THREE ESSAYS ON BANKING CONCENTRATION

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ABSTRACT

Banks warrant special attention because of the key role they play in providing liquidity to the market, transforming assets, managing risks, and monitoring borrowers. Over the past few decades, the US banking system consolidated considerably which resulted in a more concentrated system where the majority of assets are controlled by a few excessively large institutions. This dissertation examines concentration of the US banking sector and its relationship with the real economy, idiosyncratic bank stability, and financial market volatility.

Chapter 1 investigates the association between banking concentration and the real economy through the bank failures channel. To this end, we build a system of equations that estimates the association between banking concentration and the real economy by employing quarterly U.S. data from 1984 through 2013. The first equation tests the association between bank concentration and the rate of bank failure using an autoregressive Poisson model which allows for more accurate estimates than linear models. The remaining three equations model respectively, real GDP growth, unemployment, and inflation as functions of the rate of bank failure. Three interesting results are obtained. First, there is a threshold below which increasing concentration causes a reduction in bank failures and above which an increase in failures. Second, as bank failures increase, economic growth slows while unemployment and inflation both increase. Third, our results imply that the U.S. banking system is more than twice as concentrated as the optimal level as determined by the minimum rate of bank failure and is having a detrimental effect on the real economy. Our results suggest that while the

Dodd-Frank Act of 2010 introduced legislation aimed in part at restricting the level of banking concentration, additional reductions in concentration may be necessary to strengthen the economy.

Chapter 2 investigates the association between banking concentration and idiosyncratic bank stability after the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 into legislation. First, we model individual bank stability as a non-linear, as opposed to a linear, function of banking concentration allowing us to determine if rising concentration increases (decreases) bank stability up to a certain point and decreases (increases) it thereafter. Second, we differentiate between large and small banks by introducing an interaction term between concentration and bank size allowing us to determine if size-based differences alter the concentration-stability relationship. Third, we employ a fixed effects instrumental variable model and correct for reverse causality between bank stability and bank concentration. Our findings indicate that large and small banks react very differently to changes in concentration. As concentration exceeds a certain threshold, small banks become less stable, hold less capital, are less profitable, and hold more volatile portfolios. The results are the reverse for large banks. We also find that as concentration increases, large banks increasingly contribute to systemic risk, despite the fact that their idiosyncratic risk is reduced.

Chapter 3 investigates the association between financial market volatility and banking concentration. Research on this relationship has been sparse and remains ambiguous. A main difficulty with achieving this task is the low frequency (quarterly) nature of the concentration data relative to the high frequency (daily) volatility data. To

overcome this problem, we employ a GARCH-MIDAS volatility model which allows us to test the relationship between data with dissimilar frequencies. We consider the sample period 1986:1 to 2013:4. Our results indicate that higher levels of banking concentration are positively associated with higher volatility in the US stock, options, and corporate bond markets and negatively associated with the US government bond volatility. These finding fill a major void in the literature and have implications for regulators and policy makers.

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CHAPTER 1
THE ASSOCIATION BETWEEN BANKING CONCENTRATION AND THE REAL ECONOMY

1.1 Introduction

Stability of the banking sector is important in maintaining a stable and strong economy because of the key role banks play in financial intermediation, facilitating payment flows, credit allocation, and maintaining financial discipline among borrowers (Lindgren, Garcia, and Saal, 1996). This point was clearly manifested during the recent financial crisis of 2007-2009. In its simplest form, a bank is an institution that grants loans and takes deposits from the public, and in doing so, performs a critical role in allocating capital in the economy (Merton, 1993). Banks provide liquidity to the market, transform assets, manage risks, and monitor borrowers (Frexias and Rochet, 2008). They also administer the national payment mechanism and play a role in directing capital to favored sectors such as housing and agriculture (Saunders and Cornett, 2014). Without a stable banking sector, these functions cannot be performed effectively, resulting in harm to the health of the economy.

At the heart of the stability of the banking system, is the frequency and depth of bank failures. A bank fails when it can no longer meet its obligations to its depositors or other creditors. It is often argued that bank failures have a greater negative effect on the economy and are more damaging than other types of business failures (Vives, 2016). The rationale is that because of the intricate network of banks and depositors, failure of an individual bank can trigger a state of system-wide bank failures, a phenomenon known as

contagion. A greater concern is that bank failures can spread into the rest of the financial system, spillover to the real sector of the domestic economy, and thereby, to the economies of other countries (Vives 2016). Studies by Grossman (1993) and Kupiec and Ramirez (2013) have demonstrated that increases in the rate of bank failures have an adverse effect on the real economy.

A related and highly debated topic is the level of bank concentration that should be maintained. Under a highly concentrated system, a few banks hold a large share of the overall assets (deposits) while a system with a low level of concentration has a large number of banks with each bank holding a small share of assets (deposits). Research on the relationship between banking concentration and stability of the banking system has produced conflicting results. There are two main views; concentration-stability and concentration-fragility. Keely (1990), Deltuvaite (2010), Beck, Demirgüç-Kunt, and Levine (2006) all support the concentration-stability view suggesting that more concentrated banking systems are more stable. Along the same lines, Allen and Gale (2000, 2004) claim that banks in more concentrated markets earn higher profits, are more diversified, and easier to monitor because there are fewer banks to regulate. While these studies provide evidence that favor a concentrated banking system, there are potentially dangerous side effects. For example, banks operating in a highly concentrated system may become too large for the regulators to dare let them fail (too big to fail), hold too much market power and, consequently, gain too much political power, and become too complex to be managed effectively. Additionally, too big to fail banks (TBTF) banks

introduce a moral hazard problem because they have an incentive to take excessive risk resulting in costly government bailouts when they are in danger of failing (Vives, 2016).

The opposing view, concentration-fragility, argues that a more concentrated banking system is less stable. Boyd and DeNicolo (2005) and Ude and Heimeshom (2009) among others, support this view both theoretically and empirically. The argument is that banks in less concentrated markets hold less risky assets in their portfolios because borrowers have less incentive to undertake risky projects. To elaborate, this theory stems from the relationship between banks and borrowers. As markets become more concentrated and banks achieve greater market power, rates on loans given to borrowers will increase, curtailing borrower profitability[1]. To compensate for lower profits, borrowers are driven to undertake riskier projects, with a higher potential return, but also a greater risk of failure. While there is empirical evidence to support this claim (Boyd, DeNicolo, and Jalal (2006), Ude and Heimeshom (2009), markets that have a low level of concentration have their drawbacks as well. Because there are more banks in this latter system, monitoring is more costly and difficult for regulators to undertake. Also, smaller banks are less able to handle negative shocks, especially larger shocks, to the banking system, withstand competition from domestic and international financial institutions, and innovate or adopt the newest technologies which could raise their profits.

Notable problems with previous research include the lack of a clear definition of stability and the failure to capture the link between bank concentration and the real

[1] Prior to 1986, regulation Q imposed an interest rate ceiling on bank deposits. One of the objectives of the interest rate ceiling was to limit competition for deposits thereby increasing bank profits and weakening the incentives of banks to invest in risky assets (Gilbert, 1986).

economy. Some previous studies establish the link between concentration and systemic risk (e.g. Beck, Demirgüç-Kunt, and Levine, 2006), some others study the link between concentration and stability of individual banks (e.g. Boyd, DeNicolo, and Jalal, 2006), and still other studies test the impact of bank stability on the real economy, but fail to include bank concentration (e.g. Kupiec and Ramirez, 2013).

This study contributes to the literature by combining two independent strands of literature into one integrated econometric framework, thereby establishing the link between banking concentration and the real economy. To this end, we take the following steps. First, we investigate the association between bank concentration and the rate at which commercial banks fail and/or become stressed. To conduct our investigation, we build upon and significantly improve the methodology followed by Schoenmaker (1998) and Davuytan (1989) to build an autoregressive Poisson model that estimates the relationship between bank concentration and the rate of bank failure and the rate at which banks become stressed. The Poisson model employed here has a major advantage over linear models in the context of bank failures in that it provides more reliable results. Additional details on the advantages of the Poisson model are outlined in section 1.3.

Second, we investigate the relationship between the rates of bank failure and distress and real economic variables including real GDP growth, unemployment, and inflation. Our study extends the work of Grossman (1993) and Kupiec and Ramirez (2013) by simultaneously estimating the impact of bank failures and, separately, bank failures, on multiple macroeconomic variables. The results drawn from this broader framework of analysis are more reliable because the interdependencies among the

variables are accounted for, and can help policymakers understand how banking concentration affects the real economy through the bank failure and distressed bank channels.

To help reduce to bias that may result from the simultaneous nature of the model, estimation of the four equation system is carried out using the Three-Stage Generalized Method of Moments (GMM) estimator. As a check of robustness, each equation is estimated separately with either the Two-Stage GMM or the Two-Stage Least Squares (2SLS) estimators. Additional discussion of details that pertain to endogeneity bias are outlined in section 1.3.2. Employing the quarterly data from the 1984:1-2013:4 time period, we obtain two significant sets of results from our extended framework. First, we find that there is a non-linear relationship between the rates of bank failure and distress and concentration. In particular, there is an optimal level of concentration where the rates of bank failure and distress are minimized. These results are robust to various measures of concentration including the Herfindahl–Hirschman Index (HHI) and the percent of assets held at the largest three, five, and ten banks. Second, we find that higher rates of bank failure and greater rates of bank distress are negatively associated with economic growth and employment and positively associated with inflation. These results are in agreement with the findings of Grossman (1993) and Kupiec and Ramirez, (2013) but are more reliable because we employ a Poisson model and include the risk of contagion. Taken together, our model indicates that as concentration increases towards the optimal level, as indicated by the results, the rates of bank failure and distress decrease resulting in greater economic growth, higher employment, and lower levels of inflation. However,

as concentration increases and exceeds the optimal level, as indicated by the results, the rates of bank failure and distress increase and has a detrimental impact to the US economy through a reduction in economic growth and employment, and an increase in inflation.

We make several contributions to the literature. First, we add insight to the concentration-stability versus concentration-fragility debate. The findings have major implications on bank regulation, mergers and acquisition and government bailout of stressed banks. Second, we use a Poisson model of bank failure, which is superior to the linear models employed in the literature in terms of accuracy and reliability. Moreover, we extend the Poisson model to incorporate lagged terms into the analysis. This technique, which is being applied to this area of economic research for the first time, allows us to account for the effects of previous bank failures on stability. A more detailed analysis of the benefits of an autoregressive Poisson regression is outlined in the model section. Third, our model quantifies the impact of banking concentration on the real economy. Previous attempts test the impact of concentration on individual bank risk levels (Boyd, DeNicolo, and Jalal 2006) or determine if concentration affects the probability of a systemic crisis (Beck, Demirgüç-Kunt, and Levine 2006). These studies are important, but add to the concentration-stability versus concentration-fragility debate in a different way and do not test the impact of concentration on real economic variables. Fourth, we examine bank failures as well as stressed banks, the latter of which were not included in previous research. Finally, we employ a clear definition of bank stability at the aggregate level, which is lacking in previous studies.

The remaining sections of this paper are organized as follows. Section two provides an overview of previous research and explanations of the hypotheses we test. Section three discusses the model and Section four describes the data sources and variable construction. Section five presents the results and interpretation of our findings and section six contains concluding remarks and policy implications.

1.2 Literature Review

There have been numerous attempts, both theoretically and empirically, to test the relationship between banking concentration and some measure of bank stability. However, stability is defined and analyzed differently in different studies. For example, some studies consider individual banks and examine the level of risk the bank takes as a result of the system concentration level. Other studies define stability in a systemic approach and estimate the impact of concentration in the banking industry on the probability of occurrence of a crisis in the banking system. Our review of the previous research will highlight the different approaches and will discuss the array of conflicting results on the subject.

Economists have debated the effects of banking concentration for decades (e.g. Schaeck and Cihak, 2007). The level of banking concentration varies greatly between countries. For example, the banking systems of Germany and Japan are dominated by a handful of banks and provide the majority of financing to their respective economies (Allen and Gale, 2000). In contrast, the banking system of the United States is far less concentrated and consists of thousands of smaller banks (Allen and Gale, 2000). The US banking industry, however, has consolidated significantly since the mid-1980s (Jones and

Critchfield, 2005). The number of commercial banks operating in the US declined from 14,484 in 1984 to 7,630 by 2004 due to a series of bank failures during the S&L crisis of the 1980s and by a wave of mergers resulting from deregulation and technological advancements in the 1990s[2] (Mester, 2005; Vives, 2016). The result of this consolidation is a banking system where approximately ten mega-banks control roughly half of system-wide assets; the remaining half is controlled by a few thousand smaller banks (Berger, Molyneux, and Wilson, 2010). The US banking system provides a good model to study because it contains elements of both a highly concentrated and highly unconcentrated banking system. Furthermore, the consolidation of the US banking sector has prompted the concerns of regulators and policy makers.

There are two main views; concentration-stability and concentration-fragility. Keely (1990), Deltuvaite (2010), Beck, Demirgüç-Kunt, and Levine (2006) all support the concentration-stability view suggesting that more concentrated banking systems are more stable. Along the same lines, Allen and Gale (2000, 2004) claim that banks in more concentrated markets earn higher profits, are more diversified and easier to monitor because there are fewer banks to regulate. Furthermore, it is argued that more efficient banks and higher X-efficiency[3] are advantages associated with higher levels of banking concentration (Mester, 2005). However, there are potentially dangerous side effects to a highly concentrated banking system. For example, banks operating in a highly

[2] In particular, the US banking system underwent a wave of mergers after the passage of the Riegle-Neal Interstate Banking Act (RN) of 1994 which allowed bank holding companies to acquire branches across state boundaries (Heiney, 2011).

[3] X-efficiencies are cost savings that arise from greater managerial efficiency of the acquiring bank (Saunders and Cornett, 2014).

concentrated system may become too large for the regulators to dare let them fail (too big to fail), hold too much market power and, consequently, gain too much political power, and too complex to be managed effectively. Additionally, too big to fail banks (TBTF) banks introduce a moral hazard problem because they have an incentive to take excessive risk resulting in costly government bailouts when they are in danger of failing (Wheelock, 2012).

Research on the effects of banking concentration has produced conflicting results. Some theoretical arguments and empirical evidence support the concentration-stability argument claiming that concentrated banking systems are less prone to crisis than systems with many smaller banks and lower concentration (Allen and Gale, 2004). Beck, Demirgüç-Kunt, and Levine (2006) assess the impact national bank concentration has on the likelihood a country suffers a systemic banking crisis[4]. They find a negative relationship between bank concentration and the likelihood of a banking crisis occurring. However, in the same study, the authors find that countries with a high level of entry restrictions have a higher probability of experiencing a systemic crisis. In other words, countries that discourage competition and have a higher concentration level are more likely to experience a crisis; a finding that conflicts with their previous results.

[4] For this study, a banking crisis is defined as an episode where the country experienced a situation where the percentage of non-performing loans as a percentage of total bank assets exceeded 10 percent or if the government took extraordinary steps to stabilize the banking system, such as declaring a bank holiday or nationalizing the banking system. An example is Chili from 1981-1987 where it experienced severe macroeconomic conditions causing the government to nationalize a large percentage of the banking system.

Similarly, Evrensel (2008)[5] and Schaeck, Chihák, and Wolfe (2009)[6] attempt to estimate the relationship between concentration and the time until a banking crisis occurs but produce conflicting results. Evrensel (2008) concludes that high levels of concentration are associated with higher times to failure implying a more stable system while Schaeck, Chihák, and Wolfe (2009) find and inverse relationship. Each of these studies employ a similar methodology, but use a different data set which could be the reason for dissimilarity of the results.

Another strand of literature examines individual bank behavior. Banks in highly concentrated systems may have greater market power, earn higher profits, and have a greater buffer against adverse shocks (Beck, Demirgüç-Kunt, and Levin, 2006). Keely (1990) considers the "Charter Value Hypothesis (CVH)" indicating that as the charter value of a bank increases, the bank will hold a higher level of safe assets. His theoretical model indicates that bank profitability increases as a result of greater market power. As profitability increases, so does the bank's charter value. This, in turn, drives banks to hold safer assets resulting in a more stable banking system.

Keely (1990) empirically tests his theoretical findings using data from the US Savings and Loan crisis of the 1980s. The results are consistent with his theoretical findings. Specifically, when the banking system was less concentrated and composed of a large number of banks and savings associations, banks in general had a low profit margin. The rationale is that since the charter values were low, banks had incentives to hold

[5] Evrensel (2008) examines 79 countries from 1980 to 1987 and includes 50 episodes of banking crises.

[6] Schaeck, Chihák, and Wolfe (2009) examine 45 countries from 1980-2005.

riskier assets. When the value of these assets fell during the crisis, a large percentage of savings associations, as well as commercial banks, failed. In short, Keely's results indicate that higher levels of concentration will result in safer assets held by banks, and consequently lead to a more stable banking system.

Boyd and DeNicolo (2005) differ from Keely (1990) in that they shift the decision making from the bank to the borrower. In the Boyd and DeNicolo's (BDN) model, the borrower seeks to optimize his/her profits. As the concentration among banks decreases, the rates offered on loans will decrease. As a result, the borrower realizes a higher amount of profit. Conversely, as the level of concentration among banks increases, rates offered on loans increase, which negatively affect the borrower's profits. Because profits are smaller, borrowers have an incentive to undertake riskier projects in the hopes of realizing higher returns. The BDN model indicates that higher concentration results in riskier assets held by the banks.

Boyd, DeNicolo and Jalal (2006) empirically test the propositions put forward in the BDN model. They regress the individual bank's Z-scores, as a measure of bank stability[7], on bank concentration as well as various macroeconomic indicators. Their results support the theoretical model of Boyd and DeNicolo (2005) as they find a negative relationship between the Z-score and concentration. That is, as concentration increases, the Z-score decreases implying the banks are holding riskier assets and are less stable.

[7] The Z-score measures how large an adverse shock would have to be in order for the bank to become insolvent. A low Z-score implies that a small shock would be sufficient to drive the bank into insolvency.

Martinez-Miera and Repullo (2010) extend the model of Boyd and De Nicolo (2005). Their hypothesis is that while lower concentration reduces interest rates and causes borrowers to undertake less risky projects, interest rate payments on non-defaulting loans are also reduced resulting in lower profit margins for the bank. Their theoretical model indicates a U-shaped relationship between competition and the risk of bank failure, such that the risk of bank failure decreases as concentration increases up to a certain point. After that point, the effect is reversed.

The studies presented thus far highlight some of the recent contributions to the concentration-stability and concentration-fragility debate. The results of these studies are conflicting. They also fail to offer insight on the association between concentration and real economic variables which is the theme of the current study. There have been attempts, however, to study the impact of bank stability on the real economy. Kupiec and Ramirez (2013) estimate the association between U.S. bank failures and economic growth from 1900 to 1930. By using a vector auto-regression model (VAR), they estimate that bank failures have a negative association with economic growth up to three quarters following a shock to the banking system. Furthermore, their results are consistent with those of Grossman (1993) who performed a similar analysis and found that increases in bank failures lead to decreases in economic growth. These results are encouraging, but some of the techniques employed are disputable and the sample periods are dated. First, both Grossman (1993) and Kupiec and Ramirez (2013) employ VAR models and assume that bank failures are normally distributed. Because the number of bank failures in a given time period are strictly non-negative integer values, using models

designed for normally distributed data may lead to inaccurate results. As explained by Cameron and Trevedi (2013), applying a linear model to count data can lead to negative or non-integer predicted values which are not sensible and of little use for analyzing count data. Second, neither paper includes any measure of bank concentration.

Schoenmaker (1998) studies bank stability by examining monthly bank failures from 1880 to 1936. The purpose of his study is to determine if bank contagion[8] was an actual risk to the US economy during his sample period. The author uses an autoregressive Poisson model to address two shortcomings in the previous models. First, to account for the count nature of bank failure data. Second, to make it possible for bank failures to be modeled as a function of previous bank failures. Within this model, he finds that contagion did present a risk to the U.S. banking system.

Our study combines two independent strands of literature. First, we establish the relationship between bank concentration and bank failures with an autoregressive Poisson model. This allows for more reliable inference because it captures the count nature of the data and allows lagged observations of bank failures to be included in the model (Cameron and Trevedi, 2013). Second, we simultaneously estimate the association between bank failures (or bank distress) on the one hand, and economic growth, unemployment, and inflation, on the other. In this context, Lindgren, Garcia, and Saal (1996) argue that a distressed banking system fails to intermediate savings effectively, causing a detrimental effect on the real economy. These authors also contend that as soundness of banking system diminishes, normal relationships between policy

[8] This author defines contagion to be an episode where an initial bank failure generates subsequent bank failures.

instruments and targeted objectives become distorted. As an example, the credit channel for monetary policy transmission becomes less efficient because credit availability becomes less responsive to policy instruments. As a second example, transmission of monetary policy through interest rates will become constrained because of the inability of banks to adjust their reserves and lending in response to monetary policy.

As mentioned previously, the first equation of our system estimates the association between bank failures (bank stress) and bank concentration. Banks often merge when they are close to failure, or in a state of distress, in order to preserve their value, elevating the level of concentration in the industry as a result (Jones and Critchfield, 2005). Therefore, it is important to investigate the relationship between bank failures and concentration in terms of direction and magnitude of the effect and, in particular, to determine if concentration is endogenous in nature. If so, the results based on single-equation models could be biased and unreliable. An instrumental variable approach would then be needed to help correct for any bias caused by endogeneity. Therefore, we propose the following hypothesis (a summary of hypotheses is presented in Table 1-1):

Table 1-1: Hypotheses

Abbreviation	Hypothesis
H1	*The association between bank failures and banking concentration is unidirectional.*
H2	*There is no bank contagion risk.*
H3	*There is a non-linear relationship between bank failures and concentration such that increased concentration lowers failures up to a minimum point and then demonstrates a positive relationship with bank failures thereafter*.
H4	*Real GDP growth and bank failures are inversely related.*
H5	*Unemployment and bank failures move in the same direction.*
H6	*Inflation and bank failures move in the same direction.*

H1: *The association between bank failures and banking concentration is unidirectional*.

Studies by Aharony and Swary (1983) and Swary (1986) fail to offer evidence that contagion[9] is a risk to the US banking system. Schoenmaker (1998) argues that their results are disputable because their data come from a period when the Federal Reserve acted as a lender of last resort. We follow Schoenmaker (1998) and define contagion as the risk that an initial bank failure(s) may spill over to the rest of the banking industry and cause further bank failures. If contagion is in fact a threat, it is necessary to control for it in the model. Therefore, we propose the following hypothesis.

