few number of unobserved latent factors are extracted from the number of predictors. Second, we use these factors as the predictors in a linear regression model that is fit using least squares. It is well known that the first few common factors suffice to explain most of the variability among the entire set of predictors, as well as the relationship with the response. As an alternative, we can fit a model containing all *N* predictors using a technique that shrinks (or regularizes) the coefficient estimates toward zero. In the next sub-section, we provide detailed descriptions on the alternative forecasting methods we implement in this paper.

3.4.1 Principal Component Regression (PCR)

In this study, we consider three different sets of predictors, that is, bank-level predictors (N=29), stress test predictors (N=16), and macroeconomic predictors (N=117). Consider a panel of N time series predictors $\mathrm{x} = [\mathrm{x}_1, \dots, \mathrm{x}_N]$, where $\mathrm{x}_i = [x_{i,1}, \dots, x_{i,T}]'$, i = 1, …, N. The factor representation for the following factor structure for x is as

$$x_{i,t} = \lambda'_i f_t + \varepsilon_{i,t}, \tag{3.1}$$

where $x_{i,t}$ is the value of predictor i at time t after it has (i) been transformed to stationarity, (ii) centered by subtracting the mean, and (iii) standardized by dividing by the standard deviation, $\lambda_i = [\lambda_{i,1}, \dots, \lambda_{i,K}]'$ is an $K \times 1$ vector of time-invariant associated factor loadings for unit i, $f_t = [f_{1,t}, \dots, f_{K,t}]'$ is an $K \times 1$ vector of latent common factors at time t, and $\varepsilon_{i,t}$ is the idiosyncratic error term. Let $\widetilde{W}$ be $\mathrm{K} \times K$ diagonal matrix consisting of the K largest eigenvalues of xx'/NT. Then, the principal component estimates of $\widetilde{f_t} = [\tilde{f}_{1,t}, \dots, \tilde{f}_{K,t}]'$ at time t are estimated by the K largest eigenvalues of the matrix xx'/NT in decreasing order. The associated component estimator of $\widetilde{\lambda_i} = [\tilde{\lambda}_{i,1}, \dots, \tilde{\lambda}_{i,K}]'$ is $\widetilde{\lambda_i} = \mathrm{x}'\widetilde{f_t}/T$. By definition, $\tilde{\varepsilon}_{i,\mathrm{t}} = x_{i,t} - \widetilde{\lambda_i}'\widetilde{f_i}$.

To utilize this framework as a forecasting model for h-quarter ahead forecasts (h = 1, 2, ..., 12), y_{t+h} is regressed on $\tilde{f}_t$ as

$$y_{t+h}^{PC} = \beta_h \tilde{f}_t + e_{t+h}, \tag{3.2}$$

where $\beta_h = [\beta_1, \dots, \beta_K]$. Then, the h-quarter ahead forecasts from the PCR are derived directly as

$$\hat{y}_{t+h}^{PC} = \hat{\beta}_h \tilde{f}_t, \tag{3.3}$$

where $\hat{\beta}_h$ is estimated in Eq. (3.2).

3.4.2 Partial Least Squares Regression (PLSR)

Like principal components, partial least squares (PLS) is a dimension reduction method. The PC approach identifies linear combinations that best describes the relationship among the predictors, $\mathrm{x} = [\mathrm{x}_1, \dots, \mathrm{x}_N]$. In the PC method, we assume that the directions in which $\mathrm{x} = [\mathrm{x}_1, \dots, \mathrm{x}_N]$ show the most variation are the directions that are associated with the response variable. In other words, the response variable is not used to help determine the PC directions. However, unlike the PC, PLS attempts to identify directions that help explain both the response and the predictor variables. PLS first identifies a new set of features, $\mathrm{z} = [z_1, \dots, z_K]$, where $z_k = [z_{k,1}, \dots, z_{k,T}]'$, k = 1, 2, … , K, and then fits a linear model via least squares using these K new features. The first K PLS directions are computed as follows (Hastie et al., 2009):

1. Standardize each x_i by subtracting the mean and dividing by the standard deviation to have mean zero and variance one.
2. Set $\mathrm{y}^{(0)} = \bar{\mathrm{y}}$ and $\mathrm{x}_i^{(0)} = \mathrm{x}_i$, i = 1, …, N.
3. For k = 1, 2, … , K

   a) $z_k = \sum_{i=1}^{N} \phi_{ik} \mathrm{x}_i^{(k-1)}$, where $\phi_{ik} = Cov\left(\mathrm{x}_i^{(k-1)}, \mathrm{y}\right)$.
   b) $\theta_k = \frac{Cov(z_k, \mathrm{y})}{Var(z_k)}$.
   c) $\mathrm{y}^{(k)} = \mathrm{y}^{(k-1)} + \theta_k z_k$.
   d) Orthogonalize each $\mathrm{x}_i^{(k-1)}$ with respect to z_k:

$$\mathrm{x}_i^{(k)} = \mathrm{x}_i^{(k-1)} - \left(\frac{Cov(z_k, y)}{Var(z_k)}\right) z_k,\ i = 1, \ldots, N.$$

As shown in steps above, the N predictors are mean-centered and standardized to have mean zero and variance one. We then compute the first direction z_1 by setting each ϕ_{i1} equal to the coefficient from the simple linear regression of y on x_i. Note that PLS places the highest weight on the variables that are most strongly related to the response variable in computing $z_1 = \sum_{i=1}^{N} \phi_{i1}\mathrm{x}_i$. We then regress the response variable y on z_1 to obtain θ_1, and orthogonalize each of the predictor variables with respect to z_1 and take residuals. These residuals can be interpreted as the remaining information that has not been explained by the first PLS direction. To identify the second PLS direction, we compute z_2 using this orthogonalized data in exactly the same way as z_1 is calculated. This iterative approach can be repeated K times to produce K orthogonal PLS components.

To forecast the h-quarter ahead target variable y_{t+h}, we estimate $\tilde{z}_k = \sum_{i=1}^{N} \tilde{\phi}_{ik}\mathrm{x}_i^{(k-1)}$ recursively, where $\tilde{\phi}_{ik} = \widetilde{Cov}\left(\mathrm{x}_i^{(k-1)}, \mathrm{y}_h\right)$. Note that we construct $\tilde{z}_k$ using y_h, which is measured at the h-quarter ahead time point, whereas y is measured at the same time point as x_i (see, step 3.a in the algorithm). Let $\tilde{\mathrm{z}}_t = [\tilde{z}_{1,t}, \ldots, \tilde{z}_{K,t}]'$ be an $K \times 1$ vector of partial least squares factor estimates at time t. As in the PCR forecasting framework, y_{t+h} is regressed on $\tilde{\mathrm{z}}_t$ as

$$y_{t+h}^{PLS} = \gamma_h \tilde{\mathrm{z}}_t + u_{t+h}, \tag{3.4}$$

where $\gamma_h = [\gamma_1, \ldots, \gamma_K]$. Then, the h-quarter ahead forecasts from the PLSR are derived directly as

$$\hat{y}_{t+h}^{PLS} = \hat{\gamma}_h \tilde{\mathrm{z}}_t, \tag{3.5}$$

where $\hat{\gamma}_h$ is estimated in Eq. (3.4).

3.4.3 Ridge Regression

One way of dropping uninformative regressors is to use penalized regressions. By shrinking the estimated coefficients, we can often significantly reduce the variance at the cost of a negligible increase in bias (Hastie et al., 2009). Since uninformative predictors can inflate forecast error variance, penalized regressions can lead to substantial improvements in the prediction accuracy. Ridge regression is very similar to least squares regression in a way that ridge regression minimizes a quadratic loss function, but different from least squares regression that there is a quadratic penalty imposed on the coefficient estimates. Let RSS (β) be sum of squared residuals from a regression of y_{t+h} on all available regressors, x_i, as follows: $RSS = \sum_{t=1}^{T}(y_{t+h} - \beta_{0,h} - \sum_{i=1}^{N}\beta_{i,h}\, x_{it})^2$. The solution to

$$\min_{\beta} RSS + \lambda \sum_{i=1}^{N}\beta_{i,h}^2, \tag{3.6}$$

where $0 \leq \lambda < \infty$, is a penalty parameter, is a well-known ridge estimator that shrinks the least squares estimates of $\beta_{i,h}$ towards zero.

The penalty parameter, λ, controls the relative degree of the shrinkage on the regression coefficient estimates. The higher the value of λ, the greater is the amount of the shrinkage. The regularization parameter, λ, is chosen based on the data in order to minimize RSS. The effect of this penalty parameter is that the coefficient estimates are only allowed to become large if there is a proportional reduction in RSS (Kuhn and Johnson, 2013). When $\lambda = 0$, one simply obtains the least squares solution. However, as $\lambda \to \infty$, the regression coefficient estimates will approach to zero because the impact of the shrinkage grows at the same time. Note that $\sum_{i=1}^{N}\beta_i^2 = \|\beta\|_2^2$, the length of β given by the L_2 norm. By the nature of the L_2 penalty, the ridge estimates do not force any of the coefficients to be exactly zero.

Then, the h-quarter ahead forecasts from the ridge regression are derived as

$$\hat{y}_{t+h}^{RIDGE} = \hat{\beta}_{0,h}^{RIDGE} + \sum_{i=1}^{N}\hat{\beta}_{i,h}^{RIDGE}\, x_{it}. \tag{3.7}$$

3.4.4 Least Absolute Shrinkage Selection Operator (LASSO) Regression

Similar to the ridge regression, the LASSO regression relies on a penalized least squares approach. One disadvantage of ridge regression is that it will not exclude any of *N* predictors in the final model. Unless $\lambda = \infty$, the penalty function, $\lambda \sum \beta_i^2$, will shrink all of the coefficients toward zero, but not exactly zero. Such a characteristic may not be a problem for prediction accuracy but can make it difficult to interpret models in settings in which the number of predictors is large.

As with ridge regression, the LASSO shrinks some coefficient estimates towards zero but others exactly to zero (Tibshirani, 1996). Consider replacing the L_2 penalty with an L_1 penalty $\|\beta\|_1 = \sum_{i=1}^{N} |\beta_i|$. Let RSS (β) be sum of squared residuals from a regression of y_{t+h} on all available regressors, x_i. The solution to

$$\min_{\beta} RSS + \lambda \sum_{i=1}^{N} \left|\beta_{i,h}\right|, \tag{3.8}$$

where $0 \leq \lambda < \infty$, is the LASSO estimator. When the penalty parameter, λ, is sufficiently large, the L_1 penalty function has the effect of forcing some of the coefficient estimates to be exactly equal to zero. Therefore, models estimated by LASSO can include only a subset of predictors and thereby the LASSO naturally performs variable (or feature) selection (Zou and Hastie, 2005). It is clear that the LASSO has an edge over ridge regression, in that it yields simpler and more interpretable models than those estimated by ridge regression.

Then, the h-quarter ahead forecasts from the LASSO regression are derived as

$$\hat{y}_{t+h}^{LASSO} = \hat{\beta}_{0,h}^{LASSO} + \sum_{i=1}^{N} \hat{\beta}_{i,h}^{LASSO} x_{it}. \tag{3.9}$$

3.4.5. Elastic Net (EN) Regression

Similar to the LASSO, the elastic net simultaneously shrinks the coefficient estimates and performs variable selection (Zou and Hastie, 2005). Although the LASSO performs well in many situations, it has some limitations. Conceptually, there are two drawbacks as highlighted by Zou and Hastie (2005). First, if $N > T$, the LASSO can select at most T variables. Second, if there is a group of variables among which the pairwise correlations are very high, the LASSO tends to select only one variable from the group and does not care which one is selected. Such drawbacks suggest that a convex combination of the ridge and the LASSO penalty might be desirable.