H2: *There is no bank contagion risk.*

Previous studies assume a linear relationship between banking stability and concentration. This relation may, however, be non-linear, in reality. It is possible that concentration exerts a positive impact on bank stability up to a certain point and a negative impact thereafter (Martinez-Miera and Repullo, 2010). To test if there is an optimal level of bank concentration where failures are minimized, we include a linear and a squared term of concentration. The following hypothesis is tested.

H3: *There is a non-linear relationship between bank failures and concentration such that increased concentration lowers failures up to a minimum point and then demonstrates a positive relationship with bank failures thereafter*.

[9] Contagion is defined as an episode where an initial bank failure generates subsequent bank failures

As stated earlier, banking instability can have a detrimental effect on the real economy because savings cannot be intermediated effectively (Lindgren, Garcia, and Saal ,1996). To investigate this issue, we test the following hypothesis.

H4: R*eal GDP growth and bank failures are inversely related.*

If bank failures are associated with slower real GDP growth, then they are also likely to increase the unemployment level. Gatti, Rault, and Vaubourge (2012) include bank concentration as a control variable when analyzing unemployment. Their results indicate that bank concentration has a positive relationship with unemployment. Thus, we propose:

H5: *Unemployment and bank failures move in the same direction.*

As stated before, lack of soundness in the banking system can distort the transmission of monetary policy through interest rates because of the inability of banks to adjust their reserves and lending in response to monetary policy (Lindgren, Garcia, and Saal, 1996). Therefore, we test the following hypothesis.

H6: *Inflation and bank failures move in the same direction.*

Additionally, we extend the above hypotheses by considering stressed banks instead of failed banks. Analysis of stressed banks is very similar to that of failed banks and simply replaces bank failures with data on stressed banks in the model outlined in the next section. Therefore, each of the above hypotheses are tested with stressed banks.

1.3 Model and Methodology

This section contains a description of the econometric model used to test the hypotheses listed above along with a justification for each control variable. Because we

assume that bank failures (stressed banks), real GDP growth, unemployment, and inflation are simultaneously determined, the model consists of four equations. We present the model first and proceed with a detailed explanation for each equation of the model.

1.3.1 Empirical Model

Following Schoenmaker (1998), Grossman (1993), and Kupiec and Ramirez (2013), we construct the model outlined below to test the above hypotheses. The model consists of four equations written as follows.

$$\begin{aligned} Failures_t = exp\Big(& \beta_0 + \beta_1 Concentration_t + \beta_2 Concentration_t^2 + \beta_3 CER_{t-1} \\ & + \beta_4 ROA_{t-1} + \beta_5 GDPG_t + \beta_6 Unemployment_t + \beta_7 \Delta IR_t \\ & + \beta_8 Inflation_t + \beta_9 Insurance \\ & + \sum_{i=1}^{2} \gamma_i \log\ (Failure\ Rate_{t-i}^{*}) + Banks_t \Big) \end{aligned} \tag{1.1}$$

$$\begin{aligned} GDPG_t = {} & \delta_0 + \delta_1 Failure\ Rate_t + \delta_2 Unemployment_t + \delta_3 \Delta FX_t + \delta_4 \Delta IR_t \\ & + \delta_5 Inflation_t + \delta_6 GLBA_t + \delta_7 \Delta\ GOV_t + \delta_8 Recession_t \end{aligned} \tag{1.2}$$

$$\begin{aligned} Unemployment_t = {} & \theta_0 + \theta_1 FailureRate_t + \theta_2 \Delta FX_t + \theta_3 \Delta IR_t + \theta_4 GDPG_t + \\ & \theta_5 Inflation_t + \theta_6 GLBA_t \end{aligned} \tag{1.3}$$

$$\begin{aligned} Inflation_t = {} & \varphi_0 + \varphi_1 FailureRate_t + \varphi_2 \Delta FX_t + \varphi_3 \Delta IR_t + \varphi_4 Unemployment_t \\ & + \varphi_5 GDPG_t + \varphi_6 \Delta M2_t + \varphi_t Oil_t \end{aligned} \tag{1.4}$$

Following Schoenmaker (1998), we model bank failures (*Failures*) with a Poisson model as presented in equation 1.1[10]. Because the number of failures (stressed banks) is strictly a non-negative integer value, using ordinary least squares (OLS), or other models that assume normality to estimate the model, may yield inaccurate or even nonsensical results (Cameron and Trevedi, 2013). Predicted values obtained from OLS regression on count data could result in negative or non-integer values (Cameron and Trevedi, 2013). To account for the non-normal distribution of bank failures, a generalized linear model (GLM) is employed. Because the data follow a count structure, a Poisson model is the best starting point and is the benchmark parametric model for count data (Cameron and Trevedi, 2013).

OLS and Poisson predicted values are displayed in Figure 1-1 along with observed failure rate values. The negative OLS predicted values call into question the reliability of the estimated parameters. Predicted values from the Poisson regression are strictly non-negative implying the estimated parameters are more reliable. When employing a GLM, a link function must be defined that relates the independent variables to the expected value of the dependent variable. The standard link function for the Poisson model is the natural logarithm. That is, $\ln(\lambda) = \beta X$ or equivocally $\lambda = exp(\beta X)$ where X is a vector of explanatory variables, β is a vector of coefficients to be estimated, and λ is the expected value of the dependent variable.

[10] Kupiec and Ramirez (2013) examine liabilities held by failed banking institutions instead of the number of bank failures. However, as explained by Grossman (1993), it is the number of bank failures that has a substantial impact on aggregate stability.

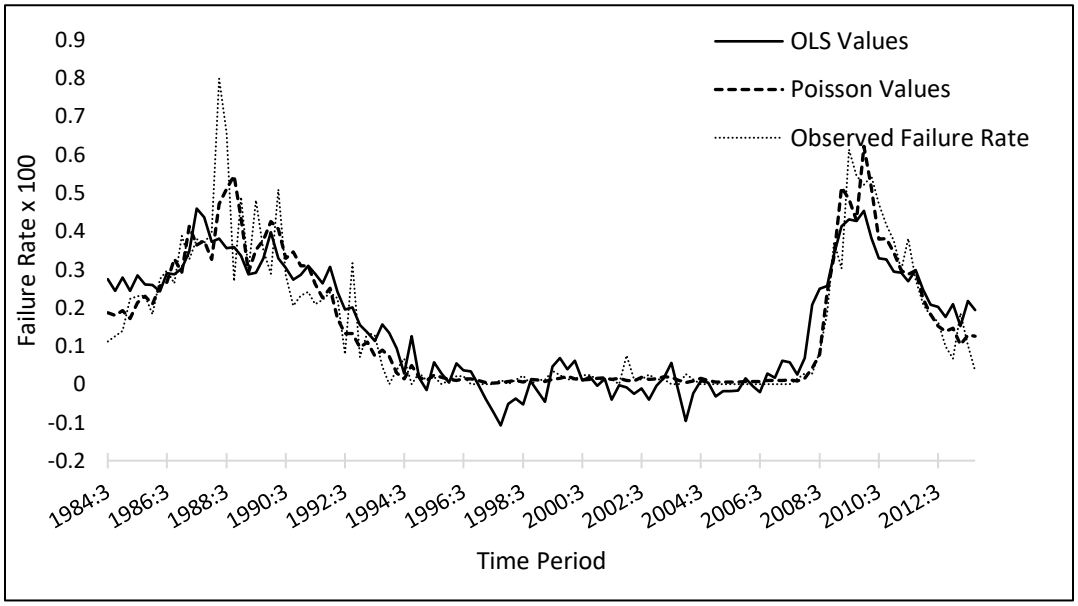

Figure 1-1: Predicted Failure Rate; OLS and Poisson

The main variable of interest in this model is *Concentration*. Consistent with the literature, we employ the HHI[11] and asset share of the largest three, five, and ten, commercial banks in the U.S. There may be reverse causality between bank failures and concentration in the sense that failures lead to greater concentration or influence banks to consolidate in the hopes of becoming more stable (Jones and Critchfield, 2005). Additional details that pertain to endogeneity issues are discussed in section 1.3.2.

It is possible that the level of concentration could reduce failures up to a certain level and increase failures above it (Martinez-Miera and Repullo, 2010). Hence, there may be a non-linear relationship between concentration and bank failures. We include the

[11] The HHI is calculated by summing the squares of market share held by each bank. For example, if two bank each hold 50 percent of the market, then the HHI is $50^2 + 50^2 = 5000$. The HHI can range from 0, indicating perfect competition, to 10,000 indicating a pure monopoly.

squared term of *Concentration* in the *Failures* equation. This will help determine if there is an optimal level of concentration where failures are minimized.

The following control variables are included in the *Failures* equation; Capital Equity to Asset Ratio (*CER*), Return on Assets (*ROA*)[12], real GDP growth (*GDPG*), interest rates (*IR*), inflation (*Inflation*), unemployment (Unemployment) and two lagged terms of the log of bank failure rate[13] (log *Failure Rate*). Higher levels of capital equity provide a greater cushion against adverse macroeconomic conditions resulting in fewer failures (Estrella, Park, and Peristiani, 2000). While the minimum level of capital a bank must hold is exogenous, the actual amount held by a bank is endogenous. Banks often alter their level of capital equity in response to economic conditions[14]. To help alleviate any issues that may arise due to simultaneity between failed banks and capital equity asset ratio, we lag *CER* by one period[15]. *ROA* measures bank profitability. As profitability strengthens, banks have a larger cushion in the event of adverse macroeconomic conditions. This should result in fewer bank failures. As with *CER*, we lag *ROA* by one period to help alleviate any issues that may arise from endogeneity.

We include real GDP growth (*GDPG)*, inflation (*Inflation)*, unemployment (*Unemployment)*, and interest rates (*IR)* into our model. As described by Lindgren,

[12] We also test Return on Equity in place of ROA as a robustness check. The results are consistent in both sign and significance.

[13] We include log *Failure Rate* instead of log *Failures* because we include an exposure variable. The exposure variable allows us to account normalize *Failures* and account for the size of the banking system. A detailed explanation of the exposure variable is provided in Appendix A.

[14] Berger, DeYoung, Flannery, Lee, and Öztekin (2008) examine capital ratios of large banking institutions. Their findings indicate that large banking institutions often maintain a higher level of capital than required.

[15] Additional lags are tested, but found to be insignificant. Therefore, we exclude them from our analysis.

Garcia, and Saal (1996), each of these variables could impact bank failures. We use the US Ten Year Treasury Bond yield as a proxy for interest rates. Because banks continuously adjust their portfolios according to market conditions (Glennon and Golan, 2003), we take the first difference of *IR* and expect the change in interest rates to affect bank failures. Additionally, we assume that *GDPG*, *Unemployment*, and *Inflation* are endogenous to the model. In section 1.5.2, we investigate if instrumenting for these variables is necessary. Life insurance companies often offer loans and compete directly with banks for asset allocation (Claessens and Laeven, 2004). The final control variable, *Insurance*, is the ratio of aggregate life insurance assets to GDP and serves as a proxy for competition to banks from non-traditional banking companies.

The number of failed banks (stressed banks) is proportional to the number of banks operating. If performing OLS, the researcher could account for proportionality by simply dividing the number of failed banks by the number of banks operating and consider the failure rate. The failure rate would either be zero if no banks failed, or some fraction between zero and one, otherwise. Since the Poisson model assumes strictly non-negative integer values for the dependent variable, we must introduce an exposure variable[16] to the right hand side of the *Failures* equation. *Banks* is our exposure variable and is the aggregate number of commercial banks at the beginning of period *t*. We restrict the coefficient of *Banks* to equal one allowing us to estimate the association between the independent variables and the *Failure Rate* without violating the assumption of the

[16] The exposure variable allows us to examine the rate of bank failure. See Appendix A for more detail.

Poisson model which requires non-negative integer values of the dependent variable. A detailed explanation and derivation is provided in Appendix A.

Bank contagion is another risk that must be accounted for. Contagion occurs when initial bank failures result in additional failures. The U.S. banking system is a complex system of interbank loans and deposits. Because banks use similar models of risk measurement, they tend to fail or succeed together. We include two lagged terms[17] of log *Failure Rate* to help capture the risk of contagion. When the failure rate is zero, as it is during multiple periods[18], including lagged logarithm terms is problematic. Therefore, we employ a transformation of $Failure\ Rate_{t-i}$ proposed by Zegar and Qaqish (1988)[19]. This model has been applied in the area of biometrics, but to our knowledge, has not been applied to the subject of bank failures. We are the first to apply this model to bank failures.

The second equation (*GDPG)*, describes the association between real GDP growth and the rate of bank failure (*Failure Rate*)[20]. We include unemployment (*Unemployment*), interest rates (*IR*), currency strength (*FX*), inflation (*Inflation*), a binary variable (*GLBA*) indicating legislation of the Gramm-Leach-Bliley Act (*GLBA*), a binary

[17] Bryant and Williams (2001) state that the standard autocorrelation (AC) and partial autocorrelation (PAC) tests can be applied to determine the optimal lag length.

[18] *Stressed Rate* is strictly positive for each observation. There is no need to apply the Zegar and Qaqish transformation.

[19] See Appendix A for further details on the Zegar and Qaqish (1988) transformation.

[20] Because we introduce an exposure variable into the (*Failures)* equation, the coefficients describe the association between the independent variables and the rate of bank failure. Therefore, we include *Failure Rate* in the subsequent equations.

variable *(Recession)* indicating time periods the US was in a recession[21], and the logarithm of government spending (*GOV)* as control variables. We assume normality and employ a standard linear model.

Okun's law states that there is an inverse relationship between unemployment (*Unemployment)* and real GDP growth (Knoteck, 2007). *IR* is included and differenced because changes in interest rates can influence investments and real GDP growth (Feldstein and Stock, 1994). We use the 10 year U.S. Treasury bond yield as a proxy for interest rates. Easterly (2005) finds that overvalued currencies have an adverse effect on GDP growth because of its effect on net exports. We employ the Federal Reserve Trade-Weighted US Dollar index as our measure of US dollar strength[22]. We difference *FX* to capture the impact of currency value changes. *Inflation* is included because it negatively affects investment and the efficiency with which production factors are used (Andres and Hernando, 1997) and could ultimately impact economic growth. *GOV* is the logarithm of government expenditures and is included because increases in government purchases (fiscal policy) could result in real GDP growth (Romer, 2006). *GOV* is differenced to capture the impact of relative changes in government spending on real GDP growth. *GLBA* is a binary variable defined earlier[23]. As discussed by Chang (2011), the passage of

[21] *Recession* is provided by the NBER. The US was in a recession during the following periods; 1990:2 to 1991:1; 2001:1 to 2001:2; and 2008:1 to 2009:2.

[22] This is a weighted average of the foreign exchange values of the U.S. dollar against a subset of currencies in the broad index that circulate widely outside the country of issue. Some of the currencies included are the Canadian dollar, British Pound, the Euro, Mexican Peso, and Swiss Franc. For a complete list, see Loretan (2005).

[23] This act relaxed the requirements of the Glass-Steagall Act of 1933 which prohibited commercial banks, investment banks, and insurance companies from merging.

this act may have contributed to the financial crisis of 2008 and subsequently had a negative impact on real GDP growth. We include *GLBA* because it represents a major shift in how financial institutions operate. Because of consolidation of commercial banks, investment banks, and insurance companies, some huge firms are created that can drive out some competitors from the market.

The third equation, *Unemployment,* examines the association between the unemployment rate and rate of bank failure. We include *GDPG*, *FX*, *IR*, *Inflation*, and *GLBA* as control variables. Gatti, Rault, and Vaubourg (2012), in their study of financial and labor market interactions, find a positive relationship between both foreign exchange rate (FX) and short term interest rates (IR) with unemployment. *FX* and *IR* were defined earlier. We difference *FX* and *IR* to capture the effect of changes on changes in the unemployment rate. Knotek (2007) studied variations of Okun's law[24] on US data from 1948 to 1960 and finds a negative relationship between GDP growth and changes in unemployment. Fuhrer (1995) studied the reliability of the Philips curve by examining US data from 1978 through 1994. Fuhrer's (1995) results support the underlying theory of the Philips curve that there is a negative relationship between inflation and unemployment. We include *GLBA* in the *Unemployment* equation because, as described earlier, it represents a major policy shift and ultimately had a negative impact on the real economy (Chang, 2011).

The fourth equation examines the relationship between inflation (*Inflation*) and the rate of bank failure (stressed banks). We include foreign exchange (*FX*), interest rates

[24] Okun's law states there is an inverse relationship between GDP growth and unemployment.

(*IR)*, unemployment (*Unemployment*), GDP growth (*GDPG*), percent change of M2 money stock (*M2*)**,** and percent change in crude oil prices (*Oil*) as control variables. As explained previously, Fuhrer (1995) finds a significant relationship between inflation and unemployment by examining the reliability of the Phillips curve. We include *FX* because changes in currency strength affect the price level through purchasing power parity. Hafer (1989) finds evidence that depreciation of the dollar results in inflation. We include *GDPG* because it is negatively associated with inflation (Henderson, 1999). We include and difference *M2* because changes in the growth of the money supply directly impact inflation (Romer, 2006). The final control variable we include is the percent change in the price of crude oil (*Oil*). Cologni and Manera (2008) find that crude oil prices have a significant and positive impact on the price level for G-7 countries.

1.3.2 Estimation Methods

This section presents a description of the methods used to estimate the model. Endogeneity could be a problem in this model, and could bias the results is not accounted for (Wooldridge, 2010). Endogeneity may occur due to simultaneity (reverse causality), omitted variables, or measurement error (Wooldridge, 2010). As previously explained, there could be reverse causality between *Failure Rate* and *Concentration* in equation 1.1. Furthermore, due to the simultaneous nature of the model, *Failure Rate, GDPG, Unemployment, and Inflation* could be endogenous to the system resulting in correlation between these variables and the error term of each equation. Failure to correct for endogeneity could result in biased estimation (Wooldridge, 2010).

Instrumental Variable (IV) techniques could help alleviate endogeneity bias. IV techniques are consistent, but if weak instruments are chosen, IV estimates will contain more bias than OLS (Bound, Jaegar, and Baker, 1995). If one of the supposed endogenous variables is actually exogenous, then IV estimates are more biased than OLS (Wooldridge, 2010). Three statistics for the *Failures* equation and four statistics for the remaining equations are calculated from the single equation IV estimates to assess the need for IV techniques and to test the suitability of the instruments. For the *Failures* equation, they include the Hausman statistic as described by Hausman (1978), for testing if the expected endogenous variable should be treated as exogenous; the J statistic as described by Hansen (1982), to test the orthogonality conditions of the excluded instruments; and the *F* statistic as described by Angrist and Pischke (2009) to assess the strength of the instruments.

For the remaining equations, the four statistics calculated are as follows; the WU-Hausman[25] statistic as described by Wu (1973) and the C-statistic as described by Hayashi (2000) for testing if the expected endogenous variable should be treated as exogenous[26]; the J statistic as described by Hansen (1982), to test the orthogonality conditions of the instruments, and the Cragg-Donaldson Wald statistic as described by Cragg and Donaldson (1993) to test the strength of the correlation between the

[25] The classical Hausman test is not applicable to equations 1-2 through 1-4 because the generated statistic is a negative value. This is common when working with small data sets (Baum, 2006). An asymptotically equivalent version of the Hausman test is suggested by Baum, Schaffer, and Stillman (2003) and is based off Wu (1973).

[26] The C-statistic does not apply to the *Failures* equation because it is a non-linear function.

instruments and the supposed endogenous variables[27]. Additional details of the endogeneity and instrument suitability tests are provided in Appendix B.

If the endogeneity tests suggest that *Concentration*, *Failure Rate*, *GDPG*, *Unemployment*, or *Inflation* should be treated as endogenous and that the instruments are valid, IV estimates are preferred. If the endogeneity tests suggest that the supposed endogenous variables should actually be treated as exogenous, then GMM[28] (without instruments) for the *Failures* equation, and OLS for the remaining equations is preferred. Results from the diagnostic tests, as well all estimation techniques, are reported in section 1.5.

If IV techniques are necessary for the *Failures* equation, the two-stage GMM estimator is appropriate because it allows for instruments in non-linear equations and is robust to misspecification errors (Cameron and Trevedi, 2013). Since the remaining equations are linear functions, 2SLS is the appropriate IV estimator. The multi-equation estimator is the three-stage GMM estimator. System estimation may improve on the efficiency of single equation estimation by accounting for correlations between the equations' residuals (Wooldridge, 2010). Three-stage GMM allows for instrumenting non-linear equations and is preferred over three stage least squares (3SLS) when different instruments are required in each equation (Wooldridge, 2010). If the model is misspecified, system estimation is less efficient than single equation estimation.

[27] The Cragg and Donaldson test does not apply to equation 1.1 because it is a non-linear function.

[28] The *Failures* equation can be estimated with ML or GMM. GMM is preferred as it is robust to misspecification (Cameron and Trevedi, 2013).

1.4 Data

This section contains a description of the data sources and variable calculations. All data are quarterly. Some variables are converted into quarterly observations using methods described below.

1.4.1 Variable Calculations

The methods used to calculate variables in the model are described in this section. *Failure Rate*[29] is the rate at which commercial banks fail or are assisted by the FDIC in merging with another institution. This variable is constructed by dividing the number of commercial banks that failed or were assisted by the FDIC in a merger during each quarter by the total number of commercial banks operating at the beginning of the quarter. *Stressed Rate* is the number of commercial banks whose Capital Equity to Asset Ratio fell below 5% during a given quarter divided by the total number of commercial banks at the beginning of the quarter. *GDPG* is the quarterly growth rate of real GDP and is calculated by taking the log difference of real GDP level between consecutive quarters. *Inflation* is the quarterly percentage change in the price level and is calculated by averaging the Consumer Price Index (CPI) of the three months within each quarter and taking the log difference between quarters. *Concentration* is calculated by summing the assets held by the three largest banks and dividing by the total assets in the system as performed by Beck, Demirgüç-Kunt, and Levin (2006). We use the largest five and ten banks to verify robustness. Additionally, we include the HHI at the national level as

[29] *Failure Rate* and *Stressed Rate* are employed in the *Growth, Unemployment, and Inflation* models.

employed by Boyd, DeNicolo and Jalal (2006). *FX* is the trade weighted US dollar index and is computed as the quarterly average of daily closing values. *Unemployment* is the quarterly unemployment rate and is calculated by averaging the monthly unemployment rates. *Oil* is calculated by differencing the logarithm of the average daily closing price of West Texas Intermediate Crude Oil.

1.4.2 Data Sources

Data for this study comes from four different sources; the FDIC, Saint Louis Federal Reserve Economic Data (FRED), Wharton Data and Research Services (WDRS), and the Federal Reserve Z.1 Financial Account of the United States Report. Bank failure data, *ROA*, and *CER* are provided by the FDIC. Bank concentration data is drawn from the Call Reports provided by WDRS. The Federal Reserve Z.1 report provides the life insurance asset data. The remaining data are provided by FRED.

1.5 Results

This section discusses the results of the empirical model along with descriptive statistics and results of the endogeneity and instrument suitability tests. We focus our discussion on the coefficient estimates from the three-stage GMM system estimation. Single equation estimates serve as a robustness check and are displayed in Appendix C for the interested reader.

1.5.1 Descriptive Statistics

Table 1-2 presents descriptive statistics for variables employed in the model. The sample contains 120 observations beginning in 1984:1 when the FDIC began to publish aggregated bank balance sheet data, and ending in 2013:4. Estimation is performed on the

Table 1-2: Descriptive Statistics

Variable |	Obs	Mean	Std. Dev.	Min	Max
Failures (count)	120	15.98	20.19	0	106
Stressed Banks (count)	120	262.5	302.7	10	1031
FailureRate x 100 (100 basis points)	120	0.177	0.0018	0	0.8
Log Failure Rate*	120	-7.89	2.22	-11.51	-4.83
Stressed Rate x 100 (100 basis points)	120	2.01	0.02	0.00	7.0
Log Stressed Rate	120	-4.50	1.28	-6.60	-2.59
GDPG(%)**	120	2.9	2.51	-8.2	9.42
Inflation (%)**	120	2.9	1.96	-8.9	7.1
Unemployment x 100 (%)	120	6.18	1.50	3.90	9.90
ROA (%)	120	0.97	0.38	-0.37	1.41
CER x 100 (%)	120	8.33	2.05	5.15	11.39
ΔFX (basis points)	120	-0.39	3.08	-8.62	8.02
ΔIR (basis points)	120	-0.07	0.45	-1.20	1.26
ΔGOV(%)**	120	5.3	4.81	-11.2	19.6
GLB (binary)	120	0.48	0.50	0	1
RN (binary)	120	0.65	0.48	0	1
Recession (binary)	120	0.09	0.29	0	1
Insurance (ratio)	120	0.276	0.06	.163	.349
Oil (%)	120	0.9	14.2	-70.1	38.9
M2Growth (%)	120	1.37	0.76	-0.32	4.27
C3 x 100 (%)	120	16.39	7.45	7.77	28.3
C5 x 100 (%)	120	22.23	9.45	10.73	38.37
C10 x 100 (%)	120	29.89	10.91	16.47	47.22
HHI (Index)	120	159.39	112.19	45.60	364.70

Note: C3, C5, and C10 refer to the percent of assets held by the largest three, five, and ten banks. ** indicates an annualized amount. * refers to the transformation outlined by Zegar and Qaqish (1988).

most recent 118 observations because two period lagged variables are employed in the model. The mean failure and distress rates are .17% and 2.01% per quarter, respectively. The failure and distress rates include the 1980s when failure was very high due to the Savings and Loan crisis. There are 25 quarters where there are no bank failures and for which we apply the Zegar and Qaqish transformation. We do not perform the Zegar and Qaqish transformation on *StressedRate* because there are no zero values.

The mean annualized real GDP growth rate and inflation rate are both approximately 2.9%. The average unemployment level is 6.18%. ΔFX and ΔIR have a mean of -.39 and -.07 basis points, respectively. This implies that the U.S. dollar currency strength index decreases by 39 basis points on average each quarter while interest rates decrease by 7 basis points. The mean of ΔGOV of 5.3 implies that government expenditures increased each quarter at an annualized rate of 5.3%.

The mean value of *Recession* is .09. This implies 9% of the observations are from the recessions. The mean value of *Insurance* is .276 indicating that the financial assets held by the life insurance industry is on average 27.6% of the size of GDP. The mean of *Oil* is .9 indicating that on average, the price of crude oil increased at a rate of .9% each quarter. The minimum and maximum values of *Oil* are -70.1% and 38.9% respectively, indicating a high level of variability. The mean concentration levels measured by assets held by the largest three, five, and ten banks is approximately 16%, 22%, and 29.9%. The maximum level of concentration is approximately 28%, 38%, and 47% for the three cases. The mean HHI is 159. Table 1-3 presents a correlation table of the left hand-side

variables. All correlations are low and multicollinearity between these variables is not a concern.

Table 1-3: Correlation Table of Left Hand Side Variables

Variable	*Failure Rate*	*Stressed Rate*	*GDPG*	*Unemployment*	*Inflation*
Failure Rate	1				
Stressed Rate	0.7606*	1			
GDPG	-0.077	0.0499	1		
Unemployment	0.5641*	0.3532*	-0.001	1	
Inflation	0.0963	0.2705*	0.26*	-0.12	1

Note: "*" indicates significance at least at the 10% level of confidence.

1.5.2 Endogeneity and Instrument Suitability Tests[30]

In this section, we provide the results of the endogeneity and instrument suitability tests. To determine if instrumenting for *Concentration* is necessary, we employ two instruments[31]. The first instrument is a binary variable representing the Riegle-Neal Interstate Banking Act (*RN*) of 1994. The variable equals one for every quarter after the act was legislated and zero otherwise. After its passage into legislation by congress, nationally chartered commercial banks were allowed to open branches across state boundaries. The result was an increase in merger activity and concentration (Heiney, 2011). The second instrument is the binary variable *GLBA* which is described earlier. We instrument for the remaining supposed endogenous variables with the exogenous

[30] The Wu-Hausman, *J, C, and C-D* statistics, as well as the 2SLS estimates were computed with the Stata user-written ivreg2 command of Baum, Schaffer, and Stillman (2010).

[31] In performing this test, we assume that *GDPG* is exogenous. If it is determined that both *Concentration* and *GDPG* should be treated as endogenous, then the IV Poisson regression with all relevant instruments is the preferred model.

variables from the corresponding equation. For example, in the *GDPG* equation, we first instrument for *Failure Rate x 100* with *Concentration* and $Concentration^2$. If the instruments are found to be either invalid or weak, we then test two lags of the supposed endogenous variable. If the two lags are poor instruments, we then assume endogeneity and lag the endogenous variable by one period in the main equation. The results of the endogeneity and instrument specification tests are displayed in Tables 1-4 and 1-5. We discuss the results of *Concentration* and provide a summary of the remaining variables in Table 1-6.

In the *Failures* equation, the Hausman test indicates that the Poisson-IV regression produces statistically identical results to the standard Poisson regression for *Concentration* and each of the other variables tested. The *J* and *F* statistics, suggest that the instruments are both valid and strong. The results from these tests suggest that the Poisson-IV model actually increases the bias and is not appropriate for our analysis. Therefore, we do not reject hypothesis H1 and treat *Concentration* as exogenous.

1.5.3 Estimation Results

1.5.3.1 Failures Equation (Equation 1.1)

This section focuses on the empirical results of the *Failures* (*Stressed Banks*) equation. Tables 1-7 and 1-8 present results from the three-stage GMM system estimation. The single equation estimates are similar and are provided in Appendix C. We perform all regressions with robust standard errors to correct for overdispersion

Table 1-4: Endogeneity and Instrument Suitability Tests, *Failures*

Variable	**Hausman Statistic**	***J* -Statistic**	***F* -Statistic**	
Panel A: *Failures* Equation				
Concentration	.001 (.999)	.0009 (.975)	26.06 (.0008)	
GDPG	2.59 (.985)	0.016 (.989)	26.51 (0.002)	
Unemployment	2.4 (.999)	0.292 (.589)	1008.13 (0.0003)	
Inflation	1.32 (.998)	0.127 (.721)	44.85 (0.005)	
Panel B: *GDPG* Equation	**Wu-Hausman**	**C-Statistic**	***J*-Statistic**	***CD*-Statistic**
Failure Rate x 100*	6.97 (.009)	7.14 (.007)	.363 (.54)	24.63
Unemployment*	6.49 (.01)	6.68 (.009)	1.297 (.2545)	2633.654
Inflation	.23 (.63)	.25 (.615)	2.31 (.128)	32.915
Panel C: *Unemployment* Equation				
Failure Rate x 100*	12.79 (.0002)	12.39 (.004)	.016 (.89)	180.586
GDPG**	2.7 (.103)	2.85 (.09)	.42 (.516)	3.32
Inflation	2.53 (.114)	2.69 (.101)	0.41 (.52)	30.798
Panel D: *Inflation Equation*				
Failure Rate x 100*	17.4 (.0005)	16.5 (0.0001)	.989 (.32)	27.09
GDPG**	.82 (.36)	.89 (.34)	.512 (.47)	3.5
Unemployment**	.21 (.64)	.23 (.63)	9.023 (.0027)	2774

Note: This table presents results from the endogeneity and suitability of instrument tests when employing *Failures* and *Failure Rate*. In Panel A, the Hausman statistics are used to determine if a Poisson-IV model is preferred over a standard Poisson. In panels B, C, and D, the WU-Hausman and C statistics are used to assess if OLS regression or 2SLS regression is preferred. The J statistic is used to test if the instruments are correlated with the error terms. The F and CD statistics are used to assess the strength of the instruments. The figures in parentheses represent the *p*-value of each test. * indicates that the variable is to be treated as endogenous in the subsequent regressions. ** indicates that the endogeneity tests suggest that the variable should be treated as endogenous, but the instruments are valid or weak. We lag ** terms by one period in the subsequent regressions to help alleviate bias from endogeneity.

Table 1-5: Endogeneity and Instrument Suitability Tests; *Stressed Banks*

Variable	**Hausman Test**	**Hansen J**	**F-Statistic**	
Panel A: *Stressed Banks* Equation				
Concentration	.06 (.999)	.051 (.821)	20.25 (.002)	
GDPG	15.09 (.13)	0.253 (.615)	22.17 (0.002)	
*Unemployment**	25.32 (.005)	0.37 (.542)	818.42 (.00003)	
*Inflation**	16.92 (.07)	0.331 (.565)	42.79 (0.002)	
Panel B: *GDPG* Equation	**Wu-Hausman**	**C-Statistic**	**J-Statistic**	**CD-Statistic**
*Stressed Rate x 100**	7.94 (.005)	8.08 (.004)	1.568 (.211)	58.357
*Unemployment**	6.9 (.009)	7.08 (.007)	2.43 (.119)	3012
Inflation	.41 (.52)	0.45 (.50)	0.151 (.697)	44.85
Panel C: *Unemployment* Equation				
Stressed Rate x 100	.79 (.37)	.85 (.35)	.124 (.725)	1300
*GDPG***	6.72 (.01)	6.85 (.008)	.597 (.439)	3.98
*Inflation**	4.25 (.04)	4.42 (.03)	1.47 (.228)	34.14
Panel D: *Inflation* Equation				
*Stressed Rate x 100**	7.84 (.006)	7.99 (.004)	.037 (.847)	113.12
*GDPG***	.101 (.75)	.112 (.73)	.425 (.51)	4.12
*Unemployment***	.53 (.46)	.58 (.44)	5.297 (.02)	3398

Note: This table presents results from the endogeneity and suitability of instrument tests when employing *Stressed Banks* and *Stressed Rate*. In Panel A, the Hausman statistics are used to determine if a Poisson-IV model is preferred over a standard Poisson. In panels B, C, and D, the WU-Hausman and C statistics are used to assess if OLS regression or 2SLS regression is preferred. The J statistic is used to test if the instruments are correlated with the error terms. The F and CD statistics are used to assess the strength of the instruments. The figures in parentheses represent the *p*-value of each test. * indicates that the variable is to be treated as endogenous in the subsequent regressions. ** indicates that the endogeneity tests suggest that the variable should be treated as endogenous, but the instruments are valid or weak. We lag ** terms by one period in the subsequent regressions to help alleviate bias from endogeneity.

Table 1-6: Endogenous Variables and Instruments Employed

Equation	Endogenous Variable(s)	Instruments
Failures	None	
Stressed Banks	Unemployment, Inflation	$Unemployment_{t-1}, \Delta Oil, \Delta M2$
GDPG (Failure Rate)	Failure Rate x 100, Unemployment	$Concentration, Concentration^2, Unemployment_{t-1}$
GDPG (Stressed Rate)	Stressed Rate x 100, Unemployment	$Concentration, Concentration^2, Unemployment_{t-1}$
Unemployment (Failure Rate)	Failure Rate x 100	$Failure\ Rate\ x\ 100_{t-1}, Failure\ Rate\ x\ 100_{t-2}$
Unemployment (Stressed Rate)	Inflation	$\Delta Oil, \Delta M2$
Inflation (Failure Rate)	Failure rate x 100	$Concentration, Concentration^2$
Inflation (Stressed Rate)	Stressed Rate x 100	$Concentration, Concentration^2$

Note: This table displays the variables that are instrumented for and the instruments employed. Variables in parentheses indicate whether *Failure Rate* or *Stressed Rate* was included.

Table 1-7: *Failures* Equation Estimates; Three-Stage GMM System Estimation

Variable	Three	Five	Ten	HHI
$\log Failure\ Rate_{t-1}$	.192**	.223**	.207**	.197**
$\log Failure\ Rate_{t-2}$	.299***	.268***	.279***	.258***
$Concentration_t$	-.383***	-.168*	-.275***	-.01
$Concentration_t^2$	.013***	.005**	.006***	.00004***
CER_{t-1}	-.501**	-.645***	-.613***	-.711***
ROA_{t-1}	.142	.001	.034	.076
$GDPG_t$	.123	.069	.078	.088
ΔIR_t	.228**	.254**	.279***	.252***
$Inflation_t$	-.199***	-.185**	-.218***	-.187**
$Unemployment_t$	.099	.144**	.131*	.121*
$Insurance_t$	3.062	7.246	4.482	8.753*
$Constant$	.964	-.293	2.042	-1.24

Note: This table reports system equation estimation results for the *Failures* equation. All variables are treated as exogenous. The top row indicates the measure of concentration employed for each regression. "Three" indicates that regression employed the share of deposits held at the largest three banks; "Five" for the largest five banks; "Ten" for the largest ten banks; "HHI" indicates the Herfindahl–Hirschman Index is the measure of concentration. The numbers listed in each column are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels of confidence.**

Table 1-8: *Stressed Banks* Equation Estimates; Three-Stage GMM System Estimation[32]

Variable	Three	Five	Ten	HHI
log $Stressed\ Rate_{t-1}$	.606***	.593***	.607***	.599***
log $Stressed\ Rate_{t-2}$	.253**	.216*	.235**	.281**
$Concentration_t$	-.078**	-.081**	-.077**	-.001
$Concentration_t^2$	.003***	.002***	.002***	.000006**
ROA_{t-1}	-.118*	-.145**	-.143**	-.14
$GDPG_t$	-.4	-.45	-.5	-.55
ΔIR_t	.12	.16	.02	.012
$Inflation_t$	.07	.075	.067	.072
$Unemployment_t$	-.012	-.012	-.016	-.021
$Insurance_t$	-4.026***	-4.637***	-4.691***	-3.766***
$Constant$	.978**	1.191***	1.548**	.622**

Note: This table reports system equation estimation results for the *Stressed Banks* equation. *Inflation* and *Unemployment* are treated as endogenous. The top row indicates the measure of concentration employed for each regression. "Three" indicates that regression employed the share of deposits held at the largest three banks; "Five" for the largest five banks; "Ten" for the largest ten banks; "HHI" indicates the Herfindahl–Hirschman Index is the measure of concentration. The numbers listed in each column are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels.**

[32] We remove *CER* in the *Stressed Banks* model. There is a high correlation between *CER* and the lagged terms of log *Stressed Rate* because the definition of a stressed bank is determined by the capital equity ratio.

bias[33]. The two lags of log *Failure Rate* are found to be highly significant for all measures of bank concentration. The first lag of log *Stressed Rate* is also highly significant across all estimation attempts while the second lag of log *Stressed Rate* is highly significant for all except one measure of concentration. Estimates of log terms in the Poisson regression are interpreted as elasticities (Cameron and Trevedi, 2013)[34]. For example, consider the estimation results of the two log lagged terms of *Failure Rate*. A 1% increase in the failure rate at date *t* results in a .19% increase in the expected failure rate at date $t+1$ and a .29% increase at $t+2$. The estimates provide evidence against hypotheses H2 and suggest that there is a significant level of contagion risk in the sense that failures are autoregressive; today's failure is a predictor of more failures in the future. These results contradict Aharony and Swary (1983) and Swary (1986) who find little evidence of contagion. However, our results suggest that the risk of bank contagion is a threat to the economy even though the Federal Reserve acts as the lender of last resort. Furthermore, the results indicate that the occurrence of failure persists for up to two quarters (six months).

Both *Concentration* and $Concentration^2$ are highly significant in all but two regressions indicating non-linearity of the relationship between failure and concentration. The two exceptions are in Tables 1-7 and 1-8 where HHI is employed. The quadratic term $Concentration^2$ is highly significant in the *Failures* equation. The negative sign of

[33] Overdispersion is present because the variance of *Failure Rate (Stressed Rate)* is greater than its expected value resulting in inaccurate standard errors. See Appendix A for further details on overdispersion. Palmer, Losilla, Vives, and Jimenez (2007) show that employing robust standard errors is a good technique for correcting inaccurate standard error estimates from overdispersion.

[34] This is because we employ the log link function which is the standard when working with a Poisson regression. Other link functions have different interpretations (Hardin and Hilbe, 2012).

Concentration and the positive sign of $Concentration^2$ implies that increasing concentration reduces bank failures (distress) up to a certain point and increases bank failures (distress) afterwards. To illustrate, consider Figure 1-2 where we plot the expected failure rate as a function of banking concentration while holding all remaining controls at their mean[35]. In this figure, the rate of bank failure decreases until concentration (percent of assets held by largest five banks) reaches roughly 16% and increases steadily thereafter.

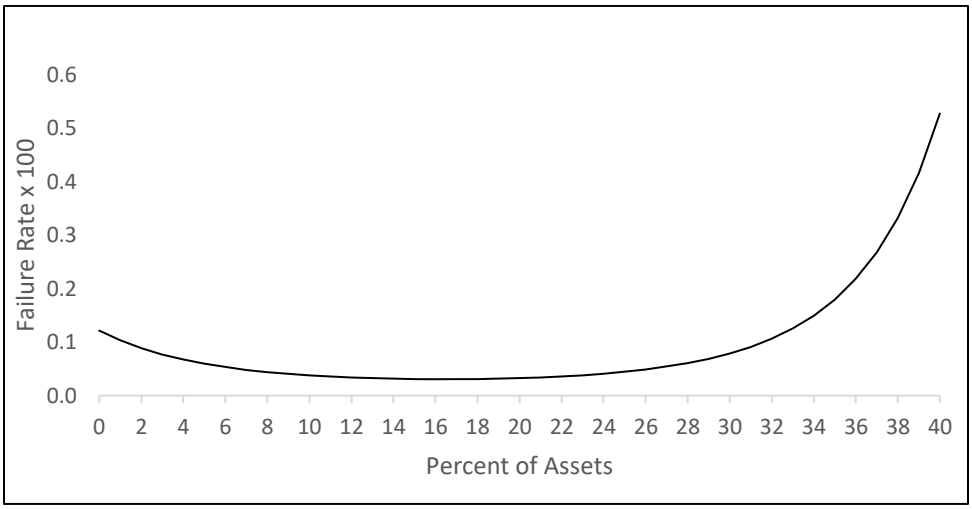

Figure 1-2: Failure Rate vs Concentration[36]

This U-shape relationship between concentration and bank failures supports the theoretical findings of Martinez-Miera and Repullo (2010) that show two opposing forces are at work. When concentration is above the optimal (minimum failure) level, the *risk-taking effect* dominates the market (Martinez-Miera and Repullo, 2010). In other words,

[35] We employ the assets held by the largest five banks from the single equation estimate. All remaining measures indicate a similar relationship where there is a level of concentration that the failure rate is minimized.

[36] The data on concentration (assets held by the largest five banks) ranges from 10.7% to 38.4%. Extrapolation outside this range is less reliable. We include values below 10.7% for illustrative purposes.

in that range of concentration, loan rates charged decrease the profits realized by borrowers, providing incentives to undertake riskier projects making banks less stable. Contrary to this, when concentration is below the optimal level, the *margin effect* dominates the market (Martinez-Miera and Repullo, 2010) in the sense that less concentration leads to lower rates on loans, thereby, reducing profit margins of and their capital buffer against losses. Our results support hypothesis H3 and suggest that as concentration increases, the bank failures diminish up to a certain threshold. After which, bank failures increase.

1.5.3.2 Growth Equation (Equation 1.2)

Results from the *GDPG* equation are presented in Table 1-9. We focus on the system estimation results, and display the single equation estimates as a robustness check. Both *Failure Rate x 100* and *Stressed Rate x 100* are negative and highly significant in all regressions. The negative signs on both variables indicates that higher rates of bank failure (stressed banks) are associated with lower levels of real GDP growth. The estimates can be interpreted as short-run effects of unit changes in the independent variables on the dependent variable. Adding lagged terms of *Failure Rate x 100 (Stressed Rate x 100)* would provide insight of the long term effects. However, since no lagged terms are significant, we exclude them from our estimations.