Consider combining the L_1 penalty with an L_2 penalty and let $RSS\ (\beta)$ be sum of squared residuals from a regression of y_{t+h} on all available regressors, x_i. The solution to

$$\min_{\beta} RSS + \lambda_2(\alpha) \sum_{i=1}^{N} \beta_{i,h}^2 + \lambda_1(1-\alpha) \sum_{i=1}^{N} |\beta_{i,h}| \tag{3.10}$$

is the elastic net estimator, where $\alpha = \lambda_2/(\lambda_1 + \lambda_2)$. Note that the elastic net solution can be reformulated as the ridge and the LASSO solutions, depending on the values of α. A computationally appealing property of the elastic net is that when $\alpha = 1$, it becomes the ridge regression and when $\alpha = 0$, it becomes the LASSO regression. For $0 < \alpha < 1$, the result is the elastic net estimator which effectively complements the drawbacks of the ridge and the LASSO estimators. In this study, we implement the elastic net with $\alpha = 0.5$.

Then, the h-quarter ahead forecasts from the elastic net regression are derived as

$$\hat{y}_{t+h}^{EN} = \hat{\beta}_{0,h}^{EN} + \sum_{i=1}^{N} \hat{\beta}_{i,h}^{EN}\, x_{it}. \tag{3.11}$$

3.5 Results

In this section, we discuss in-sample and out-of-sample prediction performance of our alternative models relative to the random walk (RW) benchmark.

3.5.1 In-sample Analysis

[Figure 3.2]

In this section, we compare the in-sample fit of dimension reduction methods with that of shrinkage methods. We start by comparing the in-sample fit of the two dimension reduction methods. As shown in Figure 3.2.a, PLS factors (orange line) provide much better in-sample performance than

PC factors (dark-green line) do. This finding is not surprising since $\widetilde{z_t}$ is estimated according to covariance between the predictor variables and the forecast target variable, whereas $\widetilde{f_t}$ is estimated according to covariance within the predictor variables. Such comparison is done, however, by eyeballing the in-sample graphs.

Figure 3.2.c and Figure 3.2.d confirms that the PLS method outperforms the PC method in more objective way. We plot the R^2 (Figure 3.2.c) obtained from least squares regressions of the target variable y_t on the estimated PC factors (dark-green line) and PLS factors (orange line) for up to 12 factors ($f = 12$) as well as their cumulative R^2 (Figure 3.2.d) for the T1CR for 5 BHCs in the sample. Note that the factors are orthogonal to each other, thus the cumulative R^2 indicate how much variation of the T1CR is explained by the bank-specific, stress test, and macroeconomic variables jointly. For example, the R^2 from PLS factors (f=1) exceeds 0.4, whereas that from PC factors (f=1) slightly exceeds 0.1. One notable point to be made is that unlike the PLS factors, the contribution of the PC factors do not necessarily diminish when the number of factors increases. This is because the PC factors are estimated solely from the variance-covariance matrix of the predictor variables, while the PLS factors are formulated to obtain the most predictive content of the target variable from the predictors. Note that the R^2 from the PC factors is the highest for the third factor estimate, whereas the contribution of the PLS factors to R^2 are the highest for the first factor estimate. That is, the marginal R^2 decreases when we regress the T1CR on subsequent PLS factors. In contrast, the PC approach considers covariance within the predictors, so that the marginal R^2 does not necessarily decrease as the number of factors increases.

We also compare the in-sample fit of the shrinkage methods. As shown in Figure 3.2.b, the LASSO (light-green line) provides much better in-sample performance than the ridge (red line) does. We omit the elastic net (α = 0.5) in Figure 3.2.b since it provides almost exact in-sample fit as that of the LASSO. The LASSO and the elastics net (α = 0.5), therefore, outperform the ridge in terms of in-sample performance.

3.5.2 Out-of-sample Analysis

To gauge the out-of-sample prediction accuracy of our alternative models, we use the ratio of the root mean square prediction error (*RRMSPE*) defined as follows:

$$RRMSPE = \sqrt{\frac{\frac{1}{T-T_0-h}\sum_{t=T_0+h-1}^{T}\left(\varepsilon_{t+h|t}^{BM}\right)^2}{\frac{1}{T-T_0-h}\sum_{t=T_0+h-1}^{T}\left(\varepsilon_{t+h|t}^{AM}\right)^2}}, \tag{3.12}$$

where $\varepsilon_{t+h|t}^{BM} = y_{t+h} - \hat{y}_{t+h|t}^{BM}$, $\varepsilon_{t+h|t}^{AM} = y_{t+h} - \hat{y}_{t+h|t}^{AM}$, *BM* = AR or RW, and *AM* = PC, PC_{RW}, PLS, PLS_{RW}, Ridge, LASSO, Enet, $Ridge_{LAG}$, $LASSO_{LAG}$, and $Enet_{LAG}$. It should be noted that our alternative models (AM) outperform the benchmark models (BM) when *RRMSPE* is greater than one.

3.5.2.1 Recursive Forecasting Scheme

To evaluate the out-of-sample predictability for the T1CR, we implement the recursive forecasting scheme. We use $p_{50\%}$ for the sample split point, that is, the initial 50 percent of observations are used as a training set to formulate the first out-of-sample forecast. After estimating common factors and/or coefficients with the initial training set, we obtain *h*-quarter ahead out-of-sample forecasts for the target variable. Then, we expand the initial training data by adding one more observation and re-estimate common factors and/or coefficients to formulate *h*-quarter ahead out-of-sample forecasts. We repeat this forecasting exercises until we forecast the last observation of the target variable. We consider $h = 1$ to $h = 12$ quarter-ahead forecasts for each of the seven information sets described in Section 3.3.[12]

[12] Because of the limited space, we only report results with $h = 1$, $h = 4$, $h = 8$, and $h = 12$ in Table 3.3.

As noted before, we implement the out-of-sample forecasting exercises using the dimension reduction methods and shrinkage approach. It should be noted that we have total ten alternative models. In addition to the two dimension reduction methods (PC and PLS), we use common factors, $\tilde{f}_t$ or $\tilde{z}_t$, extracted by PC or PLS methods to augment a nonstationary random walk process. We refer these models as principal component random walk (PC_{RW}) and partial least squares random walk (PLS_{RW}), respectively. Along with the three shrinkage methods (ridge, LASSO, and enet), we estimate each of the three models with a lagged target variable. We refer these models as $Ridge_{LAG}$, $LASSO_{LAG}$, and $Enet_{LAG}$, respectively.

[Table 3.3]

Table 3.3 shows *RRMSPE* when we employ the recursive forecasting method. For the seven subsets of predictor variables: Stress (S), macro (M), bank (B), stress-macro (SM), stress-bank (SB), macro-bank (MB), and stress-macro-bank (SMB) groups, the *RRMSPE* for each of the ten models is presented up to 12 quarter forecast horizons (3 years). Each entry shows the *RRMSPE* of the alternative models relative to the RW benchmark model. k and f denote the number of variables included in the information set and the number of factors extracted by either PC or PLS approach, respectively. Following Diebold and Mariano (1995) and West (1996), we further employ Diebold-Mariano-West (DMW) test to supplement our analysis. Clark and McCracken (2001) and McCracken (2007) show that a DMW test statistic, which tests the null of equal predictive accuracy between two forecasting models, has a nonstandard distribution when comparing forecasts from nested models. Therefore, for PC_{RW} and PLS_{RW}, we use critical values from McCracken (2007) instead of the asymptotic critical values from the standard normal distribution since these two models nest the RW benchmark model. The Diebold-Mariano-West (DMW) statistics are reported in *Appendix 4*.

As noted in Table 3.3, PC_{RW} (f=3) model always outperforms the RW benchmark model for all seven subsets of predictor variables for $h = 1$, while PLS_{RW} (f=1) model outperforms the RW benchmark model only for certain subsets of predictor. LASSO with $t - 1$ lag dependent variable as one of predictors (LASSO w/ Lag) and elastic net with $t - 1$ lag dependent variable as one of predictors (Enet w/ Lag) also outperform the RW benchmark model only when stress-bank (SB) subset of predictor variables are used. For those models that outperform the RW benchmark for $h = 1$, accurate forecasts are produced by the predictors that include stress (S), bank (B), or combination of stress-bank (SB) subsets.

For $h = 4$, only PC_{RW} (f=3) model outperforms the RW benchmark model only for bank (B) subset of predictors. None of the shrinkage approach, however, outperforms the RW benchmark model for $h = 4$. These findings show that stress (S), bank (B), or combination of stress-bank (SB) subsets are useful in forecasting relatively short-term horizons when appropriate forecasting models are implemented. The subset of macro (M) variables, however, does not help produce accurate forecasts for relatively short-term forecast horizons even when PC_{RW} (f=3) and PLS_{RW} (f=1) models are employed.

For $h = 8$, PC_{RW} (f=3) model again produces the most accurate forecasts for all seven subsets of predictor variables. Except for stress (S) and stress-bank (SB) subsets, PLS_{RW} (f=1) model outperforms the RW benchmark model. We find that the most accurate forecasts are achieved by the predictors that include the subset of macro (M) variables. For $h = 12$, all of our alternative models outperform the RW benchmark for most subsets of predictors. It is worth noting that these subsets always include macro (M) group. Our findings indicate that macro (M) variables help produce the most accurate forecasts for relatively long-term forecast horizon. Such findings sharply contrast with the previous results for the short-term forecast horizons in which the best subset does not include the subset of macro (M) variables.

[Figure 3.3]

Figure 3.3 shows the forecast accuracy for each of the ten alternative models as compared to the RW model over all 12 quarter-ahead forecast horizons, using bank (B) variables for PC_{RW} and PLS_{RW} and stress-bank-macro (SMB) variables for others.[13] As shown in Figure 3.3, no one forecasting methods outperform over all 12 quarter-ahead forecast horizons. PC_{RW} (f=3) and PLS_{RW} (f=1) models, factor-type models, outperform the other alternative models over *1* to *10*-quarter ahead forecast horizons. Shrinkage methods such as LASSO and Enet, however, tend to outperform the factor-type forecasting techniques over *11* to *12*-quarter ahead forecast horizons. Somewhat unsurprisingly, there is no single method that outperforms all alternative models for every subsets of predictor variables at every horizon, a finding that is consistent with other forecasting literature (Jiang et al., 2017).

3.5.2.2 Rolling Window Forecasting Scheme

We also employ a fixed-size rolling window method to estimate model parameters and forecast the T1CR. Using all available data recursively may lead to biased parameter estimates and forecasts if the earliest available data follow a data-generating process unrelated to the present (Clark and McCracken, 2009). The rolling window approach, however, is based on a changing subsample of fixed length that moves sequentially from the beginning of the sample to the end. Therefore, the rolling window method can be justified for two reasons (Balcilar and Ozdemir, 2013): 1) it allows the relationship between the variables evolve through time and 2) it captures instability across different subsamples caused by the presence of structural changes. In our study,

[13] The subset of bank (B) variables consistently produces accurate forecasts over varying horizons when PC_{RW} (f=3) and PLS_{RW} (f=1) models are implemented.

for example, we consider a sequence of 42 different subsamples with 41 quarter fixed window for 1 quarter-ahead out-of-sample forecast (starting with 1996:Q1 and ending with 2016:Q3).

The decade since the onset of the global financial crisis of 2007–2009 has brought about significant structural changes in the banking sector (Buch and Dages, 2018) and it revealed that many banks were not maintaining adequate capital and liquidity buffers to cope with adverse shocks. Since then, the banking sector has responded to subsequent changes in regulatory requirements by strengthening its capital positions to enhance its resilience to stressed macro-financial conditions. A marked increase in T1CR in Figure 3.1 since the end of the first quarter of 2009 shows such responses by the banking sector. Therefore, the rolling window scheme may produce more accurate forecasts than the recursive method by capturing instability across different subsamples caused by the presence of structural changes.

As in the recursive forecasting approach, the initial 50 percent of observations are used as a training set to formulate the first out-of-sample forecast. After estimating common factors and/or coefficients with the initial training set, we obtain h-quarter ahead out-of-sample forecasts for the target variable. Then, we add one observation but drop one earliest observation for the second-round forecasting. We repeat this forecasting exercises until we forecast the last observation of the target variable. Table 3.4 and Figure 3.4 present the results, which are similar to those of the recursive forecasting scheme.

[Table 3.4 and Figure 3.4]

3.5.3 Empirical Factors

Since we are mainly interested in out-of-sample prediction accuracy, we do not discuss in details on individual factors included in the model.[14] Nevertheless, the finding that accurate forecasts can

[14] Stock and Watson (2002) note that detailed discussion of the individual factors unwarranted since the factors are identified only up to a f × f matrix.

be made with only one or three factors suggests briefly characterizing the first few factors (Stock and Watson, 2002).

[Figure 3.5]

Figure 3.5 therefore presents the R^2 of the regressions of the 162 individual time series on each of the first six empirical factors from the stress-bank-macro (SMB) subset of predictors, estimated using principal component analysis over the full sample period. These R^2 are plotted as bar charts with one chart for each factor. The predictors are grouped by category and ordered numerically using the ordering in the *Appendix 3*. Generally speaking, the first factor loads primarily on group 3 (output & income) and group 4 (labor market); the second factor on group 9 (prices); the third factor on group 5 (housing); the fourth factor on group 3 (output & income), group 4 (labor market), group 8 (interest & exchange rates), and group 9 (prices); the fifth factor on group 2 (stress test), group 5 (housing), and group 8 (interest & exchange rate); the sixth factor on group 1 (bank). These six factors account for about 45% of the variance of the 162 quarterly time series in the full dataset, as measured by the cumulative R^2 (see, Figure 3.2.d).

Although most forecasting literature is mainly interested in out-of-sample prediction accuracy and does not attempt to trace the importance of individual predictors included in the model, we use the LASSO to further identify which groups of variables help forecast the T1CR, using the subsets of bank (B) or stress (S) group predictors. *Appendix 5* presents the results.

3.6 Conclusions

In this study, we have discussed several important forecasting models that allow for situations in which the number of predictor variables exceeds the number of observations and some predictor variables are highly correlated. We have proposed two dimension reduction methods – the principal component regression (PCR) and the partial least squares regression (PLSR), and three shrinkage (or regularization) methods – the ridge regression, the LASSO regression, and the elastic net regression to solve such problems. We have used these models to forecast T1CR, an extremely important banking variable and the most accurate indicator of the ability of banks to absorb losses, of five biggest BHCs.

Our results show that factor-type models dominate the other alternative models over *1*- to *10*-quarter ahead forecast horizons and shrinkage methods tend to outperform the factor-type forecasting models over *11*- to *12*-quarter ahead forecast horizons. In addition, we find that bank and stress test variables help produce the most accurate forecasts for short-term forecast horizons, while macro variables are useful in forecasting long-term horizons. Finally, we find that only six factors account for much of the variance of our 162 quarterly time series in the full dataset and that the most accurate forecasts of T1CR are obtained with just a few factors. One interpretation of such findings is that there may be only a few important sources that are necessary to accurately forecast banks' capital. As far as we know, no other study has used as many forecasting models and predictor variables to examine which model performs best in terms of forecasting accuracy of the T1CR over various horizons in the banking literature.

Our findings have important policy implications. In particular, bank regulatory authorities may be able to suggest individual banks to use different forecasting models, depending upon forecast horizons, since no single forecasting model dominates all alternative models at every horizon. Besides, more precise results of stress tests from good predictors and good models help inform the regulators and financial market participants of the likelihood of emerging crisis at a particular bank or at the banking system more generally. Therefore, the regulators will be in a better position to decide upon any actions that might be appropriate to promote safer and sounder banking system.

3.7 References

Balcilar, M., & Ozdemir, Z. A. (2013). The export-output growth nexus in Japan: a bootstrap rolling window approach. *Empirical Economics*, *44*(2), 639-660.

Barth, J. R., & Miller, S. M. (2017). A primer on the evolution and complexity of bank regulatory capital standards. Mercatus Working Paper, Mercatus Center, Geroge Mason University.

Buch, C., & Dages, G. (2018). Structural changes in banking after the crisis. Committee on the Global Financial System (CGFS) Papers No. 60, Bank for International Settlements (BIS).

Clark, T. E., & McCracken, M. W. (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics*, *105*(1), 85-110.

Clark, T. E., & McCracken, M. W. (2009). Improving forecast accuracy by combining recursive and rolling forecasts. *International Economic Review*, *50*(2), 363-395.

Covas, F. B., Rump, B., & Zakrajšek, E. (2014). Stress-testing US bank holding companies: A dynamic panel quantile regression approach. *International Journal of Forecasting*, *30*(3), 691-713.

Diebold, F. X., & Mariano, R. S. (2002). Comparing predictive accuracy. *Journal of Business & Economic statistics*, *20*(1), 134-144.

Erkens, D. H., Hung, M., & Matos, P. (2012). Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. *Journal of Corporate Finance*, *18*(2), 389-411.

Greenlaw, D., Kashyap, A., Schoenholtz, K., Shin, H., 2012. Stressed out: Macroprudential principles for stress testing. In *Chicago Booth School of Business working paper*, *No. 71*.

Hanson, S. G., Kashyap, A. K., & Stein, J. C. (2011). A macroprudential approach to financial regulation. *Journal of Economic Perspectives*, *25*(1), 3-28.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). Unsupervised learning. In *The elements of statistical learning* (pp. 485-585). Springer, New York, NY.

Hirtle, B., Kovner, A., Vickery, J., & Bhanot, M. (2016). Assessing financial stability: the capital and loss assessment under stress scenarios (CLASS) model. *Journal of Banking & Finance*, *69*, 35-55.

Huber, P. J. (1973). Robust regression: asymptotics, conjectures and Monte Carlo. *The Annals of Statistics*, *1*(5), 799-821.

Panagiotelis, A., Athanasopoulos, G., Hyndman, R. J., Jiang, B., & Vahid, F. (2019). Macroeconomic forecasting for Australia using a large number of predictors. *International Journal of Forecasting*, *35*(2), 616-633.

Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling.* Springer, New York.

McCracken, M. W. (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics*, *140*(2), 719-752.

McCracken, M. W., & Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, *34*(4), 574-589.

Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, *20*(2), 147-162.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267-288.

West, K. D. (1996). Asymptotic inference about predictive ability. *Econometrica*, *64*(5) 1067-1084.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, *67*(2), 301-320.

Table 3.1
Five Biggest Bank Holding Companies (BHCs) in Terms of Total Assets
(As of 12/31/2016)

Rank	Institution Name	Total Assets ($ million)	Percent Total Assets
1	JPMORGAN CHASE & CO.	$2,490,972	14.6%
2	BANK OF AMERICA	$2,189,266	12.8%
3	WELLS FARGO & COMPANY	$1,930,115	11.3%
4	CITIGROUP INC.	$1,792,077	10.5%
5	U.S. BANCORP	$445,964	2.6%
1-5	**5 BHCs Total Assets**	$8,848,394	**51.8%**
1-50	Top 50 BHCs Total Assets	$17,094,745	100%

Table 3.2
Descriptive Statistics

ID	Category	Data Description		
	Target Variables		**Mean**	**Std. Dev**
	Tier 1 Common Capital Ratio (T1CR)	Tier 1 Common Equity / Risk-Weighted Assets (Tier 1 Common Equity = Tier 1 capital − Perpetual preferred stock + Nonqual. perpetual preferred stock − Qual. class A minority interests − Qual. restricted core capital − Qual. mandatory convert. pref. sec)	0.088	0.016
	Bank Variables		**Mean**	**Std. Dev**
1	Size	Log (Total Assets)	22.162	0.727
2	Profitability	Income Before Extraordinary items / Total Assets	0.002	0.001
3		Noninterest Income / Total Income	0.359	0.073
4		Volatility of ROA	0.001	0.001
5		Non-Interest Earning Assets / Total Assets	0.737	0.033
6	Efficiency	Interest Expense / Total Assets	0.005	0.004
7		Noninterest Expense / Total Assets	0.008	0.002
8	Capital	Total Equity Capital / Total Assets	0.085	0.014
9	Loan	Total Loans / Total Assets	0.463	0.051
10		Real Estate Loans / Total Assets	0.196	0.019
11		Commercial and Industrial Loans / Total Assets	0.072	0.019
12		Consumer Loans / Total Assets	0.082	0.011
13		Agricultural Loans / Total Assets	0.002	0.001
14		All Other Loans / Total Assets	0.027	0.007
15		Loan Concentration	0.270	0.033
16		Nonperforming Loans / Total Assets	0.012	0.008
17		Loan Loss Provision / Total Loans	0.003	0.003
18		Loan Growth Rate	1.032	0.058
19	Deposit	Total Deposits / Total Assets	0.364	0.052
20		Core Deposits / Total Assets	0.320	0.062
21		Noncore Deposits / Total Assets	0.043	0.013
22	Liquidity	Cash + Marketable Securities / Total Assets	0.199	0.045
23		Customer and Short-Term Funding / Total Assets	0.483	0.032
24		Log (12-Month Maturity Gap)	20.648	0.837
25		Log (Derivative Trading)	25.007	0.990
26		Tobin's q	1.076	0.063
27		Stock Beta	1.183	0.307
28		Volatility of Stock Return	0.092	0.029
29		P/E Ratio	29.234	22.459

Table 3.3

Out-of-Sample Prediction: Tier-1 Common Capital Ratio

(Recursive: RW Benchmark)