The results indicate that a 100 basis point increase in *Failure Rate x 100* results in a decrease in real GDP growth by 147 basis points. A 100 basis point increase in *Stressed Rate x 100* is associated with a reduction in real GDP growth by 9.8 basis points. Our results support hypothesis H4 (*Real GDP growth and bank failures are inversely*

Table 1-9: *Growth* Equation Estimates

Variable	2SLS	Three Stage GMM	2SLS	Three Stage GMM
$\boldsymbol{Failure\ Rate\ x\ 100_t}$	-1.74***	-1.477***		
$\boldsymbol{Stressed\ Rate\ x\ 100_t}$			-0.111***	-0.098***
$\boldsymbol{Unemployment_t}$	0.110**	0.088*	0.060	0.045
$\boldsymbol{Inflation_t}$	0.173*	0.061	0.193**	0.135
$\Delta \boldsymbol{FX_t}$	-0.018	-0.020	-0.023	-0.027**
$\Delta \boldsymbol{IR_t}$	0.392***	0.373***	0.353***	0.320***
$\Delta \boldsymbol{GOV_t}$	0.022	0.028	0.040	0.033
$\boldsymbol{GLB_t}$	-0.398***	-0.408***	-0.508***	-0.492***
$\boldsymbol{Recession_t}$	-1.127***	-1.090***	-1.127***	-1.142***
$\boldsymbol{Constant}$	0.436	.587**	0.732***	.815***

Note: This table reports 2SLS and three-stage GMM estimation results for the *GDPG* equation. The top row indicates the estimation technique. The numbers listed are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels. Refer to Table 1-6 to view which variables are treated as endogenous and for the instruments employed.**

related). Furthermore, our results support those of Grossman (1993) and Kupiec and Ramirez (2013) indicating that bank failures have a detrimental effect on economic growth. However, our results are more reliable because they are drawn from an econometrically sound model. We employ a Poisson model in the *Failures* equation accurately capturing the count nature of bank failures. Both Kupiec and Ramirez (2013) and Grossman (1993) employ a VAR model and ignore the count nature of bank failures calling into the question the reliability of their results.

Combining the results of the *Growth* equation with the results of the *Failures* equation, we find that when banking concentration levels exceed a certain level[37], real GDP growth is reduced. A possible channel of effect is the impact of banking concentration on rates offered on loans and deposits. Various authors (Hannan, 1991; et. al.) find a positive association between banking concentration levels and rates offered on loans. On the deposit side, various authors (Berger and Hannan, 1989; Hannan, 1997, et. al) find a negative association between banking concentration levels and rates offered on deposits. Ultimately, the larger spreads between loan and deposit rates is likely reducing aggregate investment which is reflected in the reduced level of real GDP growth. The excessive levels of banking concentration, which are causing the rate of failure to increase, could be interfering with the economy's ability to channel financial resources effectively resulting in a reduction in economic growth (Lingren, Garcia, and Saal, 1996). Additionally, Ramirez (2009) finds evidence that bank panics weaken consumer confidence in banks resulting in a reduction in banks' lending capacity, and growth.

[37] When examining the assets of the largest five banks, the level is 16%.

It is worth noting that the coefficient estimate of *Unemployment* in the GDPG equation is positive and significant in two of the regressions. The positive coefficient disagrees with Okun's law and with some previous research. However, a study by Malley and Molana (2006) find that under certain conditions, there could be a positive association between unemployment and real GDP growth[38]. The find that 6 of the G-7 countries are considered "low effort" countries and that the association between unemployment and real GDP growth is positive. The US is included as a "low effort" country.

1.5.3.3 Unemployment Equation (Equation 1.3)

Results from the *Unemployment* equation are presented in Table 1-10. We focus on the system estimation results, and display the single equation estimates as a robustness check[39]. *Failure Rate x 100* and *Stressed Rate x 100* are positive and highly significant in all regressions. Based on the results, we find evidence supporting hypothesis H5 (*Unemployment and bank failures move in the same direction*.). The results indicate that a 100 basis point increase in *Failure Rate x 100* is associated with an increase in unemployment rate of 625 basis points[40]. A similar increase in *Stressed Rate x 100* results in an increase of 34.1 basis points.

Our results support the results found by Gatti, Rault, and Vaubourg (2012) who find a positive association between banking concentration and unemployment. However,

[38] Germany is the only exception of the G-7 nations and is considered a "high effort" country in their study.

[39] We do not include *Recession* in equation 3 due to the high correlation with *GDPG*.

[40] The average quarterly failure rate is 17.7 basis points. Therefore, an increased failure rate by 100 basis points would be quite severe and would therefore have a drastic negative impact on the level of unemployment.

Table 1-10: *Unemployment* Equation Estimates

Variable	2SLS	Three-Stage GMM	2SLS	Three-Stage GMM
$\boldsymbol{Failure\ Rate\ x\ 100_t}$	6.214***	6.254***		
$\boldsymbol{Stressed\ Rate\ x\ 100_t}$			0.342***	0.341***
$\boldsymbol{GDPG_{t-1}}$	-0.173	-0.209	-0.361*	-0.439**
$\boldsymbol{Inflation_t}$	-0.656***	-0.801***	-0.090	-0.166
$\Delta \boldsymbol{FX_t}$	-0.034	-0.028	-0.001	-0.006
$\Delta \boldsymbol{IR_t}$	-0.242	-0.239	-0.176	-0.236
$\boldsymbol{GLB_t}$	0.552**	0.606***	0.904***	1.023***
$\boldsymbol{Constant}$	5.486***	5.597***	5.284***	5.356***

Note: This table reports 2SLS and three-stage GMM estimation results for the *Unemployment* equation. The top row indicates the estimation technique. The numbers listed are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels. Refer to Table 1-6 to view which variables are treated as endogenous and for the instruments employed.**

our results are stronger because we include a channel by which banking concentration affects unemployment. We find that banking concentration increases bank failures (stressed banks) after a certain point while bank failures (stressed banks) simultaneously increase unemployment levels. As mentioned earlier, excessive levels of banking concentration, which are causing the rate of failure to increase, could be interfering with the economy's ability to channel financial resources effectively resulting in a reduction in growth and subsequently in employment (Lingren, Garcia, and Saal, 1996). An alternative explanation is provided by Koskela and Stenbacka (2004). They find that higher levels of banking concentration result in higher rates on loans resulting in higher financing costs for firms. Consequently, firms respond with a reduction in employment.

1.5.3.4 Inflation Equation (Equation 4)

Results from the *Inflation* equation are presented in Table 1-11. As with the previous equations, we focus on the system estimation results, and display the single equation estimates as a robustness check[41]. We find that *Failure Rate x 100* and *Stressed Rate x 100* are positive and highly significant in all regressions. Based on the results, we find evidence supporting hypothesis H6 (*Inflation and bank failures move in the same direction*). In particular, the results indicate that a 100 basis point increase in *Failure Rate*

[41] We do not include *Recession* in equation 4 due to the high correlation with *GDPG*.

Table 1-11: *Inflation* Equation Estimates

Variable	2SLS	Three Stage GMM	2SLS	Three Stage GMM
$Failure\ Rate\ x\ 100_t$	2.141***	2.036***		
$Stressed\ Rate\ x\ 100_t$			0.115***	0.118***
$GDPG_{t-1}$	0.116**	0.073	0.053	0.034
$Unemployment_{t-1}$	-0.177***	-0.177***	-0.098***	-0.093***
ΔFX_t	-0.005	0.001	0.001	-0.002
ΔIR_t	-0.071	-0.086	-0.020	-0.027
$\Delta M2_t$	0.013	0.018	0.033	0.053
ΔOil_t	2.122***	1.890***	2.180***	2.190***
$Constant$	1.355***	1.412***	0.984***	.961***

Note: This table reports 2SLS and three-stage GMM estimation results for the *Inflation* equation. The top row indicates the estimation technique. The numbers listed are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels. Refer to Table 1-6 to view which variables are treated as endogenous and for the instruments employed.**

x 100 is associated with an increase in inflation of roughly 204 basis points[42]. A similar increase in *Stressed Rate x 100* results in an increase of 11.8 basis points.

As with the *GDPG* and *Unemployment* equations, system estimation estimates a highly significant relationship between banking concentration and bank failures and simultaneously between bank failures and inflation. By our results, not only does concentration above a certain threshold cause a higher number of bank failures, it is ultimately leading to stagflation because of a simultaneous rise in both unemployment and inflation. In addition to rising unemployment explained in the previous section, high levels of banking concentration could ultimately be leading to relationships between policy instruments and targeted objectives becoming distorted and/or causing the credit channel for monetary policy transmission to become less efficient (Lindgren, Garcia, and Saal ,1996). As explained by English (2002), large banks likely have better access to markets for managed liabilities than do smaller banks because of reduced information costs and the smaller relative importance of fixed costs. As a result, an increase in concentration of the banking system could dampen the impact of tighter monetary policy on the supply of bank loans, thereby reducing the size of its effect on the inflation. Similarly, if high levels of concentration lead to stronger banks taking over weaker ones, then a larger share of the industry could be accounted for by banks with access to markets for managed liabilities, again dampening the effects of tighter policy through this channel (English, 2002). In 2001, the Group of Ten (G-10) performed a study on the effects of

[42] The average quarterly failure rate is 17.7 basis points. Therefore, an increased failure rate by 100 basis points would be quite severe and would therefore have a drastic negative impact on inflation.

consolidation in the financial industry[43]. The participants in this study conclude that rising levels of concentration in the US is not likely to impose difficulties in implementing monetary policy. We find a significant relationship between concentration and inflation suggesting that the conclusions of the G-10 study may need to be revisited.

Transmission of monetary policy through the money supply and interest rates could be dampened by weak and/or insolvent banks (Lindgren, Garcia, and Saal, 1996). As explained before, we find that concentration above a certain threshold causes a higher number of bank failures. These results support Cottarelli and Kourelis (1994) who find that monetary policy transmission through interest rates is less efficient in banking systems where market forces are weak. Furthermore, they explain that in periods of extreme system-wide banking unsoundness, banks will ignore risk factors and may increase the supply of credit to generate income.

An alternative explanation stems from the relationship between banking stability and exchange rate stability. Kaminsky and Reinhart (1996) find that a balance of payment crisis is typically preceded by a banking crisis supporting the notion that bank instability exerts a negative effect on the exchange rate (Lindgren, Garcia, and Saal, 1996). This potentially weakens the value of the dollar resulting in inflation. Additional research is needed on this this topic.

[43]The study's working party was chaired by Roger W. Ferguson, Jr, Vice Chairman of the Board of Governors of the Federal Reserve System. The working party included finance and central bank staff from the G-10 countries, Australia, and Spain, as well as representatives from the Bank for International Settlements, the European Central Bank, the European Commission, the International Monetary Fund, and the Organization for Economic Co-operation and Development (OECD). Further discussion of the causes of consolidation can be found in Group of Ten (2001, pp. 65-124).

1.5.3.5 Total Impact of Concentration on Real Economy

In this section, we examine the impact that excess concentration over the optimal level has on the real economy. Table 1-12 displays the detrimental effect that current levels of banking concentration are having on the economy. We focus our discussion on concentration measured by the assets held by the largest five banks and provide the remaining levels for comparison. As of 2013:4, the largest five banks in the US held about 36% of the commercial banking assets[44]. Compared to the optimal level of 16% when examining failed banks and 19% when examining distressed banks, it is clear that the US banking sector is over-concentrated resulting in a detrimental impact on the real economy. Panel A displays the impact of higher levels of concentration through the bank failure channel. All else equal, our results indicate that if the US banking system was concentrated at the optimal level, real GDP growth would be higher by an annualized rate of 108 basis points. Unemployment and inflation would both decrease by 117 and 161 basis points respectively. Other measures of banking concentration (including *HHI*) produce similar results. Panel B displays the impact of higher levels of concentration through the distressed bank channel. All else equal, our results indicate that if the US banking system was concentrated at the optimal level, real GDP growth would be higher by an annualized rate of 19 basis points. Unemployment and inflation would both decrease by 17 and 22 basis points respectively[45].

[44] The largest three and ten banks held about 26% and 45%, respectively, of the total banking system assets. HHI was roughly 325.

[45] The remaining measures of concentration produce similar results. However, we exclude HHI in Panel B because the estimates are found to be insignificant.

Table 1-12: Effect of Excess Levels of Concentration

Concentration	2013:4 Level	Optimal Level	GDP Growth*	Unemployment	Inflation*
Panel A: Failures					
Three	26%	14%	-.79	.85	1.11
Five	36%	16%	-1.08	1.17	1.61
Ten	45%	25%	-1.91	1.42	2.38
HHI*	325	110	-1.19	1.23	1.71
Panel B: Stressed Banks					
Three	26%	13%	-.21	.18	.28
Five	36%	19%	-.19	.17	.22
Ten	45%	25%	-.17	.11	.18

Note a: This table presents the effect that concentration over the optimal level has on the real economy. Figures are given in 100 basis points. "*" indicates annualized figure.

Note b: "**" indicates that only $Concentration^2$ is significant. Here, the p-value of *Concentration* is .109 implying the optimal *HHI* may be slightly different than 110.

In addition to the economic costs explained above, excess concentration can lead to too-big-to-fail (TBTF) institutions and excessive political power. Some economists argue that these institutions and the accommodating government backstops pose serious risks to the financial system and the broader economy (Wheelock, 2012). Costly government bailouts are an additional consequence of TBTF institutions because of the government's unwillingness to allow TBTF institutions to fail (Wheelock, 2012). In 2010, congress passed the Dodd-Frank Act which in part aimed to limit TBTF and restrict the level banking concentration[46] (Felsenfield and Glass, 2011). While the level of banking concentration has decreased slightly since the passing of Dodd-Frank[47], our results indicate that the US banking system is still over-concentrated resulting in slower economy growth, higher unemployment, and higher inflation. These results have major policy implications and suggest that the current level of concentration is still well above the optimal level. Additional legislation may be needed in order to reduce concentration to the optimal level.

1.6 Conclusion

There has been little research conducted on the relationship between bank concentration and the real economy. In this paper, we combine two independent strands of literature to fill this void. The first examines the relationship between bank concentration and bank stability (failures). The other examines the relationship between

[46] Dodd-Frank limits interstate bank mergers if the resulting bank was to hold 10% or more of the total system liabilities (Felsenfield and Glass, 2011).

[47] The largest three, five, and ten banks held roughly 28%, 38%, and 46% respectively of the banking system's assets.

bank stability and the real economy. We extend the work of previous authors by building a system of equations that first links bank concentration to bank failures and distressed banks. To this end, we incorporate an autoregressive Poisson model which accurately captures the count structure of the data as well as allowing us to incorporate lagged terms of bank failures. The remaining equations link bank failures and distressed banks to real economic variables including GDP growth, unemployment, and inflation. We account for endogeneity bias and test for the validity and strength of the instruments.

We have several interesting findings. First, we find that the association between bank failures (distressed banks) and banking concentration is unidirectional, rather than bidirectional. In other words, bank failures and distressed banks do not significantly impact banking concentration but bank concentration does impact bank failures and distressed banks. This conclusion is drawn from the results of the Hausman test which suggests that bank concentration should be treated as an exogenous variable in the system. Second, our results indicate that despite the presence of the Federal Reserve as a lender of last resort, contagion among failed and distressed banks is a significant risk to the banking system in the sense that failures in a given period will be followed by failures in the coming periods. Most interestingly however, we find that bank concentration reduces bank failure up to a certain level, beyond which the direction of the effect is reversed. This result implies that through the bank failures channel, there is an optimal level of concentration that the banking industry should maintain. That is, we find that bank failures are minimized when the largest three, five, and ten banks hold approximately 14%, 16%, and 25%, respectively, of the commercial banking assets.

Similarly, we find that the frequency of distressed banks is minimized when the largest three, five, and ten banks hold approximately 13%, 19%, and 25%, respectively, of the commercial banking assets. Concentration below these levels increases the rate of bank failure (distressed banks) due to less profitability thereby reducing capital reserves and the buffer against losses (Martinez-Miera and Repullo, 2010). Concentration above these levels results in higher rates of bank failure (distressed banks) due to higher loan rates charged to borrowers which reduces the profits realized by borrowers providing incentives to undertake riskier projects making banks less stable (Martinez-Miera and Repullo, 2010. Finally, our results from our model, imply that both an over-concentrated and under-concentrated banking system ultimately leads to slower economic growth, higher unemployment, and higher levels of inflation. As of 2013:4, the largest three, five, and ten banks held approximately 26%, 36%, and 45% of the assets respectively; all well above the optimal level.

There are other factors that may justify a more concentrated banking system. More efficient banks, better diversification, and higher X-efficiency are advantages associated with higher levels of banking concentration (Mester, 2005) However, our results show that these advantages, if they exist, impose a severe cost to the economy. High concentration also leads to "too-big-to-fail" (TBTF) issues. TBTF banks introduce a moral hazard problem because they have an incentive to hold excessive risk resulting in costly government bailouts when they are in danger of failing (Wheelock, 2012).

Recent legislation has been passed with the intent of ending TBTF and limiting the level of banking concentration. For example, in 2010, policy makers passed the

Dodd-Frank Act limiting interstate bank mergers if the resulting bank was to hold 10% or more of the total system liabilities (Felsenfield and Glass, 2011). While the level of banking concentration has decreased since Dodd-Frank, our study indicates that the US banking system is still over-concentrated resulting in a weaker economy. This study serves as a signal to regulators and policy makers that the excessive level of banking concentration in the US is potentially harming the banking system and the real economy.

CHAPTER 2
THE ASSOCIATION BETWEEN BANK STABILITY AND BANKING CONCENTRATION: LARGE VS. SMALL BANKS

2.1 Introduction

The relationship between concentration of the US banking system and individual bank stability has been debated by researchers, policy makers, and regulators for decades (e.g. Schaeck and Cihak, 2007). Increasing levels of banking concentration has prompted concerns about the market and political powers enjoyed by large conglomerate banks, systemic risk, distortion of loan and deposit pricing, and costs due to too-big-to-fail (TBTF) bailouts (Mishkin, 1999). One example of the dangers associated with excessively large financial institutions is the increased level of moral hazard that is engendered (Mishkin, 1999). Large financial institutions deemed to be TBTF have an incentive to take on an excessive amount of risk because they know they will be bailed out in times of distress, resulting in reduced stability of the financial system (Mishkin, 1999; Berger, Molyneux, and Wilson, 2010). This topic has received a great deal of attention in recent months as US presidential candidates have vowed to increase pressure on the large banks through increased regulatory requirements and/or to bring about forced reduction in size; a move that could prove to be costly (Worstall, 2016).

Larger banks may benefit from production efficiency because as they grow in size, they are able to spread their overhead costs more effectively (overcome indivisibility), they have better access to size-biased advanced information technologies, and they can diversify their products and portfolios more easily, thereby enjoying possible scope economies as well as reducing the relative cost of managing risk (Hughes

and Mester, 2011). However, despite the benefits enjoyed by larger banks, a potential consequence of consolidation is that smaller banks will be driven out of the market because they cannot compete in terms of pricing, convenience, and product diversity with their larger counterparts (Saunders and Cornett, 2014). As bank concentration increases, large banks could benefit while small banks could seriously suffer. While the number of small banks in the US has declined steadily over the past three decades, these banks still play an essential role in the banking system (Keeton, 2003). More specifically, small banks are important lenders in key sectors of the US economy, such as the agricultural, housing and consumer sectors, and serve the retail deposit needs of depositors in rural and smaller urban regions (Keeton, 2003). Additionally, small banks have distinct advantages in lending based on "soft-information" which is often relied upon by small businesses and informationally opaque borrowers (Thakor and Boot, 2008). Despite the decline in the overall number of small banking institutions, their importance is exemplified by the fact that in recent years a large number of "de novo" banks have been established to provide services that large banking institutions do not find profitable to provide (Berger, Molyneux, and Wilson, 2010)[48].

Research on the relationship between concentration in the banking sector and individual bank stability has produced conflicting results. Two propositions are made on this link in the literature. First, the "Charter Value Hypothesis" states that banks in highly concentrated markets are more stable because they have a greater charter value and, therefore, they avoid taking excessive risk with the aim of preserving their charter value.

[48] For example, it is noted in the literature that large banks are at a disadvantage in offering products based on "soft information" or relationship lending (e.g. Thakor and Boot, 2008).

This renders the banking system more stable (Degryse, Kim, and Ongena, 2009). Keely (1990) and Repullo (2004) both find evidence in support of this view. Second, the "Optimal Contracting Hypothesis" states that banks in less concentrated markets are more stable. The rationale is that banks in highly concentrated systems charge higher rates on loans, squeezing the borrowers' profit margins and driving the latter to undertake riskier projects in the hopes of realizing a higher profit, despite the higher loan rates. This dynamic can destabilize the banks. Studies by Boyd, DeNicolo, and Jalal (2006) and Ude and Heimeshom (2009) provide evidence in support of this second view.

Some shortcomings of the above studies on the relationship between banking concentration and individual bank stability could potentially explain their conflicting results. First, it is well noted in the literature that there are various bank operating models that are often influenced by bank size[49]. A partial listing of the different banking operations includes banks funded mostly by retail operations, wholesale funded operations, and capital market oriented banks (Roengpitya, Tarashev, and Tsatsaronis, 2014). Many of these operations changed over time and because of economic and regulatory conditions (Roengpitya, Tarashev, and Tsatsaronis, 2014). However, despite these size based differences, previous studies of banking concentration pool small and large banks in the same sample and fail to differentiate between these classes of banks. These studies find either a positive or negative association between banking concentration and individual bank stability, regardless of bank size, thus failing to capture the different underlying dynamics of the two groups. Second, previous studies make the

[49] A detailed description of size based banking operations is provided in section 2.2.

false assumption that bank stability and banking sector concentration have a linear relationship. These studies pre-date the seminal work of Martinez-Miera and Repullo (2010) who theoretically show a U-shaped relationship between concentration and the risk of bank failure where increasing concentration reduces the risk of failure up to a certain point and increases it thereafter. The conflicting results from previous studies could possibly be the result of model misspecification due to key pieces of information being absent.

In this study, we build on previous research and seek to bridge the gap between the conflicting results. To this end, we follow Boyd, DeNicolo, and Jalal (2006) by modeling bank stability as a function of banking sector concentration and extend their work in four principal ways. First, we include a linear term and a squared term of banking concentration as explanatory variables on the right hand side of our model to capture the U-shaped relationship found in the theoretical model of Martinez-Miera and Repullo (2010). Second, we introduce an interaction term between concentration and bank size to test if banks of various sizes react differently to changes in the level of banking concentration. Third, we introduce a richer set of explanatory variables accounting for additional sources of variation such as income diversity and off balance sheet activity. Fourth, we employ a broader sample period that includes observations during and beyond the financial crisis of 2008.

We focus on US commercial banks after the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 (RN) into legislation. Focusing on commercial banks instead of bank holding companies allows us to examine a much larger

data set and thereby increase the efficiency of our results. Quarterly data are obtained from 13,000 commercial banks between 1994:3 and 2013:4. Because banks may consolidate due to reductions in individual bank stability (Jones and Critchfield, 2005), we employ a fixed effects instrumental variables (FE-IV) model to help reduce the bias caused by endogeneity. Additional details of potential endogeneity bias are provided in section 2.3.2. Concentration is measured by the asset share of the ten largest commercial banks, and alternatively by the Herfindahl–Hirschman Index (HHI) calculated at the national level. We introduce interaction terms between concentration and bank size allowing us to test whether higher levels of concentration have a different impact on the stability of commercial banks dependent on size. Additionally, we account for endogeneity of concentration by introducing instrumental variables as outlined in the results section.

We find two interesting results. First, we find that large and small banks react very differently to changes in concentration. As concentration, measured by the asset share of the ten largest banks, increases past roughly 35%, small banks hold less capital, are less profitable, become less stable, and hold more volatile portfolios as measured by the standard deviation of return on assets. Second, as concentration measured by the asset share of the ten largest banks, increases past roughly 35%, large banks individually hold more capital, are more profitable, become more stable, and reduce portfolio volatility as measured by the standard deviation of return on assets. We also find that large banks increasingly contribute to systemic risk as concentration increases, despite the fact that their idiosyncratic risk is reduced. Our results are robust to multiple estimators such as

Fixed Effects (FE), Two Stage Least Squares (2SLS) and Pooled OLS, and measures of concentration.

These results produce evidence that supports both the Charter Value and Optimal Contracting hypotheses depending on bank size and the level of concentration. These results are of interest to researchers because they show the importance of the interactive effect between bank size and concentration in modeling bank stability. These results are also important to policy makers and regulators because they provide evidence of the trade-offs associated with banking concentration. As concentration measured by the asset share of the ten largest banks increases beyond roughly 35%, large banks benefit through increased idiosyncratic stability while small banks would undoubtedly be squeezed and pushed out the market as indicated by their reduction in stability[50]. The benefit of more stable large banks could be offset by the increase in systemic risk (Weiß, Neumann, and Bostandzic, 2014). If the large banks are broken up and the current level of concentration is trimmed, as some have suggested (e.g. Fisher, 2011), small banks would benefit from increased idiosyncratic stability, but the largest banks would become less stable thereby increasing their risk of failure. While their individual contribution to systemic risk is reduced, a failure of a large institution could add tremendous stress to the financial system (Wheelock, 2012). Further detail and discussion is provided in the results section.

The remainder of the paper is structured as follows. Section 2.2 contains a review of previous research. Section 2.3 contains the description of the model and section 2.4

[50] According to our data, the ten largest commercial banks held approximately 46% of the banking system assets as of 2013:4.

provides a description of the data. Section 2.5 presents a discussion of the results and section 2.6 provides concluding remarks.

2.2 Literature Review

In 1994, the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (RNA) authorized national commercial banks to establish branches across state lines and allowed bank holding companies to convert subsidiaries into branches of a single interstate bank (McLaughlin, 1995). After its passage into legislation, a wave of consolidation in the banking sector took place leading to a more concentrated banking system (Saunders and Cornett, 2014). This increase in concentration of the banking sector is considered by many policy makers and researchers to be associated with a higher degree of stability (e.g. Keely, 1990). However, others argue that concentration may reduce competition, curtail access to financial services, increase the market and political powers of large financial institutions, and destabilize the financial system as banks become too big to be disciplined and use their influence to shape banking regulations and policies (Vives, 2016). Systemic risk is also a major concern because as banks concentrate, they become more interconnected and susceptible to similar shocks (Weiß, Neumann, and Bostandzic, 2014). Generally, they also use the same models of risk measurement and risk management further strengthening the vulnerability of the banking industry (Kiff, Kodres, Klueh, and Mills, 2007).

As the banking system grew in concentration during the post RNA period, the size distribution of banks changed dramatically (Berger, Molyneux, and Wilson, 2010). During this period, the rate of consolidation among the largest US banks was very high,

propelling a small number of mega-banks to the top with control over a considerable portion of the banking system's assets (Berger, Molyneux, and Wilson, 2010). These large banks have a strong 'brand image' and their entry into local banking markets exerts a significant amount of competitive pressure on small banks (Berger and Dick, 2007). Empirical research has shown that during the 1990s and 2000s, large banks adapted new financial and information technologies quicker than small banks, placing additional pressures on small banks in the local markets (Berger, Molyneux, and Wilson, 2010).

Along with increased banking concentration, the largest banks have shifted their strategies towards non-interest income and wholesale banking where large financial institutions lend to each other and other large corporations (Berger, Molyneux, and Wilson, 2010). For example, instead of generating interest income from businesses lending, larger banks earn a fee by providing standby letters of credit to businesses that issue their own debt securities (Thakor and Boot, 2008). Similarly, securitization of mortgages and consumer loans has transformed a previously interest-based business into a fee-based business (Thakor and Boot, 2008). Large banks also earn a greater percentage of income from non-banking services such as investment banking and insurance activities (Berger, Molyneux, and Wilson, 2010). DeYoung and Roland (2001) argue that this shift has significantly altered the risk-return profiles of large banks resulting in an income stream requiring a higher level of operating leverage which amplifies revenue and earnings volatility[51].

[51] An example if this manifested itself during the financial crisis of 2007 where some of the largest institutions experienced a crippling reduction in income generated from non-interest activity (Berger, Molyneux, and Wilson, 2010).

Lending practices of large and small banks have diverged significantly as the banking system consolidated (Thakor and Boot, 2008). For example, large banks have shifted towards lending based on 'hard-information' derived from quantifiable information that requires advanced technology to collect and store (Thakor and Boot, 2008). Small banks, on the other hand, have focused on "soft information' lending that requires non-quantifiable information that is often gathered from long relationships between the bank and its borrowers (Thakor and Boot, 2008). Often customers of small banks are informationally opaque and do not have the ability to obtain loans from larger banks (Thakor and Boot, 2008).

The manner in which banks fund their operations has significantly changed as well. For example, large banks now fund the majority of their assets through a transactional approach where loans are originated and sold, whereas small banks practice a much more traditional approach relying more on deposits to fund their portfolios (Berger, Molyneux, and Wilson, 2010). These differences highlight a few of the many differences between large and small banks. Nonetheless, these characteristics provide further evidence of the divergence of large and small bank operations as a result of increasing concentration, as well as macroeconomic and regulatory conditions.

There are two competing views on how banks react to increasing levels of concentration. The "Charter Value Hypothesis (CVH)" claims that banks in a highly concentrated banking system have a higher charter value and, thus, will take less risk in order to preserve that value (Degryse, Kim, and Ongena, 2009). Conversely, banks in a banking system with low concentration realize smaller profits due to greater competition,

consequently have a low charter value, and therefore, have greater incentives to hold riskier assets. Studies by Keely (1990) and Allen and Gale (2004) find empirical evidence supporting the CVH. That is, they find that banks in less concentrated markets take more risk.

The second view, the 'Optimal Contracting Hypothesis (OCH)" claims that the optimal contract between the bank and borrower should leave enough room for borrower profitability so that the borrower has less incentive to undertake risky projects (Degryse, Kim, and Ongena, 2009). Boyd and DeNicolo (2005) present the OCH theoretically and find that as concentration among banks decreases, the rates offered on loans will also decrease. As a result, borrowers realize greater profits. Conversely, as the level of concentration among banks increases, rates offered on loans increase adversely affecting borrowers' profits. In this scenario, since profits are smaller, borrowers have greater incentives to undertake riskier projects in the hopes of realizing higher returns. The banks are therefore less stable because they hold riskier assets.

Boyd, DeNicolo and Jalal (2006) empirically test the theoretical results found by Boyd and DeNicolo (2005) using US and European banking data. In this study, each individual bank's Z-score is regressed on the industry concentration level, as well as various macroeconomic indicators. The Z-score measures how large an adverse shock would have to be in order for the bank to become insolvent. A low Z-score implies that a small shock would be sufficient to drive the bank into insolvency (Saunders and Cornett, 2014). The authors' results show a negative relationship between the Z-score and concentration, supporting the theoretical model of Boyd and DeNicolo (2005). In other

words, they find that as concentration increases, the Z-score decreases, implying the banks are holding riskier assets and thus, are less stable. These results are supported by Ude and Heimeshom (2009) who conduct a similar study that focuses on 25 countries across the European Union from 1997 to 2005. Similar to Boyd, DeNicolo and Jalal (2006), Ude and Heimeshom (2009) employ the Z-score measure and conclude that increased concentration has a negative association with individual bank stability.

We posit that these conflicting results could be due to three shortcomings of the methodologies employed by these studies. First, the conflict in results could be due to the lack of differentiation between behavioral patterns of large and small banks in response to changes in concentration (Haan and Poghosyan, 2012a). As previously discussed, large and small banks operate very differently due to differences in efficiencies, scale and scope economies, access to technologies, nature of the income streams, and portfolio risk (e.g., Hughes and Mester, 2001; Berger, Molyneux, and Wilson, 2010, Haan and Poghosyan ,2012a). Furthermore, large banks could be pushing smaller banks out of the market, consequently increasing the stability of the large banks and decreasing it for the small banks, as a result of increased concentration (Berger, Molyneux, and Wilson, 2010). Haan and Poghosyan (2012a) address the fact that large and small banks operate very differently and state that both size and concentration should be considered in studies of banking operations. In their study, they proceed to examine earnings volatility of US commercial, savings, and cooperative banks in relation to increased concentration and size. They find an inverse relationship between bank size and earnings volatility. They

also find that the impact of bank size on earnings becomes less negative as concentration increases.

Second, the majority of the stability-concentration studies pre-date the seminal work of Martinez-Miera and Repullo (2010) who theoretically show that the relationship between concentration and individual bank stability is non-linear (U-shaped). Specifically, these authors find that increasing concentration reduces the risk of failure up to a certain point and increases it thereafter. Earlier models assume linearity and, thus, are likely to be misspecified. Third, many of the existing studies do not correct for endogeneity of concentration. As explained by Jones and Critchfield (2005), banks could consolidate due to a reduction in stability, among other reasons. Not accounting for this feature could bias the results.

We correct these three shortcomings (differentiation by bank size, misspecification, and endogeneity). Specifically, we revisit Boyd, DeNicolo, and Jalal (2006)[52] to test the relationship between individual bank stability and banking concentration. To this end, we extend their model in two ways. First, we include both a linear and squared term of banking concentration. As explained by Martinez-Miera and Repullo (2010), it is possible that concentration could have a positive (negative) impact up to a certain threshold point and a negative (positive) impact thereafter. As concentration increases, rates on loans tend to increase driving bank profitability higher, resulting in a reduction in the risk of bank failure (greater stability). However, as

[52] The study by Boyd, DeNicolo, and Jalal (2006) does correct for endogeneity. However, their model may be misspecified nor does it account for differentiation by bank size.

concentration increases past a certain threshold, bank profits erode due to loan default by borrowers undertaking riskier projects. The result is in an increase in the risk of bank failure (reduced stability). Therefore, we test the following hypothesis.

H1a: *Individual bank stability and bank concentration are unassociated.*

Rejecting the null hypothesis indicates that the relationship between individual bank stability and bank concentration is non-linear (U-shaped).

The second extension differentiates between large and small banks and allows us to determine if these two groups of banks react differently to changes in concentration. If there is in fact a difference, then elements of both the CHV and OCH may be valid. Therefore, we test the following hypothesis.

H1b: *The relationship between bank stability and bank concentration does not vary with bank size.*

Our measure of individual bank stability, the Z-score, has three components; capital cushion (capital equity to asset ratio), profitability (return on assets), and portfolio return volatility (standard deviation of return on assets) (Boyd, DeNicolo, and Jalal, 2006). Each of these components could be impacted by banking concentration. Following Boyd, DeNicolo, and Jalal (2006), we test if there is a relationship between each of the Z-score components and banking concentration in a similar way as hypotheses H1a and H1b.

As with bank stability, capital equity and profitability could deteriorate as concentration increases. An increase in concentration could result in higher loan rates and a higher rate of loan default (Martinez-Miera and Repullo, 2010), which could undermine profitability and, consequently, capital equity. However, an increase in concentration could result in higher bank higher profit due to increasing rates charged to borrowers (Martinez-Miera and Repullo, 2010). Higher profits could result in increased levels of capital through greater retained earnings (Thakor and Boot, 2008). Therefore, we test the following hypotheses.

H2a: *Capital equity and bank concentration are unassociated.*

H2b: *The relationship between capital equity and bank concentration does not vary with bank size.*

H3a: *Profitability and bank concentration are unassociated.*

H3b: *The relationship between profitability and bank concentration does not vary with bank size.*

Portfolio volatility has an inverse relationship with bank stability as defined by the individual bank Z-score. This stems from the manner in which bank stability is measured. Additional detail on the measurement of bank stability is provided in section 2.3. As explained by Boyd, DeNicolo, and Jalal (2006), as concentration increases, loan rates increase providing incentive for borrowers to undertake riskier projects. This dynamic should present itself in an increase in portfolio volatility due to the increased risk of the banks' projects. However, as explained by Keely (1990), as concentration

increases, banks have a higher charter value and will therefore hold less risky assets. This dynamic should result in a reduction in portfolio volatility. We test the following hypotheses to determine if evidence of both of these hypotheses is present.

H4a: *Portfolio volatility and bank concentration are unassociated.*

H4b: *The relationship between portfolio volatility and bank concentration does not vary with bank size*.

A summary of hypotheses tested is provided in Table 2-1.

Table 2-1: Hypotheses

Hypothesis	Statement of Hypothesis
H1a	*Individual bank stability and bank concentration are unassociated.*
H1b	*The relationship between bank stability and bank concentration does not vary with bank size.*
H2a	*Capital equity and bank concentration are unassociated.*
H2b	*The relationship between capital equity and bank concentration does not vary with bank size.*
H3a	*Profitability and banking concentration are unassociated.*
H3b	*The relationship between profitability and bank concentration does not vary with bank size.*
H4a	*Portfolio volatility and bank concentration are unassociated.*
H4b	*The relationship between volatility and banking concentration does not vary with bank size.*

Note: This table provides a summary of the hypotheses tested in Chapter 2.

2.3 Model and Methodology

This section provides a description of the model used to test the hypotheses and a discussion of the control variables (section 2.3.1), followed by a detailed discussion of the estimation techniques (section 2.3.2).

2.3.1 Model Description

Our model builds upon the work of Boyd, DeNicolo, and Jalal (2006). Equation 2.1 describes bank stability as a function of concentration, interaction terms between concentration and bank size, and a list of control variables outlined below.

$$\begin{aligned} Zscore_{it} = c + u_i + \beta_1 Concentration_t + \beta_2 Concentration_t{}^2 + \beta_3 Size_{it} \\ * Concentration_t + \beta_4 Size_{it} * Concentration_t{}^2 + \beta_5 Size_{it} \\ + \theta X_t + \omega Y_{it} + \varepsilon_{it} \end{aligned} \quad (2.1)$$

Following Boyd, DeNicolo, and Jalal (2006), we employ each bank's Z-score as our measure of stability[53]. The Z-score is widely used in the literature and represents the number of standard deviations below the mean that profits would have to fall as to deplete equity capital. In a similar fashion to Boyd, DeNicolo, and Jalal (2006), we calculate each component of the Z-score over a three quarter (nine month) rolling window.

Concentration is the measure of banking concentration and is the percentage of assets in the banking industry held by the largest ten banks (C10 ratio). We check for

[53] The Z-score is defined as $(ROA + CER)/\sigma(ROA)$where ROA is the return on assets, CER is the equity capital to asset ratio, and $\sigma(ROA)$ is the standard deviation of return on assets.

robustness of the results using the Herfindahl–Hirschman Index (HHI) as an alternative measure of stability. We include the squared term of *Concentration* because there may be a non-linear relationship between bank stability and banking concentration (Martinez-Miera and Repullo, 2010). We note that there are other methods that can be employed to test for a U-shaped relationship. For example, Aghion, Bloom, Blundell, Griffith, and Howitt (2005) employ nonparametric splines to establish a U-shaped relationship in their study. However, the quadratic term method is employed extensively in the literature and is the standard in estimating U-shaped relationships.

Size is the log of assets held by bank *i* at time *t.* The interaction terms $Size_{it} * Concentration_t$ and $Size_{it} * Concentration_t{}^2$, allow us to estimate potential differences in the association between bank stability and concentration depending on bank size. To illustrate, consider the marginal effect of *Concentration* on stability measured as:

$$\frac{\partial Zscore}{\partial Concentration} = \beta_1 + 2\beta_2 Concentration + \beta_3 Size + 2\beta_4 Size * Concentration$$

If β_3 and β_4 are significant, then bank size influences the marginal effect of *Concentration* and we can conclude that banks of different sizes respond differently to increasing levels of concentration.

To account for changes in stability that are not due to changes in size or concentration, we include a set of control variables that include both individual bank and system wide characteristics. Vector *X* in equation 2.1 is a vector of macroeconomic

variables containing real GDP growth, inflation, interest rates, and currency strength. It is important to include macroeconomics variables because negative macroeconomic shocks tend to put pressure on banks' balance sheets (Lindgren, Garcia, and Saal, 1996). We include real GDP growth (*GDPG)* because fluctuations in real sector conditions impact bank stability (Lindgren, Garcia, and Saal, 1996). Hortlund (2005) finds an inverse relationship between inflation (*Inflation)* and bank stability. High levels of inflation could lead to asset bubbles and erode the value of bank capital (Lindgren, Garcia, and Saal, 1996). As explained by Schaeck and Cihak (2007), rising interest rates adversely affect borrowers' ability to repay loans and consequently have a negative association with bank stability. We employ the 10 year US treasury constant maturity rate (*Rate*) as a proxy for interest rates. Currency strength (*FX*) can impact bank stability because increases in the strength of the US dollar make exports more expensive. Domestic corporations could lose money in the wake of lower exports and could ultimately default on debt held by banking institutions (Lindgren, Garcia, and Saal, 1996). Conversely, reduction in currency strength will negatively affect profit margins of domestic corporations reliant on imports and cause them to default on debt held by banking institutions (Lindgren, Garcia, and Saal, 1996). We employ the trade weighted US dollar index as a proxy for currency strength[54].

[54] This is a weighted average of the foreign exchange values of the U.S. dollar against a subset of currencies in the broad index that circulate widely outside the country of issue. Some of the currencies included are the Canadian dollar, British Pound, the Euro, Mexican Peso, and Swiss Franc. For a complete list, see Loretan (2005).

In addition to the macroeconomic variables outlined above, we include three binary variables corresponding to the passage of the Gramm Leach Bliley Act of 1999 (*GLBA)*, recessionary periods (*Recession*), and the period pertaining to the financial crisis of 2008 (*Crisis)*. *GLBA* takes the unit value each period after 1999:4, when the Gramm Leach Bliley Act was set into legislation, and zero otherwise[55]. Additionally, we interact *GLBA* and *Size* because large banks and other financial institutions benefited more from GLBA than smaller firms because larger firms had more resources to enter new markets and benefited from scope economies (Mamun, Hassan, and Lai, 2004, and Hendershott, Lee, and Tompkins, 2002). *Recession* takes the unit value each period the US economy was in a recession and zero otherwise. According to the NBER, the US was in a recession during the periods; 2001:1 to 2001:2; and 2008:1 to 2009:2. *Crisis* takes the unit value between the time periods 2007:4 and 2009:2, corresponding to the 2008 financial crisis and zero otherwise (Haan and Poghosyan, 2012b).

Y is a vector of individual and systemic banking variables. Life insurance companies compete directly with banks for asset allocation and can have a negative impact on bank stability (Claessens and Laeven, 2004). We include the ratio of life insurance industry assets to banking assets (*Insurance)* to account for outside competition to the banking sector. Banks often engage in non-traditional banking activities as a means to hedge against risk or to speculate within their trading accounts, but could also create

[55] This act relaxed the requirements of the Glass-Steagall Act of 1933 which prohibited commercial banks, investment banks, and insurance companies from merging and had a profound impact on how banks operate. After its passage into legislation, these institutions could merge into larger Financial Holding Companies (FHC).

incentives for banks to take on additional risk (Ziadeh-Mikati, 2013). We include the ratio of off-balance sheet assets to total assets (*OBS)* to measure the risk associated with engagement in non-traditional banking activities. Due to data availability issues, we employ the total amount of unused commitments as our measure of off-balance assets[56]. As shown by (Ziadeh-Mikati, 2013), unused certificates are the most widely used type of off-balance sheet asset with 98.6% of banks holding these contracts. Following Demirgüç-Kunt and Detragiache (2010), we include the ratio of total loans to total assets as a measure of illiquidity (*Illiquidity).* Following Haan and Poghosyan (2012a), we include the ratio of non-interest expenses to income as a measure of inefficiency (*Inefficiency). Diversification* is the ratio of non-interest income to total income and is included because income diversification can have a significant impact on bank performance (DeYoung and Rice, 2004). *Stress* is the Chicago Federal Reserve Financial Conditions index and measures the level of stress the financial system is under[57]. As noted by Schaeck and Chihák (2007), systemic stress could negatively impact bank stability. A summary list of variables employed in the model is provided in Table 2-2.

[56] Off balance sheet data from the Call Reports are incomplete with many banks not reporting off balance sheet activity. Unused commitments are the most widely recorded off balance sheet asset and serves as a good proxy for overall off balance sheet activity.

[57] The National Financial Conditions Index (NFCI) measures risk, liquidity and leverage in money markets and debt and equity markets as well as in the traditional and "shadow" banking systems. Positive values of the NFCI indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average. We employ an adjusted index which isolates components uncorrelated with economic conditions.

Table 2-2: Variable Descriptions

Variable	Description
Z-score	Z-score (number of standard deviations *ROA* must fall below its mean to depreciate its capital equity).
CER	Capital Equity Ratio (capital equity /TA)
ROA	Return on Assets (Net Income/TA)
Volatility	Log of standard deviation of *ROA*
Concentration	Percent of assets held by largest ten banks
Size*Concentration	Interaction between Concentration and Size
OBS	Off-balance sheet assets (Unused Certificates / TA)
Illiquidity	Illiquidity (Net loans / TA)
Inefficiency	Non-Interest Expenses / Total Income
Diversification	Non-interest Income / Total Income
Insurance	Ratio of life insurance industry assets to total banking system assets
Stress	Chicago Fed Adjusted Financial Conditions Index
GDPG	GDP growth (percentage)
Inflation	Inflation rate (percentage)
FX	Trade weighted dollar index (basis points)
Rate	10-year treasury bond rate (basis points)
Crisis	Binary variable equal to one each quarter of the 2008 financial crisis (2007:4-2009:2)
Recession	Binary Variable equal to one each quarter the US was in a recessionary period (2001:1-2001:2; 2008:1-2009:2)
GLBA	Binary Variable equal to one each quarter after the passage of the GLB act (1999:4)
Size*GLBA	Interaction between GLBA and Size
Size	Logarithm of Total Assets (TA in thousands)

Note: This table provides a summary of variables employed in the model.