	S (k=16)	M (k=117)	B (k=29)	SM (k=133)	SB (k=45)	MB (k=146)	SMB (k=162)	
				h=1				Best Subset
PC (f=6)	0.244	0.266	0.282	0.263	0.272	0.279	0.279	B
PC_{RW} (f=3)	**1.120**	**1.062**	**1.131**	**1.091**	**1.233**	**1.132**	**1.171**	***SB***
PLS (f=6)	0.251	0.356	0.309	0.356	0.291	0.371	0.371	MB
PLS_{RW} (f=1)	**1.029**	0.964	**1.019**	0.970	**1.023**	0.971	0.975	***S***
Ridge	0.245	0.263	0.283	0.264	0.273	0.269	0.271	B
Lasso	0.251	0.383	0.287	0.368	0.277	0.358	0.369	M
Enet	0.248	0.369	0.282	0.364	0.279	0.362	0.360	M
Ridge w/ Lag	0.840	0.272	0.737	0.273	0.580	0.277	0.278	S
Lasso w/ Lag	0.968	0.891	0.915	0.890	**1.046**	0.913	0.934	***SB***
Enet w/ Lag	0.907	0.779	0.884	0.805	**1.019**	0.848	0.824	***SB***
Best Model	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	
				h=4				Best Subset
PC (f=6)	0.532	0.460	0.566	0.465	0.538	0.459	0.473	B
PC_{RW} (f=3)	0.912	0.957	**1.054**	0.959	0.882	0.931	0.931	***B***
PLS (f=6)	0.500	0.606	0.558	0.624	0.549	0.608	0.625	SMB
PLS_{RW} (f=1)	0.937	0.912	0.996	0.913	0.950	0.916	0.916	B
Ridge	0.495	0.542	0.552	0.550	0.531	0.550	0.557	SMB
Lasso	0.501	0.542	0.564	0.590	0.536	0.516	0.541	SM
Enet	0.502	0.542	0.564	0.595	0.530	0.511	0.571	SM
Ridge w/ Lag	0.683	0.559	0.782	0.566	0.691	0.564	0.570	B
Lasso w/ Lag	0.684	0.630	0.830	0.648	0.744	0.596	0.631	B
Enet w/ Lag	0.668	0.622	0.825	0.679	0.740	0.579	0.640	B
Best Model	RW	RW	PC_{RW}	RW	RW	RW	RW	
				h=8				Best Subset
PC (f=6)	0.721	0.767	0.770	0.742	0.746	0.774	0.741	MB
PC_{RW} (f=3)	**1.004**	**1.153**	**1.134**	**1.144**	**1.086**	**1.138**	**1.128**	***M***
PLS (f=6)	0.667	0.812	0.661	0.879	0.619	0.762	0.814	SM
PLS_{RW} (f=1)	0.944	**1.012**	**1.006**	**1.011**	0.996	**1.017**	**1.016**	***MB***
Ridge	0.697	0.759	0.722	0.762	0.717	0.760	0.762	SM
Lasso	0.683	0.691	0.708	0.928	0.684	0.729	0.903	SM
Enet	0.680	0.718	0.710	0.862	0.695	0.753	0.852	SM
Ridge w/ Lag	0.675	0.762	0.769	0.765	0.738	0.762	0.765	B
Lasso w/ Lag	0.662	0.710	0.758	0.877	0.703	0.738	0.864	SM
Enet w/ Lag	0.667	0.759	0.761	0.855	0.707	0.756	0.849	SM
Best Model	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	
				h=12				Best Subset
PC (f=6)	0.854	**1.488**	0.877	**1.530**	0.885	**1.447**	**1.549**	***SMB***
PC_{RW} (f=3)	**1.118**	**1.488**	**1.156**	**1.418**	**1.229**	**1.478**	**1.409**	***M***
PLS (f=6)	0.809	**1.235**	0.818	**1.254**	0.803	**1.126**	**1.129**	***SM***
PLS_{RW} (f=1)	**1.054**	**1.323**	**1.082**	**1.266**	**1.093**	**1.297**	**1.268**	***M***
Ridge	0.838	**1.094**	0.835	**1.083**	0.833	**1.104**	**1.071**	***MB***
Lasso	0.816	**1.445**	0.837	**1.445**	0.827	**1.370**	**1.365**	***M***
Enet	0.818	**1.424**	0.837	**1.401**	0.832	**1.361**	**1.343**	***M***
Ridge w/ Lag	0.781	**1.085**	0.754	**1.056**	0.780	**1.072**	**1.045**	***M***
Lasso w/ Lag	0.747	**1.446**	0.730	**1.424**	0.686	**1.401**	**1.376**	***M***
Enet w/ Lag	0.754	**1.411**	0.735	**1.407**	0.704	**1.342**	**1.344**	***M***
Best Model	PC_{RW}	PC	PC_{RW}	PC	PC_{RW}	PC_{RW}	PC	

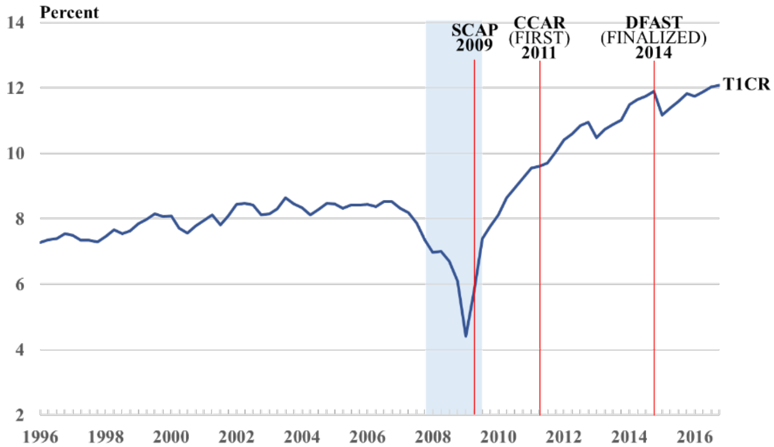
Table 3.4

Out-of-Sample Prediction: Tier-1 Common Capital Ratio

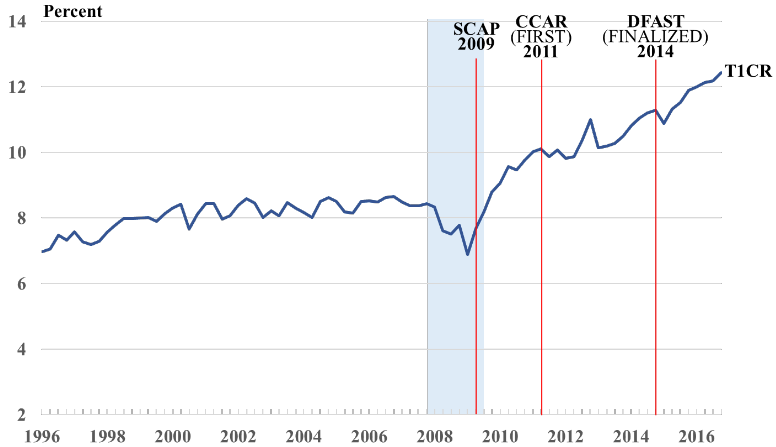
(Rolling: RW Benchmark)

	S (k=16)	M (k=118)	B (k=29)	SM (k=134)	SB (k=45)	MB (k=147)	SMB (k=163)	
				h=1				Best Subset
PC (f=6)	0.301	0.383	0.326	0.376	0.332	0.393	0.387	MB
PC_{RW} (f=3)	**1.093**	**1.085**	**1.173**	**1.098**	**1.333**	**1.171**	**1.209**	***SB***
PLS (f=6)	0.332	0.547	0.411	0.526	0.400	0.524	0.511	M
PLS_{RW} (f=1)	**1.012**	0.960	**1.023**	0.964	**1.019**	0.966	0.969	***B***
Ridge	0.314	0.335	0.381	0.336	0.281	0.342	0.343	B
Lasso	0.323	0.616	0.376	0.597	0.376	0.569	0.555	M
Enet	0.321	0.614	0.370	0.599	0.366	0.570	0.563	M
Ridge w/ Lag	0.755	0.342	0.750	0.343	0.297	0.348	0.349	S
Lasso w/ Lag	0.950	0.817	0.892	0.795	0.935	0.798	0.820	S
Enet w/ Lag	0.906	0.763	0.906	0.723	0.915	0.709	0.699	SB
Best Model	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	
				h=4				Best Subset
PC (f=6)	0.595	0.520	0.598	0.527	0.581	0.533	0.558	B
PC_{RW} (f=3)	0.889	**1.027**	0.974	**1.017**	0.859	0.991	0.969	***M***
PLS (f=6)	0.560	0.692	0.651	0.699	0.618	0.692	0.702	SMB
PLS_{RW} (f=1)	0.914	0.883	0.942	0.885	0.912	0.887	0.888	B
Ridge	0.549	0.608	0.624	0.614	0.581	0.619	0.624	B
Lasso	0.557	0.558	0.603	0.623	0.607	0.577	0.587	SM
Enet	0.571	0.584	0.576	0.631	0.610	0.599	0.619	SM
Ridge w/ Lag	0.586	0.618	0.720	0.623	0.601	0.628	0.632	B
Lasso w/ Lag	0.653	0.630	0.737	0.666	0.720	0.594	0.637	B
Enet w/ Lag	0.634	0.623	0.740	0.660	0.710	0.612	0.648	B
Best Model	RW	PC_{RW}	RW	PC_{RW}	RW	RW	RW	
				h=8				Best Subset
PC (f=6)	0.727	0.690	0.798	0.694	0.766	0.784	0.748	B
PC_{RW} (f=3)	0.967	**1.220**	**1.065**	**1.197**	**1.009**	**1.205**	**1.171**	***M***
PLS (f=6)	0.664	0.712	0.758	0.739	0.710	0.727	0.751	B
PLS_{RW} (f=1)	0.900	0.966	0.958	0.962	0.953	0.973	0.969	MB
Ridge	0.711	0.742	0.807	0.743	0.760	0.750	0.750	B
Lasso	0.690	0.640	0.787	0.742	0.750	0.671	0.758	B
Enet	0.696	0.674	0.779	0.745	0.758	0.689	0.756	B
Ridge w/ Lag	0.687	0.746	0.773	0.748	0.766	0.753	0.755	B
Lasso w/ Lag	0.661	0.697	0.805	0.787	0.723	0.699	0.788	B
Enet w/ Lag	0.667	0.742	0.810	0.794	0.752	0.741	0.791	B
Best Model	RW	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	PC_{RW}	
				h=12				Best Subset
PC (f=6)	0.832	**1.679**	0.911	**1.635**	0.873	**1.632**	**1.693**	***SMB***
PC_{RW} (f=3)	**1.029**	**1.663**	**1.093**	**1.565**	**1.096**	**1.576**	**1.473**	***M***
PLS (f=6)	0.785	**1.097**	0.832	**1.073**	0.817	**1.015**	**1.000**	***M***
PLS_{RW} (f=1)	0.978	**1.179**	**1.028**	**1.157**	**1.033**	**1.183**	**1.162**	***MB***
Ridge	0.833	**1.055**	0.872	**1.030**	0.870	**1.047**	**1.036**	***M***
Lasso	0.822	**1.318**	0.854	**1.232**	0.850	**1.281**	**1.227**	***M***
Enet	0.825	**1.268**	0.871	**1.212**	0.867	**1.252**	**1.207**	***M***
Ridge w/ Lag	0.792	**1.029**	0.846	**1.018**	0.850	**1.022**	**1.021**	***M***
Lasso w/ Lag	0.813	**1.336**	0.775	**1.244**	0.809	**1.271**	**1.208**	***M***
Enet w/ Lag	0.821	**1.262**	0.796	**1.217**	0.820	**1.254**	**1.179**	***M***
Best Model	PC_{RW}	PC	PC_{RW}	PC	PC_{RW}	PC	PC	

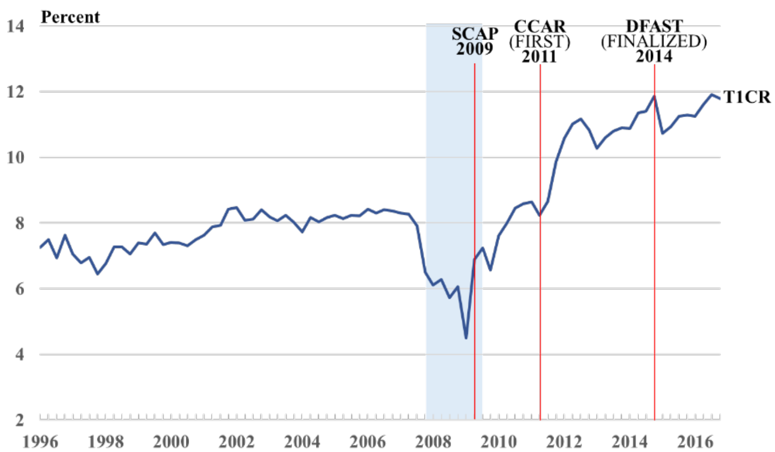
Figure 3.1
Tier 1 Common Capital Ratio (T1CR) of the 5 BHCs



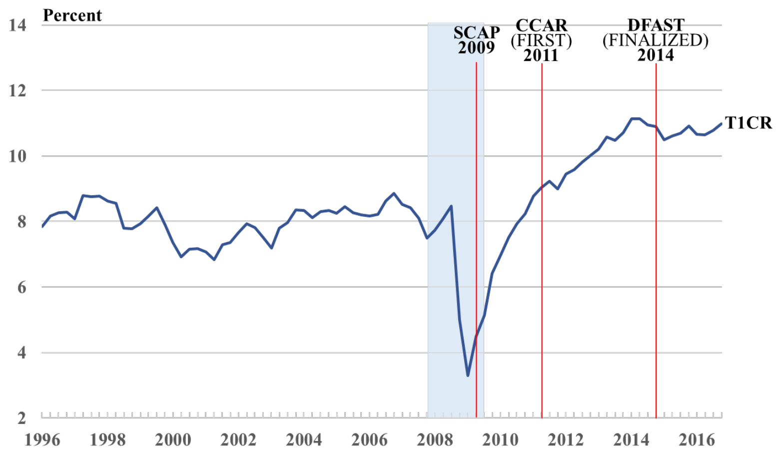
(a) All 5 BHCs (Aggregate)



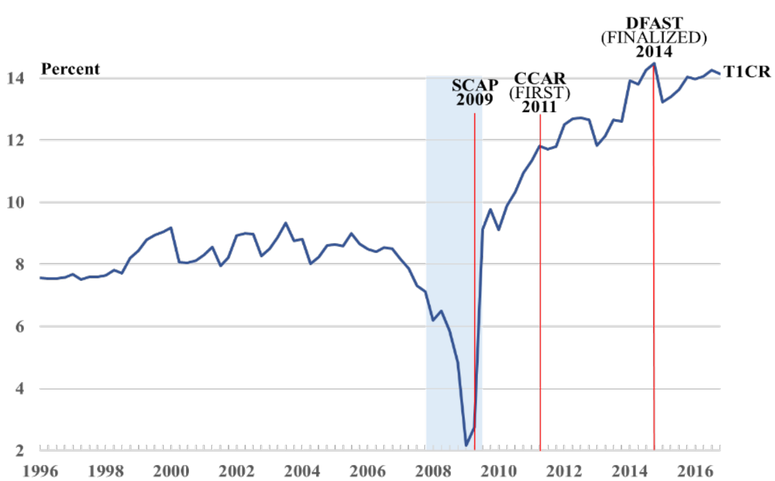
(b) JPM



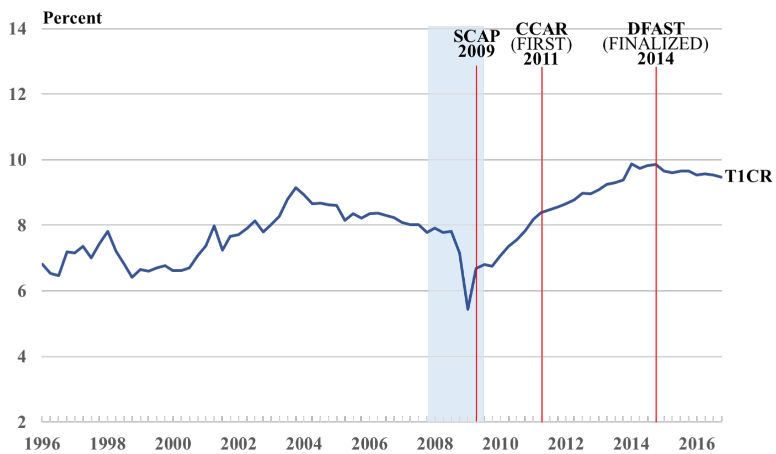
(c) BAC



(d) WFC



(e) CITI

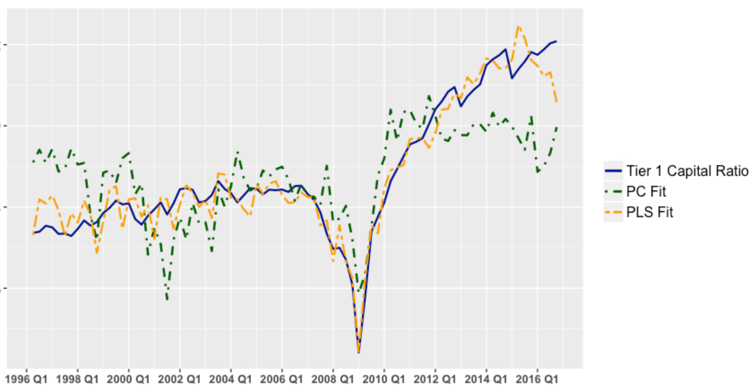


(f) USB

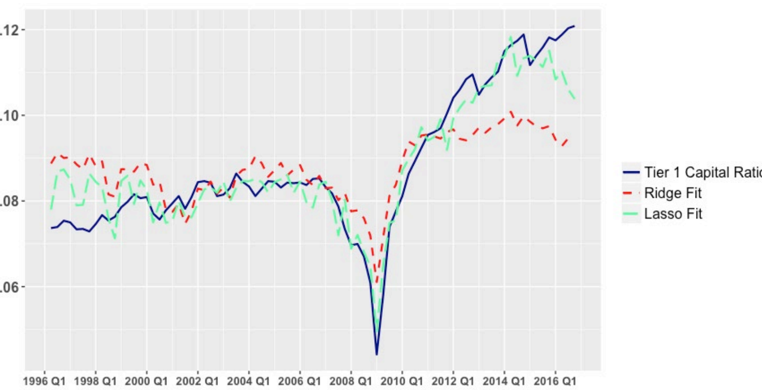
Note: JPM, BAC, WFC, CITI, and USB refer to JPMorgan Chase & Co., Bank of America, Wells Fargo & Company, Citigroup Inc., and U.S. Bancorp, respectively. Shaded area indicates the most recent recession which began in December 2007 and ended in June 2009.

Figure 3.2
In-Sample Fit Analysis: Tier 1 Common Capital Ratio

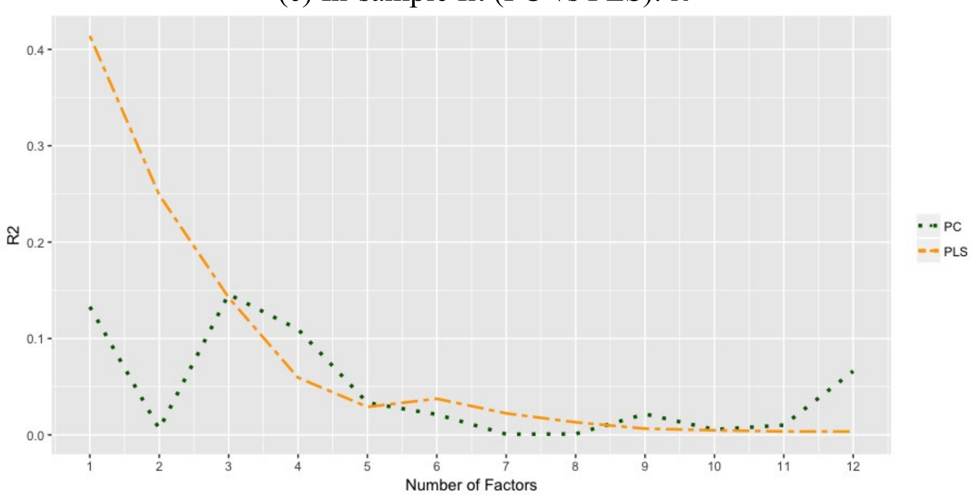
(a) In-sample fit (PC vs PLS)



(b) In-sample fit (Ridge vs LASSO)



(c) In-sample fit (PC vs PLS): R^2



(d) In-sample fit (PC vs PLS): Cumulative R^2

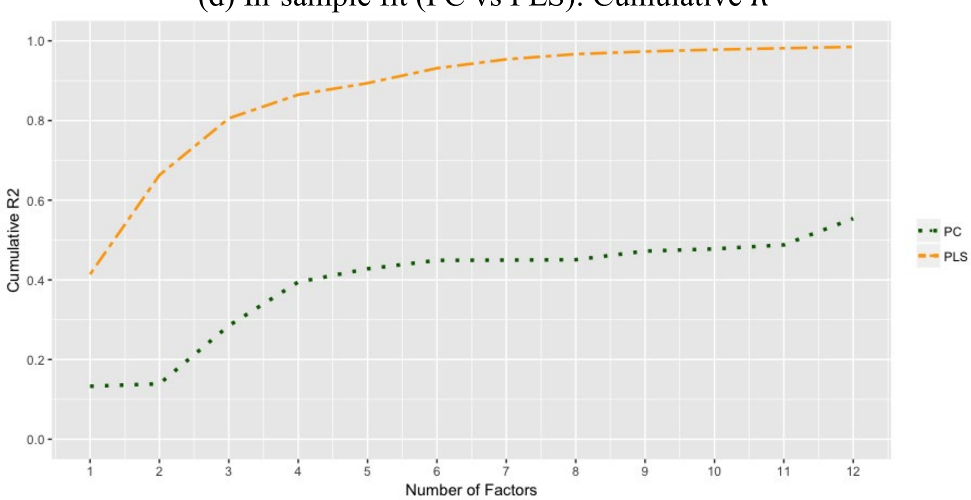


Figure 3.3
Out-of-Sample Prediction: Tier-1 Capital Ratio
(Recursive: RW Benchmark)

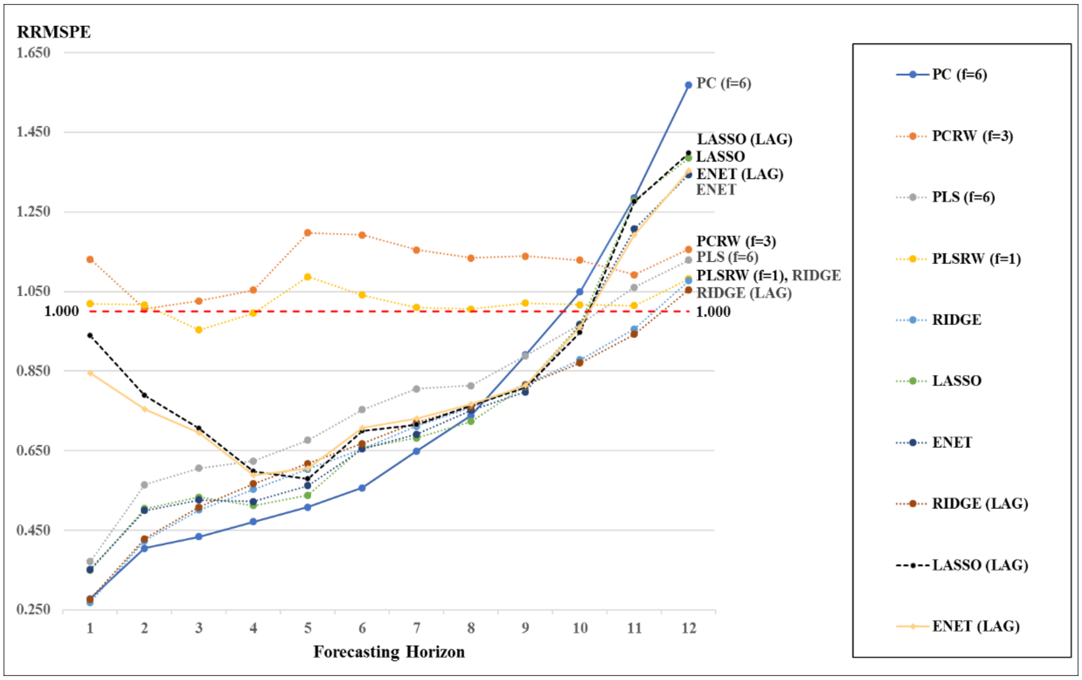


Figure 3.4
Out-of-Sample Prediction: Tier-1 Capital Ratio
(Rolling: RW Benchmark)