The term u_i is an unobserved control variable that pertains to each individual bank fixed effect. An unobserved effect could arise from bank specific data that is not readily available or from managerial quality or structure (Lindgren, Garcia, and Saal, 1996). In section 2.3.2, we explain if this variable should be treated as fixed or random across banks.

In order to test hypotheses H2 through H4, we modify equation (2.1). Following Boyd, DeNicolo, and Jalal (2006), we will replace *Z-score* with each of its components; capital equity ratio *(CER),* return on assets *(ROA)*, and portfolio volatility (*Volatility*) defined as log $\sigma(ROA)$[58]. This allows us to test which components of *Z-score* are impacted by banking concentration. Additionally, we recognize that there is often a trade-off between each *Z-score* component. For example, there is a trade-off between capital and profitability (Osborne, Fuertes, and Milne, 2009). In equations (2.2) through (2.4), where each component of *Z-score* is the dependent variable, we include the remaining components as independent variables[59]. The resulting set of equations are estimated and listed as follows[60].

[58] Following Boyd, DeNicolo, and Jalal (2006), we employ log $\sigma(ROA)$ instead of $\sigma(ROA)$to ensure positive predicted values.

[59] We do not include the individual components into equation (2-1) because the Z-score is a linear combination of the components. For the same reason, we do not include *Z-score* as an independent variable in equations (2-2) through (2-4).

[60] A strongly unbalanced panel prohibits seemingly unrelated regression estimation. The number of banks reduces from roughly 14 thousand in 1994:3 to roughly 6 thousand by 2013:4.

$$Zscore_{it} = c + u_i + \beta_1 Concentration_t + \beta_2 Concentration_t^{\,2} + \beta_3 Size_{it} + \beta_4 Size_{it} * Concentration_t + \beta_5 Size_{it} * Concentration_t^{\,2} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \quad (2.1)$$

$$CER_{it} = c + u_i + \gamma_1 ROA_{it} + \gamma_2 Volatility_{it} + \beta_1 Concentration_t + \beta_2 Concentration_t^{\,2} + \beta_3 Size_{it} * Concentration_t + \beta_4 Size_{it} * Concentration_t^{\,2} + \beta_5 Size_{it} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \quad (2.2)$$

$$ROA_{it} = c + u_i + \delta_1 CER_{it} + \delta_2 Volatility_{it} + \beta_1 Concentration_t + \beta_2 Concentration_t^{\,2} + \beta_3 Size_{it} * Concentration_t + \beta_4 Size_{it} * Concentration_t^{\,2} + \beta_5 Size_{it} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \quad (2.3)$$

$$Volatility_{it} = c + u_i + \varphi_1 CER_{it} + \varphi_2 ROA_{it} + \beta_1 Concentration_t + \beta_2 Concentration_t^{\,2} + \beta_3 Size_{it} * Concentration_t + \beta_4 Size_{it} * Concentration_t^{\,2} + \beta_5 Size_{it} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \quad (2.4)$$

2.3.2 Estimation

There are two major sources of bias within this model that must be addressed. First, it is likely that *Concentration* is endogenous. Endogeneity bias may occur from simultaneity (reverse causality), measurement error, or from omitted variables (Wooldridge, 2010). Reverse causality likely exists between bank stability and concentration because banks often consolidate because of low stability, profitability, and/or high volatility and thereby cause an increase in bank concentration (Schaeck and Ĉihâk ,2007). Second, it is likely that the unobserved individual effect, u_i , is correlated with other independent variables that pertain to individual banks. For example, it is likely that the individual effect of a particularly well managed bank is correlated with other

independent variables associated with a well performing bank, such as high efficiency. Failing to account for either of these issues and employing the Ordinary Least Squares (OLS) method will introduce bias into the model (Wooldridge, 2010). We take the following steps to address these issues.

First, to address the endogeneity issue, we employ an Instrumental Variable (IV) estimator. IV techniques could help to reduce the bias if good instruments are employed (Bound, Jaeger, and Baker, 1995). However, if the instruments are weak, the bias could be worse than the OLS case (Bound, Jaeger, and Baker, 1995). The same holds if a supposed endogenous regressor is actually exogenous (Wooldridge, 2010). We perform three procedures to assess the need for instrumental variables and their statistical validity. They include the Davidson-MacKinnon test, as proposed by Davidson and MacKinnon (1993), to test if the supposed endogenous variables should be treated as exogenous; the Sanderson-Windmeijer *Chi-squared* test, as proposed by Sanderson and Windmeijer (2016), to test if the model is identified; and the Kleibergen-Paap *F* test, as proposed by Kleibergen and Paap (2006), to determine the strength of the instruments. If the test results imply that *Concentration* should be treated as endogenous and the instruments are strong, then IV estimation is preferred over OLS. Additional details on each specification test are provided in Appendix B.

Second, to account for correlation between the unobserved individual effect, u_i, and the other independent variables, we employ bank fixed effects with a Fixed Effects (FE) estimator, which resolves the problem by essentially removing the bank fixed effect (Wooldridge, 2010). The FE estimator, however, is not efficient if u_i is not correlated

with the other independent variables (Wooldridge, 2010). In such a situation, a Random Effects (RE) estimator is preferred due to its greater efficiency (Wooldridge, 2010). We perform the Hausman test, as proposed by Hausman (1978), to assess the superiority of the FE estimator over the RE estimator. The results of all tests are reported in section 2.5.1.

Additionally, we perform all of the tests outlined above on the remaining equations (equations 2.2-2.4). It is worth noting that since all equations share the same set of regressors, a system estimation approach of all equations simultaneously should theoretically provide more efficient results (Wooldridge, 2010). However, since every equation is exactly identified (i.e. the number of instruments equals the number of endogenous variables), system estimation will yield results identical to the single equation estimates and no efficiency is gained or lost (Hayashi, 2000).

2.4 Data and Variable Construction

Quarterly data on bank-specific variables come from the Call Reports provided by Wharton Research and Data Services (WRDS). The Federal Reserve Bank of Saint Louis Economic Data (FRED) and the Federal Reserve Financial Accounts of the United States (Z.1) provide the macroeconomic and life insurance data.

2.4.1 Descriptive Statistics

Table 2-3 presents descriptive statistics for the variables employed in the model. The data contain approximately 590,000 observations from 1994:3 through 2013:4 corresponding to the time period after the passage of RN into legislation. There are data

Table 2-3: Descriptive Statistics

Variable	Mean	St. Dev.	Minimum	Maximum
Z-score	43.62	35.02	4.43	312.42
CER x 100	10.57	3.50	5.59	40.08
ROA x 100	0.60	0.46	-2.30	2.04
Volatility	-1.19	0.60	-3.31	0.76
Concentration x100	34.83	9.04	19.31	47.22
$Concentration^2$	1,295.25	612.35	372.87	2,229.72
Concentration * Size	413.92	122.04	154.66	1,008.67
$Concentration^2$****Size***	15,413.91	7,711.38	2,986.45	47,629.23
HHI	204.36	100.25	62.65	364.7
HHI^2	51,816.02	43,030.2	3,925.02	133,006.1
HHI * Size	2,432.008	1,260.18	501.79	7,790.38
HHI^2****Size***	617,860.5	528,074.3	31,436.91	2,841,154
OBS	0.09	0.08	0	1
Illiquidity	0.61	0.15	0	1.2
Inefficiency	.67	.163	.32	2.09
Diversification	.135	.097	0	.86
Insurance	0.36	0.03	0.28	0.44
Stress	-.028	.699	-1.1	3.04
GDPG	0.62	0.62	-2.13	1.87
Inflation	0.59	0.47	-2.31	1.52
FX	87.64	11.09	69.52	111.57
YR x 100	4.76	1.47	1.64	7.84
Crisis	0.07	0.26	0	1
Recession	0.09	0.29	0	1
GLBA	0.67	0.46	0	1
GLBA * Size	8.02	5.72	0	21.4
Size	11.86	1.25	7.5	21.4

Note: This table provides descriptive statistics for all variables employed in the model. The individual bank variable, *Z-score, CER, ROA, Volatility, OBS, Illiquidity, Inefficiency,* and *Diversification* are winsorized at the 1% and 99% levels to remove outliers. Winsorizing the remaining bank invariant variable would remove a very large number of observations and is therefore not performed. *Size* is given in 2006 dollars.

on over 13,000 individual commercial banks included in this analysis. As previously explained, data on commercial banks is richer and provides a significantly greater number of observations. The dependent variables (*Z-score, CER, ROA, and Volatility*) and bank-specific variables (*OBS, Illiquidity, Inefficiency, and Diversification*) are winsorized at the 1% and 99% percentiles to remove the effect of extreme outliers. We do not winsorize the macroeconomic variables because doing so would remove a very large number of observations.

The main variable of interest, *Concentration*, ranges from 19.31 percent (assets held by the largest ten banks) to 47.22 percent with a mean of 34.58 percent. Figure 2-1 displays *Concentration* over the sample period (1994:3 to 2013:4). The banking system consolidated significantly as can be seen by the upward trend of concentration since the beginning of this data set. As of 2013:4, concentration stood at 44.6 percent.

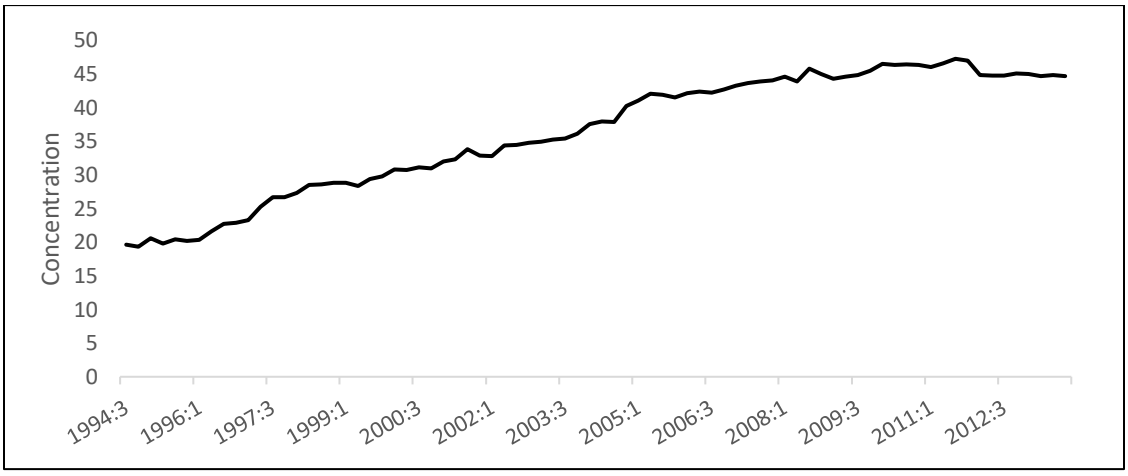

Figure 2-1: *Concentration* Over the Sample Period; 1994:3-2013:4

2.5 Results[61]

2.5.1 Specification and Endogeneity Tests

The results of the specification tests, reported in Tables 2-4 and 2-5, suggest that the FE-IV estimator is superior to other estimators considered; FE, 2SLS, and Pooled OLS. First, a robust version of the Hausman test indicates that a fixed effects approach is preferred to a random effects approach in all models[62, 63]. Second we test for endogeneity of *Concentration* and for the strength of the instruments. $Concentration^2$, *Size*Concentration*, and $Size * Concentration^2$ may also be endogenous because of their significant correlation with *Concentration.* Furthermore, we test for endogeneity of *ROA*, and *Volatility* in equations 2.2-2.4, and for endogeneity of *CER* in equations 2.3, 2.4 and 2.4. We choose a two quarter lag of each endogenous variable as instruments because each dependent variable at time *t* does not have an impact on observations at time *t-2.* Furthermore, we do not include any additional instruments because the bias introduced by IV methods is minimized when the number of instruments is identical to the number of endogenous variables (Angrist and Pischke, 2009).

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[61] The parameter estimates as well as the Sanderson-Windmeijer *Chi-squared* and the Kleibergen-Paap *F* statistics are provided by the Stata *xtivreg2* command written by Schaeffer (2010). The estimates of the Davidson-MacKinnon test are provided by the Stata *dmexogxt* command written by Baum and Stillman (2003). The results of the robust Hausman test are provided by the Stata command *xtoverid* written by Schaeffer and Stillman (2010).

[62] The standard Hausman statistic produces a negative value which renders the test inconclusive. This occurs frequently in both small and large samples (Schreiber, 2008). An alternative test of model selection is offered by Wooldridge (2002) that is a robust version of the standard Hausman test. This procedure guarantees a positive test statistic and can be extended to accommodate data that suffer from heteroskedasticity (Wooldridge, 2010).

[63] The robust Hausman statistics are 2,603.91, 3,069.144, 6,212.9, and 1,539.2 corresponding to the *Z-score*, *CER*, *ROA*, and *Volatility* models respectively.

Table 2-4: Test for Random vs. Fixed Effects

Dependent Variable	Sargan-Hansen Statistic	*p*-Value
Z-score	2,603.91	0.00***
CER	3,069.144	0.00***
Volatility	6,212.9	0.00***
ROA	1,539.2	0.00***

Note: This robust version of the Hausman test allows for comparison between the fixed and random effects models. It is robust to heteroscedasticity and is guaranteed to produce a positive test statistic. The test is available via the *xtoverid* Stata command written by Schaeffer and Stillman (2010). The first column indicates the test statistic. The second column indicates the p-value and level of significant. "*" indicates significance at the .01 level.**

Table 2-5: Endogeneity and Instrumental Variable Suitability Tests

	Purpose	**Statistic**	**P-Value**
Panel A: Davidson-MacKinnon Test	Endogeneity		
Dependent Variable			
Z-score		651.14	0.00***
CER		856.18	0.00***
Volatility		578.41	0.00***
ROA		514.4	0.00***
Panel B: Instrument Tests			
Sanderson-Windmeijer *Chi-squared*	Underidentification		
Concentration		8,191.9	0.00***
$Concentration^2$		11,942.5	0.00***
*Size*Concentration*		2,612.7	.037**
$Size * Concentration^2$		3,502.4	.025**
Kleibergen-Paap *F*	Strength of Instruments	401.9	

Note: This table presents results from the endogeneity and instrument suitability tests. Panel A displays the Davidson-MacKinnon statistic and tests if the supposed endogenous variables should be treated as exogenous. A rejection of the null hypothesis indicates that an IV model is superior to OLS. The test is available via the *dmexogxt* Stata command written by Baum and Stillman (2003). Panel B reports the Sanderson-Windmeijer Chi-squared and the Kleibergen-Paap *F* statistics and test the strength of the instruments employed in the *Z-score* model. These test statistics are very similar to those of the remaining models; C*ER, ROA,* and *Volatility.* For simplicity, we do not report those test statistics but can provide them upon request. These tests are available via the Stata command *xtivreg2* written by Schaffer (2010).

The results of the Davidson-MacKinnon test[64] suggest that an IV approach is preferred to a model without IVs and that all variables mentioned above should be treated as endogenous. Furthermore, the Sanderson-Windmeijer *Chi-squared* and Kleibergen-Paap *F*[65] tests suggest that the instruments are strong. Additional details on each specification tests are provided in Appendix B.

2.5.2 Empirical Results

2.5.2.1 The Z-score model

This section provides the estimation results of the *Z-score* model. Following Brambor, Clark, and Golder (2006), we discuss the marginal effect of concentration on each dependent variable. The results of the FE-IV estimation are presented in Table 2-6. As a robustness check, we also estimate the models using three additional techniques: FE (Fixed Effects without IV), the two-stage least squares (2SLS), and the Pooled OLS. The results of the latter techniques are qualitatively similar to those of the FE-IV model and are displayed in Appendix C for the interested reader. We focus our discussion on concentration measured by the asset share of the ten largest commercial banks but also display the results based on the HHI for comparison in Table 2-7. We cluster the standard errors on each individual bank to correct for any bias introduced from error correlation within each cluster (Wooldridge, 2010)[66].

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[64] The Davidson-MacKinnon statistics are 651.14, 856.18, 578.41, and 514.4 corresponding to the *Z-score*, *CER*, *ROA*, and *Volatility* models respectively.

[65] The Sanderson-Windmeijer *Chi-squared* statistics are 8,191.9, 11,942.5, 2,612.7, and 3,502.4 corresponding to the two quarter lag instruments for *Concentration*, $Concentration^2$, *Size*Concentration*, and $Size * Concentration^2$ respectively. The Kleibergen-Paap *F* statistic is 401.9.

[66] Additionally, we introduce a lagged dependent variable to the right hand side of each regression as a robustness check. The results are qualitatively the same and we do not report the results.

Table 2-6: Fixed Effects IV Estimation Results, *Concentration* measured by C10 Ratio

Regressors/ Dependent Variables	*Z-score* *(1)*	*CER* *(2)*	*ROA* *(3)*	*Volatility* *(4)*
Concentration	45.56***	7.93***	0.33***	-0.77***
$\boldsymbol{Concentration^2}$	-0.65***	-0.11***	-0.004***	0.01***
Concentration*Size	-3.46***	-0.63***	-0.02***	0.06***
$\boldsymbol{Concentration^2 * Size}$	0.05***	0.009***	0.0003***	-0.0008***
CER			-0.02***	0.04***
ROA		-2.15***		0.47***
Volatility		3.27***	0.343***	
OBS	-13.32***	3.24***	0.49***	0.02
Illiquidity	-17.92***	-3.12***	-0.16***	0.35***
Inefficiency	35.72***	-1.20***	-1.64***	0.36***
Diversification	-28.72***	-0.65***	0.23***	0.47***
Insurance	-150.25***	-10.01***	-0.29***	1.94***
Stress	-2.23***	-0.02***	0.01***	0.03***
GDPG	2.12***	0.07***	-0.02***	-0.03***
Inflation	-2.42***	-0.11***	-0.03***	0.05***
FX	-0.25***	-0.03***	-0.01***	0.01***
YR	1.02***	-0.12***	-0.03***	0.04***
Crisis	1.44***	0.30***	0.10***	-0.08***
Recession	-5.05***	-0.61***	-0.16***	0.16***
GLBA	-69.69***	-12.72***	-0.48***	1.10***
GLBA*Size	5.79***	1.10***	0.05***	-0.10***
Size	49.97***	8.97***	0.36***	-0.93***
Constant	-532.63***	-87.70***	-1.81***	8.16***
Number of Observations	582,296			
Number of Banks	13,436			

Note: This table presents results from the fixed effects IV model when the concentration is measured as the percent of assets held by the largest ten banks. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table 2-7: Fixed Effects IV Estimation Results, Concentration measured by HHI

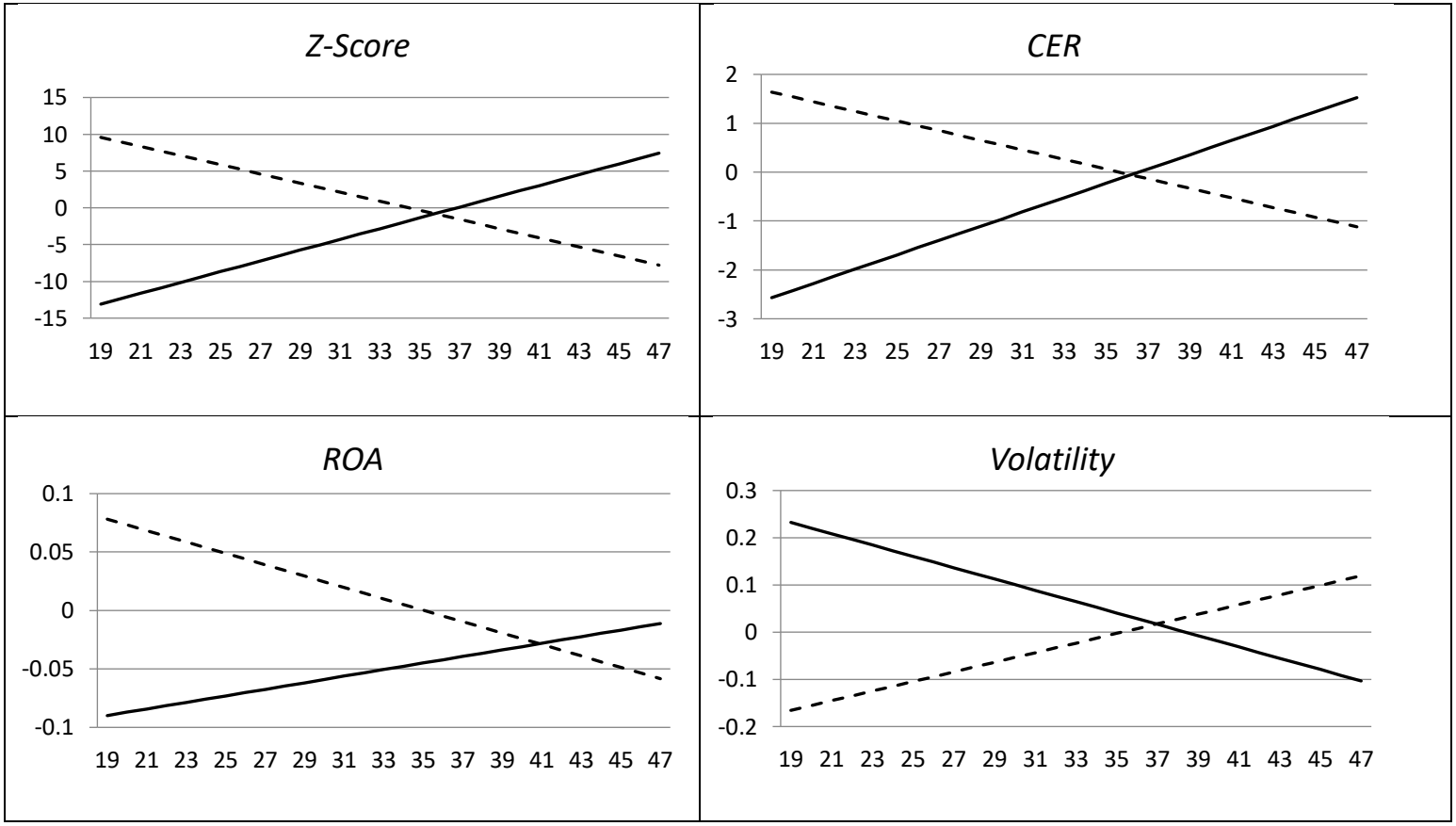
Regressors/ Dependent Variables	*Z-score* *(1)*	*CER* *(2)*	*ROA* *(3)*	*Volatility* *(4)*
Concentration	1.44***	0.26***	0.01***	-0.02***
$\boldsymbol{Concentration^2}$	-0.003***	-0.0006***	-0.00001***	0.00005***
Concentration*Size	-0.12***	-0.02***	-0.00055***	0.0019***
$\boldsymbol{Concentration^2 * Size}$	0.0003***	0.00005***	0.0000008***	-0.000004***
CER			-0.02***	0.04***
ROA		-2.21***		0.46***
Volatility		3.30***	0.34***	
OBS	-10.13***	2.98***	0.43***	0.02
Illiquidity	-17.03***	-2.96***	-0.15***	0.32***
Inefficiency	36.19***	-1.22***	-1.63***	0.34***
Diversification	-26.80***	-0.79***	0.22***	0.46***
Insurance	-87.15***	-6.77***	0.09*	0.97***
Stress	-1.18***	0.02***	0.01***	0.02***
GDPG	2.60***	0.11***	-0.02***	-0.04***
Inflation	-1.96***	-0.13***	-0.03***	0.05***
FX	0.04***	-0.01***	-0.004***	0.002***
YR	-1.26***	-0.21***	-0.03***	0.05***
Crisis	3.14***	0.39***	0.11***	-0.11***
Recession	-5.52***	-0.63***	-0.16***	0.16***
GLBA	-44.32***	-8.72***	-0.16***	0.63***
GLBA*Size	3.91***	0.75***	0.02***	-0.06***
Size	4.43***	0.34***	0.02***	-0.12***
Constant	12.53***	17.29***	2.63***	-1.74***
Number of Observations	582,296			
Number of Banks	13,436			

Note: This table presents results from the fixed effects IV model when the concentration is measured by HHI. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Both *Concentration* and *Concentration*^{2}, in the *Z-Score* equation, are found to be highly significant with positive and negative signs, respectively (Table 2-6). These coefficient signs indicate that *Z-score* increases with concentration up to a certain threshold and decreases thereafter. Moreover, the positive and significant interaction term $Size_{it} * Concentration_t{}^2$ indicates that the effect of concentration on bank stability (Z-Score) increases with bank size. The marginal effect pattern alternates from a downward to an upward slope when *Size* exceeds approximately $1 billion in assets.