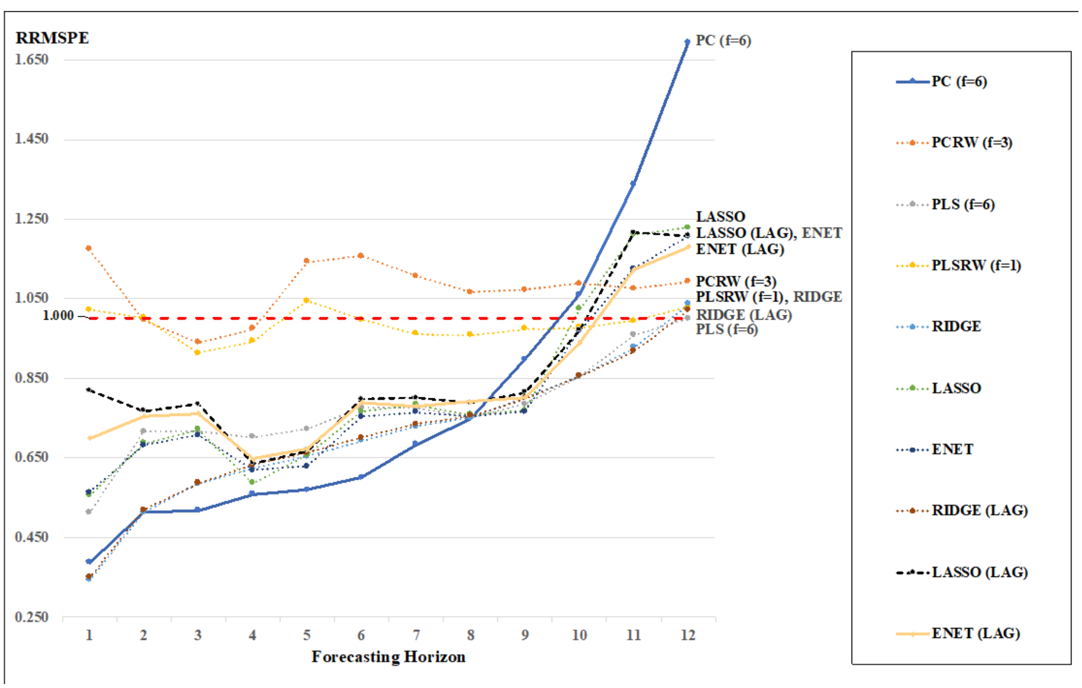


Figure 3.5

R^2 Between Factors and Individual Time Series

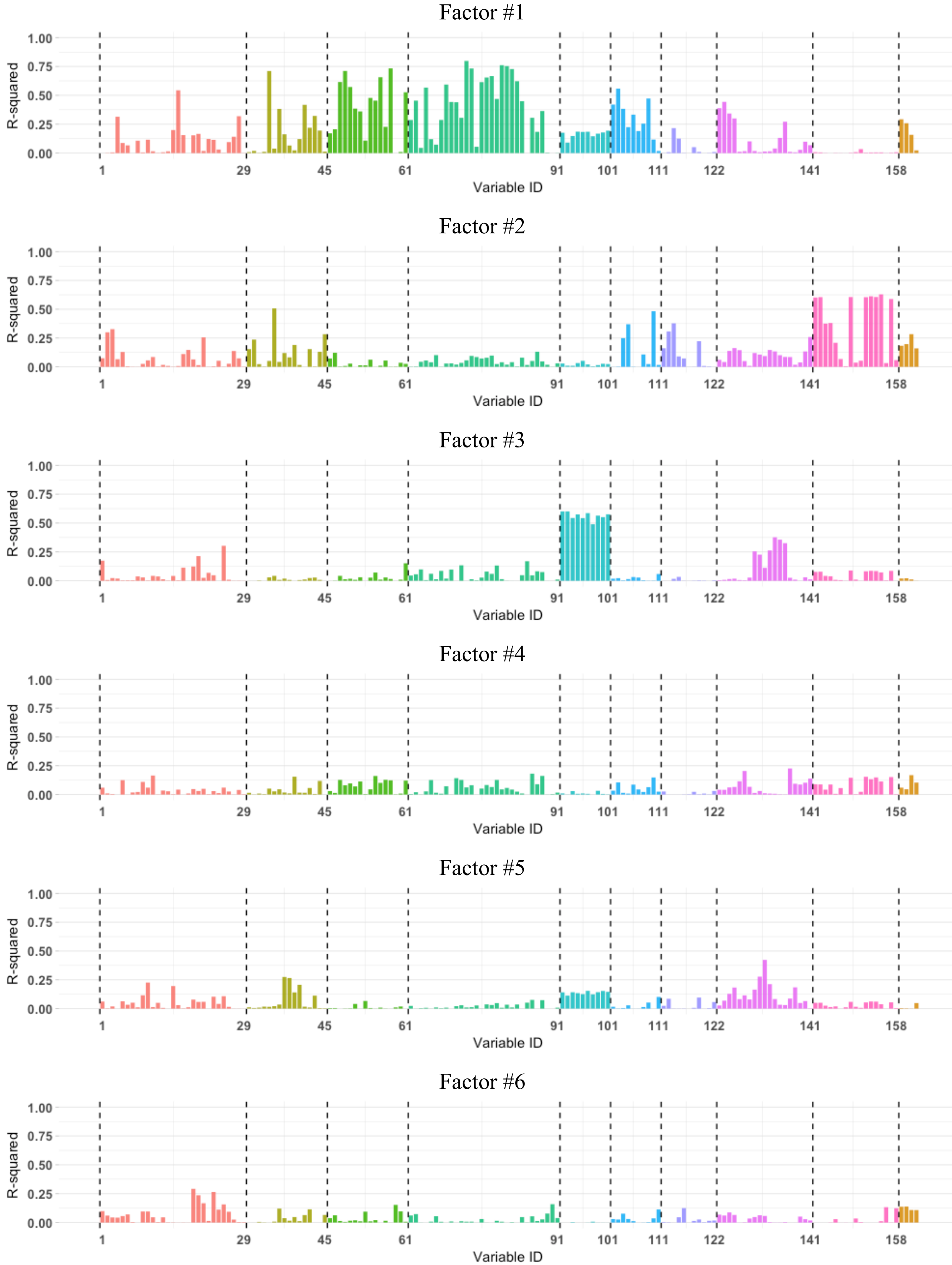
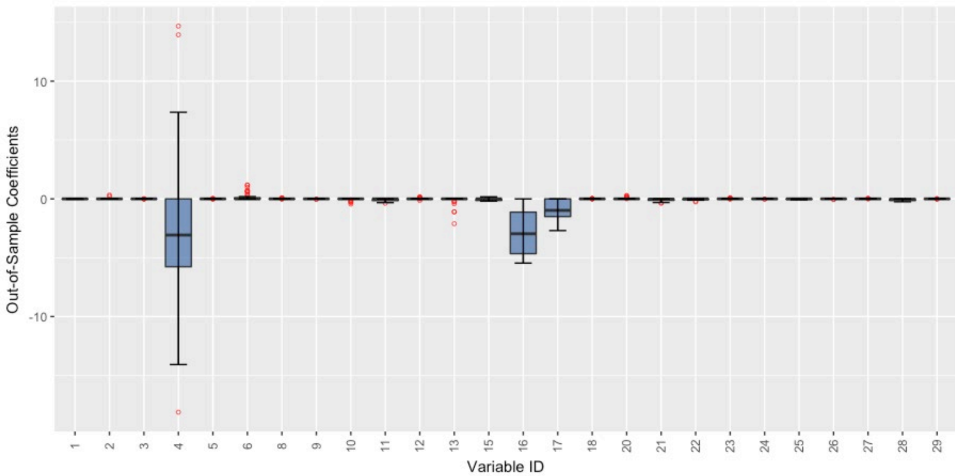
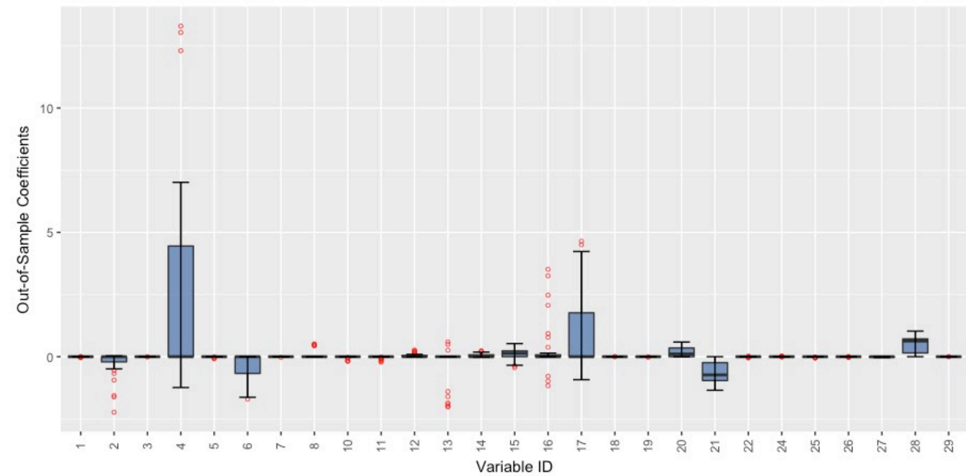


Figure A5.1
Coefficient Estimates of Selected Variables in Out-of-sample Prediction by LASSO

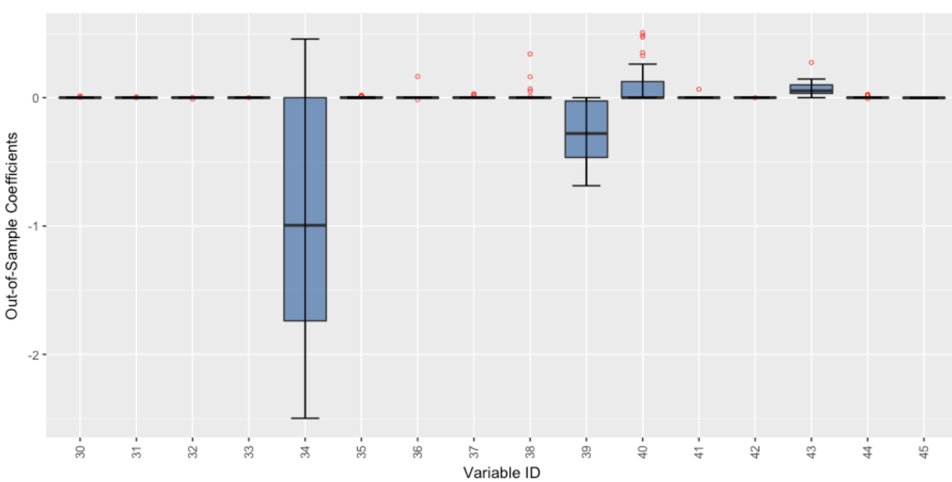
(a) Bank variables

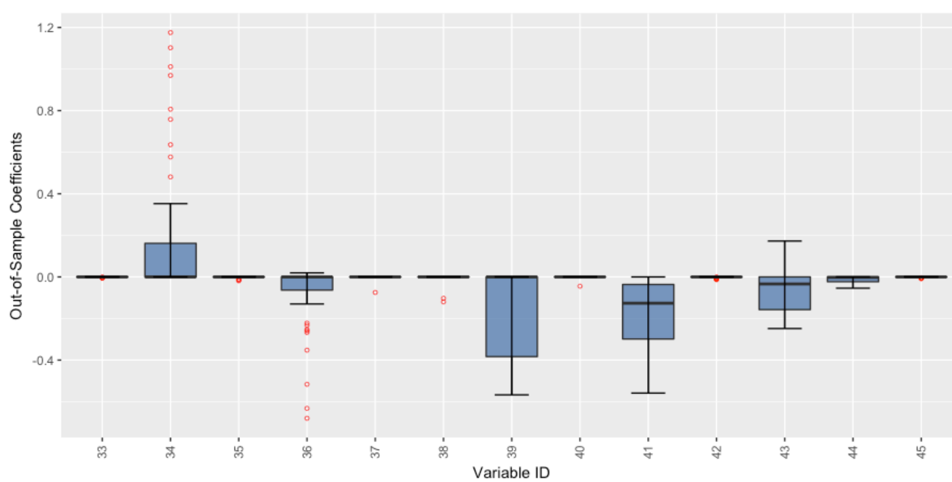




Short-Term: 1 Quarter Ahead **Long-Term: 12 Quarter Ahead**

(b) Stress variables





Appendix 2

Top 50 Bank Holding Companies (BHCs) in Terms of Total Assets

(As of 12/31/2016)