To illustrate, we display how the marginal effect changes with concentration conditional on bank size in Figure 2-2. The marginal effect, $\partial\, Zscore/\partial\, Concentration = \beta_1 + 2\beta_2 Concentration + \beta_3 Size + 2\beta_4 Size * Concentration,$ is a function of both concentration and size. The second order mixed derivative is $\partial^2 Zscore/\partial Concentration\, \partial\, Size = \beta_3 + 2\beta_4 Concentration$. To ease the interpretation, we divide *Size* into two groups; small banks (total assets less than $1B) and large banks (total assets greater than $1B). The minimum and maximum of *Size* are used in the marginal effect calculations to illustrate the differences.

The graph in the upper left panel of Figure 2-2 implies that the effect of concentration on stability (*Z-score*) is very different for small and large banks. As concentration increases the marginal effect decreases for small banks while it increases for large banks. Our results stand in conflict with Haan and Poghosyan (2012a) who find that the Z-score for larger banks continuously decreases as concentration strengthens. An explanation may be that these authors do not correct for endogeneity and non-linearity of the relationship, leaving their results disputable. Based on our results, we reject



Note: These graphs display the marginal effect of concentration at various levels of concentration and is given by $\beta_1 + 2\beta_2 Concentration + \beta_3 Size + 2\beta_4 Size * Concentration$. To ease with the interpretation, we use the maximum and minimum value of bank size; 21.4 and 7.5. This allows us to examine the effect of concentration for large and small banks. In each graph, the solid line corresponds to large banks while the dashed line corresponds to small banks. The graph in the upper left represents the marginal effect of concentration on *Z-score.* The upper right, lower left, and lower right represent the marginal effect of concentration on *CER, ROA,* and *Volatility* respectively. The C10 ratio is the concentration measure in all graphs and is displayed on the horizontal axis. We display the marginal effects over the range of concentration.

Figure 2-2: Marginal Effect of Concentration for Large and Small Banks

hypothesis H1a (*Individual bank stability and bank concentration are unassociated*) and find evidence that there is an inverted U-shaped relationship between stability and concentration. We also reject hypothesis H1b (*The relationship between bank stability and bank concentration does not vary with bank size*) and conclude that the stability-concentration relationship does vary with bank size.

These results are quite interesting. First, the behavior of smaller banks agrees with the theoretical findings of Martinez-Miera and Repullo (2010) that show two opposing forces are at work; a *risk-taking* effect and a *margin effect.* To elaborate, as concentration increases, rates offered on loans increase, profit margins and the capital buffer against losses also increase, resulting in greater bank stability (lower risk of failure)[67]. However, as concentration increases past a certain threshold, rates on loans increase, thereby reducing profits realized by borrowers and providing the latter incentives to undertake riskier projects, making banks less stable (greater risk of failure) as a result. Eventually, the *risk-taking* effect dominates resulting in reduced stability. Second, our empirical results provide evidence that the stability-concentration relationship is very different for larger banks as they demonstrate the opposite behavioral relationship.

This dissimilarity between large and small banks could potentially be explained by the differences in how large and small banks operate in both funding and income generating strategies. On the funding side, small banks rely on traditional core deposits whereas larger banks tend to fund their operations through overnight Federal Funds loans

[67] We note that while the stability-concentration relationship is that of an inverted U-shape, it agrees with Martinez-Miera and Repullo (2010) due to the inverse relationship between *Z-score* and the risk of bank failure.

from the interbank network repurchase agreements, and large CDs (Berger, Molyneux, and Wilson, 2010). On the income side, large banks have a distinct advantage in 'hard information' lending which is based on quantifiable information that can easily be modelled and compared across borrowers (Thakor and Boot, 2008). Small banks, however, have an advantage in 'soft information' where lending decisions are based on knowledge about the borrowers' integrity and reputation (Thakor and Boot, 2008; Berger, Molyneux, and Wilson, 2010). As concentration increases and larger banks expand into new markets through acquisition, the remaining small banks are able to charge higher rates on loans to informationally opaque borrowers due to an initial reduction in competition (Berger, Molyneux, and Wilson, 2010). The difference is reflected in the average interest margin of 2.82 for large banks compared to 3.63 for small banks (Berger, Molyneux, and Wilson, 2010). Small banks also offer a greater volume of syndicated loans and foreign government loans which carry greater margins. However, in general, this advantage enjoyed by small banks is eventually muted by the ability of large banks to generate high levels of non-interest income and from their ability to offer convenient services such ATMs, online banking, and credit scoring (Berger, Molyneux, and Wilson, 2010).

As noted by Berger, Molyneux, and Wilson (2010) the increase in concentration over the last three decades in the US has been dominated by the mergers of the largest commercial banks. They proceed to note that the operational efficiency of bank holding company (BHC) affiliates declined as they were located further from their headquarters (Berger, Molyneux, and Wilson, 2010). These losses have been mitigated over time

through advancements in communications and information technologies. Additionally, over time, large banks have improved their efficiency and productivity more than small banks, placing additional pressure on small banks in local markets (Berger, Molyneux, and Wilson, 2010).

Our empirical results are consistent with the claim that large banks place pressure on small banks (Berger, Molyneux, and Wilson, 2010) and push many of them out of the market (Saunders and Cornett, 2014). This dynamic could be detrimental to the real economy. As a consequence of this trend, loans to consumers, small corporations, housing, agriculture, and generally informationally opaque borrowers shrink. Various studies (e.g. Berger, Kashyap, and Scalise, 1995) have shown that large banks allocate a significantly smaller percentage of their assets to small business lending. Small businesses that rely on relationship lending suffer because as small banks deteriorate, the credit available to them diminishes (Berger, Molyneux, and Wilson, 2010). In Chapter 1, we provide evidence that as banking concentration increases, the rate of bank failure and the rate of bank distress both increase resulting in slower economic growth, higher unemployment, and higher inflation. The results in this study extend the findings of Chapter 1 and indicate that as concentration increases, it is the small banks that become increasingly stressed. Despite their relatively small size, they are large in number and collectively play a very important role in the aggregate economy by providing loans to consumers, small businesses, agriculture, and informationally opaque borrowers and still hold a large share of the aggregate commercial banking assets. They serve a niche that large banks do not want to, and perhaps, cannot fill. Furthermore, deteriorating stability

of small banks has a negative impact on depositors. Associated with higher levels of concentration are lower interest rates paid on deposits which ultimately hurts depositors (Berger, Demsetz, and Strahan, 1999; Keeton, 2001).

We note that the *Crisis* variable is positive and highly significant which contradicts what most would expect. Gorton and Metrick (2012) claim that the financial crisis of 2008 was mainly driven by instability in the *shadow banking* sector and not the commercial banking sector. It is also noted by Keister and McAndrews (2009) that commercial banks held reserves during and after the crisis well in excess of the reserve requirement. We suspect that in general, commercial banks altered their portfolios, in response to the shadow banking crisis, by holding additional capital and less volatile portfolios; thereby increasing the *Z-score* and ultimately stability.

2.5.2.2 Z-Score Components

Following Boyd, DeNicolo, and Jalal (2006), we replace *Z-score* with each of its three components as dependent variables (equations 2.2-2.4). This allows us to determine which components are driving the stability-concentration relationship and to provide a robustness check. We focus our discussion on the FE-IV estimator as various tests suggest that it is superior to the other estimators considered including FE, 2SLS, and Pooled OLS. The FE-IV estimation results for equations 2.2-2.4 are presented in Table 2-6 columns 2 through 4. The results based on the latter techniques are qualitatively similar to those reported in Table 2-7 and are displayed in Appendix C for the interested reader. We note, however, that the results of the *ROA* model vary across estimators. Nonetheless, the FE-IV estimator is shown to be superior to the remaining models, and therefore more

reliable. We cluster the standard errors on each individual bank in order to correct for any bias introduced from error correlation within each cluster (Wooldridge, 2010).

The results of the capital equity ratio (*CER)* and return on asset (*ROA)* models are very similar to those of the *Z-score* model and reinforce the latter. We find that both *Concentration* and *Concentration*^{2} are highly significant, as reported in Table 2-6 columns 2 (*CER*) and 3 (*ROA*), with positive and negative signs, respectively. These signs indicate that both the capital-equity ratio (*CER*) and return on assets *(ROA)* increase with concentration up to approximately 35% and decrease thereafter. Moreover, the positive and significant coefficient of the interaction term $Size_{it} * Concentration_t{}^2$ indicates the marginal effect of concentration on capital equity and return on assets increases with bank size. To illustrate, we display how the marginal effect changes with concentration conditional on bank size in Figure 2-2. The marginal effect, $\partial\, CER/_{\partial\, Concentration} = \beta_1 + 2\beta_2 Concentration + \beta_3 Size + 2\beta_4 Size * Concentration$ and $\partial\, ROA/_{\partial\, Concentration} = \beta_1 + 2\beta_2 Concentration + \beta_3 Size + 2\beta_4 Size * Concentration$, is a function of both concentration and size. To ease the interpretation, we divide *Size* into two groups; small banks (assets less \$1B) large banks (assets greater than \$1B). The minimum and maximum of *Size* are used in the marginal effect calculations to illustrate the differences.

The graphs in the upper right and lower left panels of Figure 2-2 imply that the impact of concentration on capital equity (*CER)* and profitability (*ROA)* respectively, is very different for small and large banks; as concentration increases, the marginal effect decreases for small banks while it increases for large banks. Based on our results, we

reject hypotheses H2a (*Capital equity and bank concentration are unassociated)* and H3a (*Profitability and bank concentration are unassociated*). We find evidence that there is an inverted U-shaped relationship both aforementioned variables and concentration. We also reject hypotheses H2b (*The relationship between capital equity and bank concentration does not vary with bank size*) and H3b (*The relationship between profitability and bank concentration does not vary with bank size*) and conclude that the capital equity-concentration and profitability-concentration relationships vary with bank size.

We first focus our attention on large banks and the increasing effect that concentration has on the capital equity ratio and on profitability. We consider several potential explanations for our findings. First, the unusual period of bank profitability over the majority of sample period (1994:3 – 2013:4) may have facilitated the increase in the bank capital equity ratio through increased retained earnings. During this time, bank managers did not respond to increasing profits through raising dividends or repurchasing their outstanding shares, bringing about an increase in capital equity ratio as a result (Flannery and Rangan, 2008). Second, our results for large banks supports the Charter Value Hypothesis set forth by Keely (1990) and indicates that as large banks consolidate, profits increase thereby increasing their charter value. Large banks therefore hold additional capital to protect their charter value (Keely, 1990). Third, regulatory authorities introduced a stricter set of capital standards during the early 1990s (Thakor and Boot, 2008). In particular, the FDIC Improvement act of 1991 introduced prompt corrective actions to banks violating capital requirements providing incentives for banks

to hold capital well above the required levels in order to avoid such actions (Flannery and Rangan, 2008). Fourth, technological progress increased scale economies for larger institutions over time allowing them to operate with lower average costs and manage larger operations more effectively and thereby driving profitability upwards (Berger, Dick, Goldberg, and White, 2007). Additionally, technological progress allowed larger banks to have better access to advances in applied financial models allowing them to manage risks more effectively (Berger, Dick, Goldberg, and White, 2007). Finally, increased reliance of banks on non-interest income derived from activities such as standby letters of credit, loan commitments, and options and futures positions required greater capital levels for large banks because they wanted to attract new customers in these areas of activity (Stiroh, 2006, Flannery and Rangan, 2008, Berger, Molyneux, and Wilson, 2010).

For small banks, the results, reported in Table 2-6 columns 2 (*CER*) and 3 (*ROA*) and the upper right panel lower left panels of Figure 2-2, indicate that the impact of concentration on capital equity and profitability decreases as concentration increases. We attribute these dynamics to increased pressure from large banks. First, we note the previously explained fact that small banks have a distinct advantage in 'soft information' lending (Thakor and Boot, 2008). As large banks move into smaller markets, the availability of funds to borrowers requiring loan approvals based on 'soft information' is reduced resulting in higher loan rates to these borrowers and higher interest income for the small banks (Thakor and Boot, 2008). This initial advantage enjoyed by small banks seems to be exhausted as concentration increases and more pressure is placed on them

from larger multimarket banks. As illustrated by Hannan and Prager (2009), large multimarket banks have distinct advantages over small banks that serve a single market. For example, large banks have better access to cheaper wholesale funds allowing them to charge lower rates on loans to borrowers with good credit and informationally transparent. Moreover, they can offer banking products more efficiently due to their geographic scope, and can offer a wide array of products that small banks cannot provide (Hannan and Prager, 2009; Berger, Dick, Goldberg, and White, 2007). The competitive pressure exerted by large banks appears to be driving overall profitability of small banks lower and causing the capital equity level of small banks to deteriorate.

The final Z-score component is portfolio volatility (*Volatility*) measured by the logarithm of the standard deviation of return on assets. We find that both *Concentration* and *Concentration*^{2} are highly significant, as reported in Table 2-6 column 4, with negative and positive signs, respectively. These signs indicate that return volatility decreases with concentration up to approximately 35% and increases thereafter. Moreover, the negative and significant coefficient of the interaction term $Size_{it} * Concentration_t{}^2$ indicates the marginal effect of concentration on return volatility decreases with bank size. To illustrate, we display how the marginal effect changes with concentration conditional on bank size in Figure 2-2. The marginal effect, $\partial\, Vol/_{\partial\, Concentration} = \beta_1 + 2\beta_2 Concentration + \beta_3 Size + 2\beta_4 Size * Concentration$ is a function of both concentration and size. To ease the interpretation, we divide *Size* into two groups; small banks (assets less $1B) large banks (assets greater

than $1B). The minimum and maximum of *Size* are used in the marginal effect calculations to illustrate the differences.

The graph in the lower right panel of Figure 2-2 implies that the impact of concentration on volatility $(\log \sigma(ROA))$ is very different for small and large banks. The marginal effect increases with concentration for small banks while the opposite holds for large banks. Based on our results, we reject hypothesis H4a (*Portfolio volatility and bank concentration are unassociated*) and find evidence that there is a U-shaped relationship between portfolio volatility and concentration. We also reject hypothesis H4b (*The relationship between portfolio volatility and bank concentration does not vary with bank size*) and conclude that the volatility-concentration relationship does vary with bank size.

We provide two possible explanations for our results on volatility; managerial expertise and profits. First, our results for small banks are consistent with the empirical findings of Boyd, DeNicolo, and Jalal (2006) who find a positive association between portfolio volatility and concentration. This positive association suggests that as concentration increases, small banks hold riskier portfolios to compensate for a reduction in profits as previously explained. Second, it has been well noted in the literature that increased reliance on non-interest income is associated with higher levels of income volatility and that large banks have become increasingly reliant on non-interest activities (DeYoung and Rice, 2004). Based on this relationship, one would expect large banks to have greater earnings volatility. However, our results indicate that the marginal effect of concentration on portfolio volatility for large banks is decreasing as concentration goes up. However, as concentration increases, large banks that consolidate have better access

to size-biased advanced information technologies, can better diversify their portfolios across product lines (Hughes and Mester, 2011), and are able to operate over a wider geographic area (Berger, Molyneux, and Wilson, 2010). Furthermore, when large banks grow in size due to concentration, they benefit considerably from production and managerial synergies and, therefore, possess greater expertise in managing more diverse income streams (Berger, Molyneux, and Wilson, 2010). Our results suggest that the gains from product and geographic diversifications, as well as expertise and managerial synergies, outweigh the increase in volatility from non-interest income activities.

Small banks have also increased their reliance on non-interest income, albeit at a slower rate (Stiroh, 2006). Nonetheless, as concentration increases, small banks might attempt to diversify their portfolios through non-interest activities with the ambition of remaining competitive with larger institutions (Stiroh, 2006). Small banks, however, may lack the expertise to manage these activities well and may fail to realize the product or geographic diversification benefits enjoyed by their large counterparts (Stiroh, 2006). Furthermore, small banks in general may not have the technology nor the scale to successfully operate in this area (Stiroh, 2006). This dynamic could in part explain some of the upward force that concentration is placing on small bank volatility.

2.5.2.3 Sharpe Ratio

In this section, we consider the risk-return tradeoff of increased volatility because banks are often concerned with rate of return per unit of volatility (DeYoung and Rice, 2004). To this end, we replace *Volatility* with the Sharpe ratio (*Sharpe*) in equation (2.5) and consider how the risk-return tradeoff is affected by concentration. Following Hann

and Poghosyan (2012a), we calculate the Sharpe ratio by dividing *ROA* by its standard deviation, $\sigma(ROA)$.

$$Sharpe_{it} = c + u_i + \beta_1 Concentration_t + \beta_2 Concentration_t{}^2 + \beta_3 Size_{it} * Concentration_t + \beta_4 Size_{it} * Concentration_t{}^2 + \beta_5 Size_{it} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \quad (2.5)$$

The estimation results of equation 2.5 using the FE-IV model are presented in Table 2-8. The specification tests again suggest the FE-IV estimator is superior to FE, 2SLS, and Pooled OLS. We find that both *Concentration* and $Concentration^2$ are highly significant, as reported in Table 2-8 column 1 with positive and negative signs, respectively. These results imply an inverted U-shaped relationship between the Sharpe ratio and concentration indicating that when concentration (measured by the asset share of the ten largest banks) exceeds roughly 34%, the Sharpe ratio decreases for small banks. However, the positive and highly significant interaction term $Size_{it} * Concentration_t{}^2$ indicates that the marginal effect of concentration on the Sharpe ratio increases with bank size. This result does not agree with Hann and Poghosyan (2012a) who find the marginal effect to decrease with bank size. Potential explanations for the differences include their failure to correct for endogeneity and the shorter time period examined[68]. Our results suggest that small banks could be holding riskier portfolios to compensate for reductions in profitability which is reflected in the decreasing Sharpe ratio. Large banks, on the other hand, are increasingly able to exploit their advantages

[68] Hann and Poghosyan (2012a) examine 2004:1 to 2009:4. Our time period covers 1994:3 to 2013:4.

Table 2-8: Fixed Effects IV Estimation Results, Dependent Variable is the Sharpe ratio

Variable	*C10* *(1)*	*HHI* *(2)*
Concentration	1.118***	0.020***
$\boldsymbol{Concentration^2}$	-0.015***	-0.00004***
Concentration*Size	-0.071***	-0.002***
$\boldsymbol{Concentration^2 * Size}$	0.001***	0.00003***
OBS	0.350***	0.260***
Illiquidity	-0.510***	-0.453***
Inefficiency	-3.508***	-3.475***
Diversification	0.155***	0.162***
Insurance	-5.632***	-2.414***
Stress	-0.082***	-0.050***
GDPG	0.074***	0.090***
Inflation	-0.232***	-0.251***
FX	-0.025***	-0.011***
YR	0.048***	-0.011***
Crisis	0.490***	0.592***
Recession	-0.585***	-0.608***
GLBA	-1.569***	-0.437***
GLBA*Size	0.159***	0.062***
Size	1.271***	0.224***
Constant	-9.948***	3.920***
Number of Observations	587,109	
Number of Banks	13,931	

Note: This table presents results from the fixed effects IV model when Sharpe ratio is the dependent variable. Columns (1) and (2) contain results for the C10 ratio and HHI respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

and earn a higher profit per unit of volatility. These results stand in conflict with DeYoung and Rice (2004) who that find that larger banks have a lower risk-return profile due to non-interest activities and that that small banks have a higher risk-return profile due to the reduced volatility associated with relationship lending. It is worth noting that their time period (1993-2003) is significantly shorter and less recent than ours (1994:3-2013:4).