Rank	Institution Name	Total Assets ($ million)	Rank	Institution Name	Total Assets ($ million)
1	JPMORGAN CHASE & CO.	$2,490,972	26	UNITED SERVICES AUTOMOBILE ASSOCIATION	$147,519
2	BANK OF AMERICA CORPORATION	$2,189,266	27	FIFTH THIRD BANCORP	$142,177
3	WELLS FARGO & COMPANY	$1,930,115	28	RBC USA HOLDCO CORPORATION	$141,917
4	CITIGROUP INC.	$1,792,077	29	UBS AMERICAS HOLDING LLC	$137,698
5	GOLDMAN SACHS GROUP, INC., THE	$860,185	30	SANTANDER HOLDINGS USA, INC.	$137,367
6	MORGAN STANLEY	$813,049	31	KEYCORP	$136,826
7	U.S. BANCORP	$445,964	32	BNP PARIBAS USA, INC.	$132,521
8	PNC FINANCIAL SERVICES GROUP, INC., THE	$366,872	33	BMO FINANCIAL CORP.	$128,089
9	CAPITAL ONE FINANCIAL CORPORATION	$357,158	34	REGIONS FINANCIAL CORPORATION	$126,194
10	TD GROUP US HOLDINGS LLC	$343,933	35	NORTHERN TRUST CORPORATION	$123,927
11	BANK OF NEW YORK MELLON CORPORATION, THE	$333,469	36	M&T BANK CORPORATION	$123,449
12	TEACHERS INSURANCE & ANNUITY ASSOCIATION OF AMERICA	$282,442	37	HUNTINGTON BANCSHARES INCORPORATED	$99,714
13	HSBC NORTH AMERICA HOLDINGS INC.	$277,783	38	DISCOVER FINANCIAL SERVICES	$92,308
14	STATE STREET CORPORATION	$242,709	39	SYNCHRONY FINANCIAL	$90,245
15	CHARLES SCHWAB CORPORATION, THE	$223,383	40	BBVA COMPASS BANCSHARES, INC.	$87,080
16	BB&T CORPORATION	$219,276	41	COMERICA INCORPORATED	$73,130
17	CREDIT SUISSE HOLDINGS (USA), INC.	$214,138	42	CIT GROUP INC.	$64,170
18	SUNTRUST BANKS, INC.	$205,214	43	ZIONS BANCORPORATION	$63,239
19	BARCLAYS US LLC	$204,485	44	E*TRADE FINANCIAL CORPORATION	$48,999
20	DB USA CORPORATION	$186,603	45	NEW YORK COMMUNITY BANCORP, INC.	$48,927
21	ALLY FINANCIAL INC.	$163,728	46	SVB FINANCIAL GROUP	$44,692
22	AMERICAN EXPRESS COMPANY	$158,885	47	PEOPLE'S UNITED FINANCIAL, INC.	$40,611
23	CITIZENS FINANCIAL GROUP, INC.	$150,023	48	MIZUHO AMERICAS LLC	$39,248
24	MUFG AMERICAS HOLDINGS CORPORATION	$148,144	49	POPULAR, INC.	$38,662
25	STATE FARM MUTUAL AUTOMOBILE INSURANCE COMPANY	$147,697	50	MUTUAL OF OMAHA INSURANCE COMPANY	$38,465

Appendix 3

Descriptive Statistics for All Predictor Groups

ID	Category	Data Description		
	Target Variable		**Mean**	**Std. Dev**
	Tier 1 Common Capital Ratio (T1CR)	Tier 1 Common Equity / Risk-Weighted Assets (Tier 1 Common Equity = Tier 1 capital − Perpetual preferred stock + Nonqual. perpetual preferred stock − Qual. class A minority interests − Qual. restricted core capital − Qual. mandatory convert. pref. sec)	0.088	0.016
	Bank-Level		**Mean**	**Std. Dev**
1	Size	Log (Total Assets)	22.162	0.727
2	Profitability	Income Before Extraordinary items / Total Assets	0.002	0.001
3		Noninterest Income / Total Income	0.359	0.073
4		Volatility of ROA	0.001	0.001
5		Non-Interest Earning Assets / Total Assets	0.737	0.033
6	Efficiency	Interest Expense / Total Assets	0.005	0.004
7		Noninterest Expense / Total Assets	0.008	0.002
8	Capital	Total Equity Capital / Total Assets	0.085	0.014
9	Loan	Total Loans / Total Assets	0.463	0.051
10		Real Estate Loans / Total Assets	0.196	0.019
11		Commercial and Industrial Loans / Total Assets	0.072	0.019
12		Consumer Loans / Total Assets	0.082	0.011
13		Agricultural Loans / Total Assets	0.002	0.001
14		All Other Loans / Total Assets	0.027	0.007
15		Loan Concentration	0.270	0.033
16		Nonperforming Loans / Total Assets	0.012	0.008
17		Loan Loss Provision / Total Loans	0.003	0.003
18		Loan Growth Rate	1.032	0.058
19	Deposit	Total Deposits / Total Assets	0.364	0.052
20		Core Deposits / Total Assets	0.320	0.062
21		Noncore Deposits / Total Assets	0.043	0.013
22	Liquidity	Cash + Marketable Securities / Total Assets	0.199	0.045
23		Customer and Short-Term Funding / Total Assets	0.483	0.032
24		Log (12-Month Maturity Gap)	20.648	0.837
25		Log (Derivative Trading)	25.007	0.990
26		Tobin's q	1.076	0.063
27		Stock Beta	1.183	0.307
28		Volatility of Stock Return	0.092	0.029
29		P/E Ratio	29.234	22.459
	Stress Test		**Mean**	**Std. Dev**
30	GDPC1	Real GDP Growth	0.024	0.025
31	GDP	Nominal GDP Growth	0.044	0.028
32	DPIC96	Real Disposable Income Growth	0.028	0.038
33	DPI	Nominal Disposable Income Growth	0.046	0.040
34	UNRATE	Unemployment Rate	0.059	0.017
35	CPIAUCSL	CPI Inflation Rate	0.022	0.021
36	TB3MS	3-month Treasury Rate	0.022	0.022
37	GS5	5-year Treasury Yield	0.034	0.018
38	GS10	10-year Treasury Yield	0.040	0.015
39	FL073163013	BBB Corporate Yield	0.061	0.014
40	MORTGAGE30US	Mortgage Rate	0.058	0.022
41	RIFSPBLP_N	U.S. Prime Rate	0.055	0.311
42	DOWJONES	Log (Dow Jones Total Stock Market Index)	9.432	0.214
43	FL075035243	Log (House Price Index)	4.900	0.256

44	FL075035503	Log (Commercial Real Estate Price Index)	5.140	0.310
45	VXOCLS	Log (Market Volatility Index)	3.267	0.012
	Macroeconomic			
		Output & Income	**Mean**	**Std. Dev**
46	RPI	Real Personal Income	11,666	1,622.4
47	W875RX1	Real personal income ex transfer receipts	9,863.2	1,206.3
48	INDPRO	IP Index	95.828	7.1703
49	IPFPNSS	IP: Final Products and Nonindustrial Supplies	99.446	5.8398
50	IPFINAL	IP: Final Products (Market Group)	97.525	5.8967
51	IPCONGD	IP: Consumer Goods	104.30	5.0455
52	IPDCONGD	IP: Durable Consumer Goods	108.62	11.168
53	IPNCONGD	IP: Nondurable Consumer Goods	103.16	3.7932
54	IPBUSEQ	IP: Business Equipment	85.953	11.960
55	IPMAT	IP: Materials	91.799	9.8778
56	IPDMAT	IP: Durable Materials	87.016	14.903
57	IPNMAT	IP: Nondurable Materials	105.11	5.8068
58	IPMANSICS	IP: Manufacturing (SIC)	97.176	7.2402
59	IPB51222s	IP: Residential Utilities	98.906	7.7705
60	IPFUELS	IP: Fuels	91.439	10.454
61	CUMFNS	Capacity Utilization: Manufacturing	76.149	4.1667
		Labor Market	**Mean**	**Std. Dev**
62	HWI	Help-Wanted Index for United States	4,078.2	853.20
63	HWIURATIO	Ratio of Help Wanted/No. Unemployed	0.5169	0.2115
64	CLF16OV	Civilian Labor Force	148,904	7,328.1
65	CE16OV	Civilian Employment	140,004	6,222.5
66	UEMPMEAN	Average Duration of Unemployment (Weeks)	22.648	9.0116
67	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	2,654.4	205.75
68	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	2,471.9	511.87
69	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	3,780.2	2,302.0
70	UEMP15T26	Civilians Unemployed for 15-26 Weeks	1,372.6	557.07
71	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	2,407.7	1,806.3
72	CLAIMSx	Initial Claims	358,784	76,471
73	PAYEMS	All Employees: Total nonfarm	132,963	5,723.3
74	USGOOD	All Employees: Goods-Producing Industries	21,380	2,300.1
75	CES1021000001	All Employees: Mining and Logging: Mining	629.49	107.96
76	USCONS	All Employees: Construction	6,472.4	674.66
77	MANEMP	All Employees: Manufacturing	14,215	2,160.0
78	DMANEMP	All Employees: Durable goods	8,871.9	1,335.6
79	NDMANEMP	All Employees: Nondurable goods	5,343.2	835.34
80	SRVPRD	All Employees: Service-Providing Industries	111,583	7,064.6
81	USTPU	All Employees: Trade, Transportation & Utilities	25,732	779.73
82	USWTRADE	All Employees: Wholesale Trade	5,746.2	155.18
83	USTRADE	All Employees: Retail Trade	15,027	436.61
84	USFIRE	All Employees: Financial Activities	7,901.2	333.47
85	USGOVT	All Employees: Government	21,510	909.47
86	CES0600000007	Avg Weekly Hours : Goods-Producing	40.567	0.6235
87	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	4.3000	0.4909
88	AWHMAN	Avg Weekly Hours : Manufacturing	41.164	0.6222
89	CES0600000008	Avg Hourly Earnings : Goods-Producing	18.142	2.8440
90	CES2000000008	Avg Hourly Earnings : Construction	20.592	3.3175
91	CES3000000008	Avg Hourly Earnings : Manufacturing	16.786	2.3742
		Housing	**Mean**	**Std. Dev**
92	HOUST	Housing Starts: Total New Privately Owned	1,320.7	468.18
93	HOUSTNE	Housing Starts, Northeast	131.21	42.300
94	HOUSTMW	Housing Starts, Midwest	239.90	104.69

95	HOUSTS	Housing Starts, South	630.35	214.90
96	HOUSTW	Housing Starts, West	319.17	126.89
97	PERMIT	New Private Housing Permits (SAAR)	1,354.1	475.71
98	PERMITNE	New Private Housing Permits, Northeast (SAAR)	143.05	48.786
99	PERMITMW	New Private Housing Permits, Midwest (SAAR)	244.68	102.45
100	PERMITS	New Private Housing Permits, South (SAAR)	636.30	212.93
101	PERMITW	New Private Housing Permits, West (SAAR)	330.04	131.98
		Consumption, Orders, & Inventories	**Mean**	**Std. Dev**
102	DPCERA3M086SBEA	Real personal consumption expenditures	95.169	13.726
103	CMRMTSPLx	Real Manu. and Trade Industries Sales	1,045,566	108,468
104	RETAILx	Retail and Food Services Sales	337,830	71,657
105	ACOGNO	New Orders for Consumer Goods	157,540	34,477
106	AMDMNOx	New Orders for Durable Goods	198,401	26,472
107	ANDENOx	New Orders for Nondefense Capital Goods	66,159	11,204
108	AMDMUOx	Unfilled Orders for Durable Goods	757,046	250,524
109	BUSINVx	Total Business Inventories	1,361,031	259,645
110	ISRATIOx	Total Business: Inventories to Sales Ratio	1.3437	0.0682
111	UMCSENTx	Consumer Sentiment Index	87.290	12.867
		Money & Credit	**Mean**	**Std. Dev**
112	M1SL	M1 Money Stock	1,692.1	693.05
113	M2SL	M2 Money Stock	7,458.2	2,748.1
114	M2REAL	Real M2 Money Stock	3,607.6	861.20
115	BUSLOANS	Commercial and Industrial Loans	1,225.4	355.39
116	REALLN	Real Estate Loans at All Commercial Banks	2,728.8	1,023.1
117	NONREVSL	Total Nonrevolving Credit	1,531.9	559.30
118	CONSPI	Nonrevolving consumer credit to Personal Income	0.1329	0.0169
119	MZMSL	MZM Money Stock	7,922.9	3,375.3
120	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	228,783	77,624
121	DTCTHFNM	Total Consumer Loans and Leases Outstanding	670,137	192,451
122	INVEST	Securities in Bank Credit at All Commercial Banks	1,934.4	714.95
		Interest & Exchange Rates	**Mean**	**Std. Dev**
123	FEDFUNDS	Effective Federal Funds Rate	2.4513	2.3161
124	CP3Mx	3-Month AA Financial Commercial Paper Rate	2.5779	2.3004
125	TB6MS	6-Month Treasury Bill:	2.3238	2.1470
126	GS1	1-Year Treasury Rate	2.5249	2.2127
127	AAA	Moody's Seasoned Aaa Corporate Bond Yield	5.5724	1.2583
128	BAA	Moody's Seasoned Baa Corporate Bond Yield	6.5824	1.2171
129	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	0.1265	0.2263
130	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	-0.2355	0.3002
131	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	-0.1275	0.3150
132	T1YFFM	1-Year Treasury C Minus FEDFUNDS	0.0736	0.3804
133	T5YFFM	5-Year Treasury C Minus FEDFUNDS	0.9738	0.9345
134	T10YFFM	10-Year Treasury C Minus FEDFUNDS	1.5763	1.2640
135	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	3.1211	1.5159
136	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	4.1311	1.7457
137	TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies	86.901	11.216
138	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	1.2222	0.2555
139	EXJPUSx	Japan / U.S. Foreign Exchange Rate	108.38	14.454
140	EXUSUKx	U.S. / U.K. Foreign Exchange Rate	1.6321	0.1662
141	EXCAUSx	Canada / U.S. Foreign Exchange Rate	1.2572	0.1951
		Prices	**Mean**	**Std. Dev**
142	WPSFD49207	PPI: Finished Goods	162.97	25.012
143	WPSFD49502	PPI: Finished Consumer Goods	168.56	30.407

144	WPSID62	PPI: Crude Materials	172.91	55.776
145	OILPRICEx	Crude Oil, spliced WTI and Cushing	54.419	30.684
146	PPICMM	PPI: Metals and metal products:	172.26	57.442
147	CPIAPPSL	CPI : Apparel	124.87	4.8750
148	CPIMEDSL	CPI : Medical Care	339.37	74.490
149	CUSR0000SAC	CPI : Commodities	164.11	16.622
150	CUSR0000SAD	CPI : Durables	116.74	7.1375
151	CUSR0000SAS	CPI : Services	236.61	38.805
152	CPIULFSL	CPI : All Items Less Food	200.57	26.967
153	CUSR0000SA0L2	CPI : All items less shelter	191.45	25.470
154	CUSR0000SA0L5	CPI : All items less medical care	193.44	25.524
155	PCEPI	Personal Cons. Expend.: Chain Index	94.532	10.977
156	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	107.46	12.918
157	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	94.730	12.720
158	DSERRG3M086SBEA	Personal Cons. Exp: Services	92.569	14.216
		Stock Market	**Mean**	**Std. Dev**
159	S&P 500	S&P's Common Stock Price Index: Composite	1,307.9	379.96
160	S&P: industry	S&P's Common Stock Price Index: Industrials	1,626.9	554.65
161	S&P div yield	S&P's Composite Common Stock: Dividend Yield	1.8413	0.4080
162	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio	24.601	10.080

Appendix 4

Diebold-Mariano Test: Tier-1 Common Capital Ratio Out-of-Sample Prediction

(Recursive: RW Benchmark)

	S (k=16)	M (k=117)	B (k=29)	SM (k=133)	SB (k=45)	MB (k=146)	SMB (k=162)	
				h=1				**Best Subset**
PC (f=6)	-6.991	-6.961	-6.294	-7.128	-6.679	-6.951	-6.845	B
PC$_{RW}$ (f=3)	**1.175**	**0.624**	**1.723**	**0.955**	**1.916**	**1.544**	**1.802**	***SB***
PLS (f=6)	-7.487	-6.024	-5.520	-6.143	-5.300	-5.712	-5.933	MB
PLS$_{RW}$ (f=1)	0.515	-0.367	0.307	-0.324	0.360	-0.313	-0.275	S
Ridge	-7.401	-7.279	-7.263	-7.348	-7.446	-7.294	-7.361	B
Lasso	-7.372	-5.594	-6.728	-5.833	-6.886	-6.046	-6.259	M
Enet	-7.420	-6.244	-6.829	-6.238	-6.981	-6.061	-6.135	M
Ridge w/ Lag	-1.242	-7.171	-3.014	-7.211	-3.445	-7.172	-7.231	S
Lasso w/ Lag	-0.310	-1.102	-1.776	-1.326	0.444	-0.870	-0.667	SB
Enet w/ Lag	-0.769	-2.474	-2.326	-1.957	0.313	-1.465	-1.503	SB
Best Model	PC$_{RW}$	PC$_{RW}$	PC$_{RW}$	PLS$_{RW}$	PC$_{RW}$	PC$_{RW}$	PC$_{RW}$	
				h=4				**Best Subset**
PC (f=6)	-1.749	-2.845	-1.993	-2.902	-2.073	-2.868	-2.787	B
PC$_{RW}$ (f=3)	-1.251	-0.484	**0.695**	-0.509	-1.308	-0.664	-0.712	***B***
PLS (f=6)	-1.988	-1.835	-1.915	-1.654	-1.626	-1.860	-1.691	SMB
PLS$_{RW}$ (f=1)	-0.622	-0.823	-0.114	-0.817	-0.695	-0.818	-0.812	B
Ridge	-2.031	-2.354	-1.909	-2.315	-2.105	-2.344	-2.293	SMB
Lasso	-2.184	-2.374	-1.891	-2.394	-2.311	-2.242	-2.374	SM
Enet	-2.127	-2.229	-1.838	-2.330	-2.267	-2.505	-2.604	SM
Ridge w/ Lag	-1.417	-2.364	-1.185	-2.315	-1.370	-2.358	-2.306	B
Lasso w/ Lag	-1.691	-1.346	-1.584	-1.405	-1.181	-1.397	-1.486	B
Enet w/ Lag	-1.759	-1.389	-1.350	-1.470	-1.337	-1.491	-1.551	B
Best Model	RW	RW	RW	RW	RW	RW	RW	
				h=8				**Best Subset**
PC (f=6)	-0.676	-0.770	-0.557	-0.865	-0.590	-0.716	-0.890	MB
PC$_{RW}$ (f=3)	0.123	**1.191**	**0.770**	**1.160**	**0.737**	**1.229**	**1.194**	***M***
PLS (f=6)	-0.906	-0.619	-0.896	-0.359	-1.076	-0.824	-0.587	SM
PLS$_{RW}$ (f=1)	-4.527	0.475	0.268	0.416	-0.146	0.680	0.601	MB
Ridge	-0.755	-0.694	-0.699	-0.704	-0.725	-0.687	-0.692	SM
Lasso	-0.972	-2.523	-0.721	-1.764	-0.832	-1.606	-1.724	SM
Enet	-0.873	-1.821	-0.720	-1.087	-0.806	-1.134	-1.165	SM
Ridge w/ Lag	-0.683	-0.688	-0.598	-0.694	-0.638	-0.690	-0.696	B
Lasso w/ Lag	-0.747	-1.722	-0.638	-1.068	-0.798	-1.509	-1.130	SM
Enet w/ Lag	-0.790	-1.175	-0.622	-1.012	-0.762	-1.188	-1.057	SM
Best Model	RW	PC$_{RW}$	PC$_{RW}$	RW	PC$_{RW}$	PC$_{RW}$	RW	
				h=12				**Best Subset**
PC (f=6)	-0.244	0.665	-0.217	0.651	-0.188	0.675	0.667	SMB
PC$_{RW}$ (f=3)	**1.080**	**2.405**	**5.053**	**2.561**	**1.516**	**2.505**	**2.679**	***M***
PLS (f=6)	-0.348	0.337	-0.294	0.353	-0.321	0.183	0.186	SM
PLS$_{RW}$ (f=1)	0.676	**2.798**	**1.336**	**2.766**	**1.182**	**2.765**	**2.724**	***M***
Ridge	-0.238	0.149	-0.293	0.115	-0.261	0.159	0.122	MB
Lasso	-0.280	0.586	-0.281	0.588	-0.243	0.510	0.498	M
Enet	-0.282	0.548	-0.285	0.522	-0.242	0.473	0.454	M
Ridge w/ Lag	-0.345	0.132	-0.402	0.082	-0.323	0.113	0.086	M
Lasso w/ Lag	-0.385	0.582	-0.447	0.580	-0.440	0.530	0.512	M
Enet w/ Lag	-0.380	0.544	-0.459	0.531	-0.409	0.461	0.458	M
Best Model	PC$_{RW}$	PC	PLS$_{RW}$	PC	PLS$_{RW}$	PC	PC	

Note: DM statistics in bold indicate the rejection of the null hypothesis of equal predictability at the 5% significance level in favor of our alternative models.

Appendix 5

Variable (Feature) Selection by LASSO

As noted in Section 3.4.4, models estimated by the LASSO can include only a subset of predictors and thereby the LASSO naturally performs variable (or feature) selection (Zou and Hastie, 2005). In this section, we use the LASSO to identify which groups of variables help forecast the T1CR, using the subsets of bank or stress predictor variables. Note that 16 stress test variables must be included in stress test models and these stress test variables, if selected correctly, should be useful in forecasting the T1CR.

[Figure A5.1]

Figure A5.1 presents coefficient estimates of selected variables in out-of-sample prediction by LASSO. Figure A5.1 (a) shows coefficient estimates of bank variables for the short-term (*1*-quarter ahead) and the long-term (*12*-quarter ahead). For the short-term, volatility of ROA (id 4), nonperforming loans/total assets (id 16), and loan loss provision/total assets (id 17) are selected to be most useful predictors in out-of-sample forecasts by the LASSO. Interestingly, for the long-term, the coefficient estimates of these three variables have opposite signs. The T1CR for the short-term is projected to decline under stressful economic condition which can be captured by an increase in volatility of ROA, nonperforming loans/total assets, and loan loss provision/total assets. For the long-term, however, the coefficient estimates of these same variables show opposite signs. This inverse relation is consistent with a ‘‘precautionary” view of bank capital structure. Such a view contends that a bank involved in more volatile or risky activities will endogenously choose to hold a larger capital buffer, in order to minimize the likelihood of becoming undercapitalized (Hirtle et al., 2016).

Figure A5.1 (b) presents coefficient estimates of stress test variables for the short-term and the long-term. For the short-term, unemployment rate (id 34), BBB corporate yield (id 39), mortgage rate (id 40), and house price index (id 43) are selected to be most useful predictors in out-of-sample forecasts by the LASSO. For the long-term, 3-month T-bill rate (id 36) and U.S. prime rate (id 41) are additionally selected to be useful predictors in out-of-sample forecasts by the LASSO. It should be noted that we are not trying to test the statistical significance of these variables since we are mainly interested in variables that help increase out-of-sample prediction accuracy.