2.5.2.4 Systemic Risk

In this section, we examine systemic risk because as banks consolidate, they become more similar in terms of products, models of risk measurements and techniques of risk management (Weiß, Neumann, and Bostandzic, 2014). They rely more on securitization, make larger syndicated and foreign loans, take greater derivatives positions, and, therefore, they become more vulnerable to similar shocks (Weiß, Neumann, and Bostandzic, 2014). In all likelihood they also become bolder in taking risk. The financial system can become increasingly fragile as banks become increasingly interconnected (Bostandzic, 2014) and the risks of individual banks have the potential to more severely spillover throughout the system (Wagner, 2010). Excessively large banks also have an additional incentive to consolidate in order to become TBTF and enjoy a government safety net resulting in increased systemic risk (Deng, Elyasiani, and Mao, 2007).

We model systemic risk as a function of banking concentration in a similar way as equations 2.1-2.4. We employ two measure of systemic risk. The first measure, *SRISK,* is an estimate of the dollar amount of capital that a financial institution would need to raise

in order to function normally if another financial crisis occurs (Acharya, Engle, and Richardson, 2012). The second measure, Marginal Expected Shortfall (*MES*), is the expected loss an equity investor in a financial firm would experience if the market declined substantially (Brownless and Engle, 2012).

We collect systemic risk data on 29 of the largest bank holding companies from the NYU Stern V-lab from 2000:1 through 2013:4 and estimate the following two regressions. A list of banks examined is provided in Table 2-9. We are able to collect complete data on these particular 29 bank holding companies.

$$SRISK_{it} = c + u_i + \alpha\, CER_{it} + \beta_1 Concentration_t + \beta_2 Concentration_t^{\,2} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \tag{2.6}$$

$$MES_{it} = c + u_i + \alpha\, CER_{it} + \beta_1 Concentration_t + \beta_2 Concentration_t^{\,2} + \theta X_t + \omega Y_{it} + \varepsilon_{it} \tag{2.7}$$

SRISK and *MES* are available at the parent bank holding company level. Due to data availability issues, we keep the right hand side variables at the commercial bank level. This ensures a richer set and consistent set of explanatory variables. We also focus on the largest US bank holding companies due to data availability. Furthermore, the systemic risk of large bank holding companies is significantly larger than that of smaller banking organizations (Demsetz and Strahan, 1997). Because our sample contains the largest banks, we remove $Size_{it} * Concentration_t$ and $Size_{it} * Concentration_t^{\,2}$. We remove

Table 2-9: List of Banks included in Systemic Risk Model

Bank of America Corp	JPMorgan Chase & Co
Bank Of New York Mellon Corp/The	Keycorp
BB&T Corp	M&T Bank Corp
Capital One Financial Corp	Morgan Stanley
Charles Schwab Corp/The	New York Community Bancorp
Citigroup	Northern Trust Corp
Comerica	People's United Financial
Compass Bancshares	PNC Financial Services Group
E*TRADE Financial Corp	Regions Financial Corp
Fifth Third Bancorp	Sovereign Bank
Goldman Sachs Group	State Street Corp
Hudson City Bancorp	SunTrust Banks
Huntington Bancshares	

Note: This table contains the names of the 29 banks used in our systemic risk model. They represent the 29 largest bank holding companies for which SRISK, MES, and the required call report data is available. The right hand side data corresponds to the largest commercial bank of each holding company.

GLBA because our entire sub-sample for these regressions corresponds to the time period after the passage of the Gramm-Leach-Bliley Act of 1999. We include capital equity ratio (*CER)* because bank holding companies could hold additional capital as a means to offset systemic risk (Demsetz and Strahan, 1997). The remaining control variables from the previous regressions are employed in our systemic risk model as they represent a very broad representation of bank behavior.

The systemic risk results are displayed in Table 2-10. Because there may be a bi-directional relationship between our measures of systemic risk and *CER,* we employ a two quarter lag of *CER* as an instrument and test for the suitability of an IV model. The FE estimator without instruments, however, is found to be more appropriate than the FE-IV estimator when systemic risk is the dependent variable. The results are similar for both measures of systemic risk and are similar for both measures of concentration. We find that both *Concentration* and *Concentration*^{2} are highly significant, as reported in Table 2-10 columns 1 and 3 with negative and positive signs, respectively. These signs indicate that *SRISK* and *MES* decreases with concentration (as measured by the assets share of the ten largest banks) up to approximately 39% and 41% respectively, and increases thereafter. The results, combined with the results of the capital equity model, equation 2.2, suggest that as concentration increases, capital equity and systemic risk both increase concurrently. These dynamics conflict with conventional thought because capital is often employed as a means to offset systemic risk (Demsetz and Strahan, 1997). As stated previously, a benefit usually associated with increased concentration is the greater ability

Table 2-10: Fixed Effects Results, Systemic Risk of 29 of the Largest Banks

Independent /Dependent Variable	*SRISK* *(1)*	*SRISK* *(2)*	*MES* *(3)*	*MES* *(4)*
C10	-16,880.11**		-0.68**	
$C10^2$	214.04**		0.01**	
HHI		-574.85**		-0.02**
HHI^2		1.25**		0.00004**
CER	-214.35	-234.99	0.01	0.01
OBS	-41,641.00	-41,565.22	-0.89*	-0.91*
Illiquidity	-4,696.39	-1,732.25	2.27	2.32
Inefficiency	-8,272.71	-8,518.06	1.12**	1.12**
Diversification	-4,104.67	-4,744.41	0.73	0.74
Insurance	-147,653.30**	-43,833.26	-12.16***	-2.17
Stress	-1,256.64	-26.04	-0.29***	-0.22***
GDPG	1,620.66*	1,081.64	0.05	0.03
Inflation	-315.17	346.24	-0.28***	-0.24***
FX	-27.10	129.85	-0.02**	0.01
YR	-3,670.86**	-4,300.84**	0.07	-0.03
Crisis	13,052.50**	16,308.66***	2.34***	2.60***
Recession	-200.78	-1,870.74	0.37***	0.32***
Size	1044.78	981.22	-0.62***	-0.63***
Constant	402,419.20*	8,6724.84	32.76***	14.75***
Number of Observations	1,319	1,319	1,319	1,319
Number of Banks	29	29	29	29

Note: This table presents results from the fixed effects model when systemic risk is the dependent variable. Columns (1) and (2) contain results for the *SRISK* models. Columns (3), and (4) contain results for the *MES* models. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

of banks to diversify their risks across product lines (Hughes and Mester, 2011) and across a wider geographic area (Berger, Molyneux, and Wilson, 2010) driving idiosyncratic risk downwards. Portfolio theory states that increased diversification should reduce systemic risk (Demsetz and Strahan, 1997). However, our results agree with Wagner (2010) who finds that systemic risk increases with diversification because banks become more exposed to similar shocks. Our results support Weiß, Neumann, and Bostandzic (2014) who find that banks contribute more to systemic risk after they merge and consolidate due to the existence of an explicit permanent deposit insurance often associated to TBTF institutions.

2.5.2.5 Drivers of Bank Stability

In the previous sections, we established that banking concentration is a significant driver of bank stability. We now examine the extent to which bank concentration drives the variability observed by the Z-score. This information is critical from a policy perspective because it allows policy makers and regulators to determine if concentration is the main driver of bank stability, as opposed to macroeconomic and individual bank characteristics.

To test the proportion of explained variation in bank stability explained by concentration, we estimate equation 2.1 with three different sets of independent variables; concentration and size, macroeconomic and systemic banking variables, and individual bank characteristics respectively. Following Peria and Schmuckler (2001), we record the R-squared term from each specification and divide it by the R-squared term from the

model containing all variables. This process should theoretically capture the variation in the Z-score caused by concentration, macroeconomic variables, and individual bank characteristics. We perform this analysis for large banks (totals assets > $1B) and small banks (total assets < $1B) and report the results in Table 2-11.

Table 2-11: Variance Decomposition

	Large Banks (1)	**Small Banks (2)**
R-squared (full model)	.1642	.1457
R-squared (Concentration and Size variables only)	.0836	.0456
% Explained by Concentration and Size	50.91%	30.92%
% Explained by Macroeconomic Variables	50.73%	25.36%
% Explained by Individual Bank Characteristics	46.83%	78.85%

Note: This table displays the variation in Z-score explained by concentration and size variables *(Concentration,* $Concentration^2$*, Size, Concentration*Size, and* $Concentration^2 * Size$) , and macroeconomic and systemic banking variables (*Insurance, Stress, GDPG, Inflation, FX, YR, Crisis, Recession, and GLBA*) and individual bank characteristics (*OBS, Illiquidity, Inefficiency, and Diversification*) in isolation. We divide the sample into two subgroups; large banks (assets > $1B) and small banks (assets < $1B). The OLS R-squared term is found for each grouping and compared to the R-squared term of the complete model (equation 2.1). This test is derived from Peria and Schmukler (2001). The percentages correspond to independent sets of variables, but do not sum to one due to non-zero correlation between variables.**

The variability in bank stability explained by concentration, macroeconomic variables, and individual bank characteristics are approximately 50.9%, 50.7%, and 46.8% respectively for large banks and approximately 30.9%, 25.4%, and 78.9% respectively for small banks[69]. Banking concentration and macroeconomics conditions are very similar in terms of magnitude, according to our results, in explaining the variability of large bank stability. Individual bank characteristics explain slightly less of

[69] Note, the percentages do not sum to 100% due to non-zero correlations between sets of variables.

the variation. However, small banks stability seems to react less to concentration and macroeconomic conditions than to individual bank characteristics.

As previously explained, the consolidation US banks over our sample period (1994:3-2013:4) was dominated by a small number of mega-banks with control over a considerable portion of the banking system's assets (Berger, Molyneux, and Wilson, 2010). These mega-banks are able to exploit economies of scale, higher profits, and therefore gain greater stability (Berger, Molyneux, and Wilson, 2010). Small bank stability, however, is mostly driven by individual characteristics versus concentration or macroeconomic conditions (78.9% versus 30.9% and 25.4% respectively). This difference between large and small bank could be due to the fact that small community banks are more likely to operate in a small rural market and rely more heavily on local economic conditions versus national macroeconomic activity (Brickley, Linck, and Smith, 2003). Large banks, in all likelihood may be more susceptible to macroeconomic shocks due to their vast geographic span as compared to small banks (Berger, Molyneux, and Wilson, 2010). Additionally, competitive pressure is placed on small banks when large banks that offer superior products, such as ATMs and online banking, enter their market (Berger, Molyneux, and Wilson, 2010). Small banks are therefore forced to improve their efficiency in order to remain competitive (DeYoung, Hasan, and Kirchhoff, 1998).

2.6 Conclusion

Previous research has produced conflicting results on the association between bank concentration and bank stability. Multiple studies (e.g., Keely, 1990; Repullo, 2003;

Allen and Gale, 2004) conclude that banks in concentrated banking systems have a higher charter value and hold less risk in order to preserve that value. Boyd, DeNicolo and Jalal (2006), among others, find evidence that supports the opposite view. They conclude that banks in concentrated systems provide an incentive for borrowers to undertake riskier projects causing the bank to hold riskier portfolios.

In this study, we attempt to extend the model put forward by Boyd, DeNicolo, and Jalal (2006) in three ways. First, following the theoretical study of Martinez-Miera and Repullo (2010), we introduce a quadratic term of banking concentration into our empirical model allowing us to estimate a non-linear (U-shaped) relationship between bank stability and concentration. Second, we interact concentration and bank size allowing us to determine whether the stability-concentration relationship varies by bank size. Third, we gather data on a panel of US commercial banks from 1994:3 to 2013:4 which is more recent and considerably richer than previous studies. We estimate the model with a fixed effects instrumental variable panel estimator to help correct for reverse causation by employing a two quarter lag of the concentration variable. Multiple tests are conducted on the strength and suitability of the instruments. Our results are robust to various estimators and measures of concentration.

Several results are obtained. First, we find an inverted U-shaped relationship exists between small bank stability and banking concentration. Furthermore, as concentration (measured by the asset share of the ten largest banks) exceeds approximately 35%, small banks become less stable, hold less capital, are less profitable, and hold more volatile portfolios. Second, we find that the stability-concentration

relationship varies greatly by bank size. As banks exceed roughly $1B in assets, the stability-concentration relationship shifts (from an inverted U-shaped relationship) to a U-shaped relationship. Furthermore, as concentration exceeds approximately 35%, large banks become more stable, hold more capital, are more profitable, and hold less volatile portfolios in response to greater concentration. Third, despite the increase in their idiosyncratic stability, large banks increasingly contribute to systemic risk as concentration increases beyond 39%.

These results are significant because they offer evidence that supports both the concentration-stability and concentration-fragility hypotheses. Furthermore, our results indicate that trimming the current level of US banking concentration[70] would result in an increase in stability for the smallest banks but a reduction in stability for the largest banks. These results are important to researchers because they indicate that sized-based behavioral differences should be considered when studying the stability-concentration relationship. Furthermore, these results are important to policy makers and regulators because they provide evidence of the trade-offs associated with banking concentration. If the banking system concentrates further, large banks would be the beneficiaries and small banks (roughly those with total assets < $1B) would be squeezed and perhaps pushed out the market. This would likely restrict funds available to small businesses and borrowers that rely on relationship-based lending. Furthermore, should the banking system continue to concentrate, the benefit of more stable large banks (roughly those with total assets > $1B) could be offset by the increase in systemic risk. If the large banks are broken up,

[70] As of 2013:4, the C10 ratio stood at roughly 46%.

small banks would benefit from increased stability, but the largest banks would become less stable increasing the risk of failure and could add tremendous stress to the financial system.

CHAPTER 3
THE ASSOCIATION BETWEEN FINANCIAL MARKET VOLATILITY AND BANKING CONCENTRATION

3.1 Introduction

The US banking system has become increasingly interconnected with financial markets over the past few decades (Berger, Molyneux, and Wilson, 2010). Deregulation and advances in information technology have allowed banks to offer new products and services that enable them to both compliment and compete directly with financial markets (Berger, Molyneux, and Wilson, 2010). For example, securitization allows banks to originate loan contracts with funds raised in financial markets. The coevolution of banks and financial markets has resulted in a co-dependence between the two, raising concerns among regulators because of the difficulties associated with isolating financial market risks from banking risks (Berger, Molyneux, and Wilson, 2010).

The increasing interconnection between banks and financial markets has both benefits and consequences. On the one hand, increased interconnection provides banks access to greater liquidity and provides banks better access to financial markets where capital can be raised at a lower cost than traditional deposit taking (Berger, Molyneux, and Wilson, 2010). On the other hand, risks to banks and financial markets have become more strongly intertwined, increasing the channels for negative shocks to be distributed through the financial system, thereby increasing the level of systemic risk (Bilio, Getmansky, Lo, and Pelizzon, 2012).

A closely related issue is concentration of the banking system and how it impacts the stability of financial markets. Since the 1980s, the US banking system consolidated

considerably resulting in a more concentrated banking system with larger and more complex financial institutions that share a similar customer base, offer similar products, and share similar risk models (Jones and Critchfield, 2005; Saunders and Cornett, 2014). These large firms compete fiercely with each other, and as a result, have been driven to raise funds in capital markets, where there is access to greater liquidity and lower cost of capital, as a means to boost profit margins (Berger, Molyneux, and Wilson, 2010). Additionally, financial markets have evolved considerably and exert significant competitive pressure on banks (Berger, Molyneux, and Wilson, 2010). In response, banks have consolidated (Hawkins and Mihaljek, 2001) and created new products and services that combine market and bank services, such as securitized debt and back up lines of credit, to compete with financial markets (Berger, Molyneux, and Wilson, 2010).

Some economists argue that banks in a highly concentrated system are able to diversify better and insulate themselves against macroeconomic and financial market shocks, and thereby reducing the risk of failure and ultimately reducing the risk of systemic bank distress (Beck, Demirgüç-Kunt, and Levine, 2006). Other economists claim that if a large complex bank fails, other firms could have difficulty absorbing the failing bank's business causing disruptions in the flow of credit and significantly impairing the financial markets (Labonte, 2014). Additionally, problems at large complex banks could lead to a fire sale in securities markets leading to significant losses across the financial system (Labonte, 2014). Liquidity could be severely reduced and markets could freeze as a consequence (Hendricks, Kambhu, and Mosser, 2007). This situation manifested itself after the collapse of the now defunct investment bank Lehman Brothers,

in the fall of 2008, when an acute shock to the sub-prime mortgage market rapidly spread through the global financial system sending financial market volatility to an all-time high[71] (Mehl, 2013). Furthermore, as concentration increases, the largest banks become increasingly sophisticated and complex, and therefore less transparent, making the role of market and regulatory discipline less effective (Cetorelli, Hirtle, Peristani, and Santos, 2007).

In this study, we examine the relationship between banking concentration and financial market volatility in the United States. This relationship is important to study because the majority of financial resources in the US are allocated through financial markets (Allen and Gale, 2000). Other financial systems, such as those found in Japan and Germany, are bank oriented systems where the majority of financial resources are allocated through banks. Financial market volatility is an important variable in risk management, regulation, and investment decisions (Mittnik, Robinsinov, and Spindler, 2015). It also exerts an impact on systemic risk (Cetorelli, Hirtle, Peristani, and Santos, 2007). Up to this point, little research has been performed on the relationship between banking concentration and financial market volatility. Cetorelli, Hirtle, Peristani, and Santos (2007) attempt to establish a link between concentration of various financial markets (including banking concentration) and financial market volatility, but do not find any concluding evidence and fall short of reaching any significant conclusions. Hence, the dynamics of this relationship are largely unknown. A major obstacle of statistically establishing the banking concentration-financial market stability relationship has been

[71] Mehl (2013) shows that in the months following the collapse of Lehman Brothers, the VIX reached an all-time high of 80% annum.

modeling daily volatility measures to quarterly concentration measures. To circumvent this problem, we apply a multiplicative two-component GARCH-MIDAS volatility model recently proposed by Engle, Ghysels, and Sohn (2013) to investigate the subject. The GARCH-MIDAS volatility model is superior to other volatility models because it allows us to model daily market volatility directly as a function of quarterly banking concentration and other macroeconomic variables. Prior to GARCH-MIDAS, either 1) the high frequency variable(s) was pre-filtered to agree with the low frequency explanatory variable(s); or 2) the low frequency data was discarded all together and no relationship was established. A detailed analysis of the GARCH-MIDAS model is provided in section 3.3.

We focus our analysis on the time period from 1986:1 to 2013:4 which represents the maximum time span our data allow. We examine seven different financial markets covering US equities including the S&P 500 and Nasdaq markets, investment and speculative grade corporate bonds, options, US treasury bonds, and foreign exchange. Our analysis indicates that positive changes in the level of banking concentration are associated with greater volatility in the equity, corporate bond, and options markets. We also find that positive changes in the level of banking concentration are associated with reduced volatility of US treasury bonds. We do not find conclusive results for foreign exchange markets.

Our study makes a significant contribution to the literature. First, to our knowledge, this is the only study to empirically establish the relationship between banking concentration and financial market volatility. Second, we apply recent

developments in volatility models that allow for direct analysis between data sampled at dissimilar frequencies; namely daily financial market volatility and quarterly banking concentration data. This model, called a GARCH-MIDAS volatility model, is superior to other volatility modeling techniques. Additional detail on the GARCH-MIDAS model and is provided in section 3.3. To our knowledge, we are the first authors to apply this model to banking concentration. Third, we investigate various financial markets and find that they are not affected by banking concentration similarly. That is, we find that volatility in the equity, corporate bond, and options markets are amplified as a result of increased banking concentration, while volatility of US treasury bonds is dampened.

Our results are important to policy makers, regulators, and investors because they provide evidence suggesting that increasing banking concentration could be amplifying financial market volatility. This is a serious consequence because more volatile markets could have an impact on capital investment, consumption, and business cycle variables (Schwert, 1989). The remainder of the paper is organized as follows. Section 3.2 contains a literature review of previous research. Section 3.3 provides details on the GARCH-MIDAS model. Section 3.4 provides a detailed description of the data and variable calculations. Section 3.5 provides an analysis of the results. Section 3.6 provides concluding remarks and recommendations.

3.2 Literature Review

The US banking sector has consolidated considerably since the 1980s due to various factors including advances in technology, globalization, and deregulation (Jones and Critchfield, 2005). The consolidation trend accelerated after the passage of the

Riegle-Neal Interstate Banking and Branching Efficiency Act (RN) in 1994 which authorized national banks to establish new branches across state lines and to convert subsidiaries into branches (Saunders and Cornett, 2014). In 1999, the passage of the Gramm-Leach-Bliley Act (GLBA) into legislation relaxed some of the restrictions put in place by the Glass-Steagall Act of 1933. After GLBA, banks were able to engage in non-traditional banking activities such as equity and debt underwriting, securities brokerage, and insurance products (Berger, Molyneux, and Wilson, 2010). These deregulatory acts, coupled with advances in technology, allowed for banks to develop into extremely large and complex financial institutions (FSHCs) with portfolios that were diversified across product lines and geographic boundaries (Berger, Molyneux, and Wilson, 2010).

Deregulation and technological advances also have led to an increase in both interbank competition, and increased competition from financial markets and non-bank financial intermediaries (Vives, 2016). Advancements in market technology have allowed borrowers to bypass bank funding and obtain funds directly from financial markets (Vives, 2016). For example, credit scoring models make it easier for borrowers to obtain funds from nonbank lending institutions (Vives, 2016). The development of "shadow banks", non-bank financial intermediaries that offer products similar to commercial banks but are outside normal financial regulations, has also drawn customers away from traditional banks (Vives, 2016). In response, banks have further consolidated (Hawkins and Mihaljek, 2001) and have created new products similar those offered by financial markets to maintain market share (Berger, Molyneux, and Wilson, 2010). Also, increased interbank competition has placed significant pressure on profit margins forcing banks to

access financial markets, which are less costly than traditional deposits, as a means to raise capital and boost profits (Berger, Molyneux, and Wilson, 2010). For example, securitization allows banks to turn illiquid loans, such as mortgages, into assets that are financed and tradable in financial markets (Vives, 2016). This transformation of the banking industry has blurred the boundaries between banks, non-bank intermediaries and, financial markets and has increased their interconnection (Berger, Molyneux, and Wilson, 2010).

The impact of these large and complex financial institutions is debated by academics, regulators, and policy makers. The concentration-stability argument claims that since large FSHCs in concentrated markets are able to diversify risks across product lines, they can improve the risk-return frontier in their own favor (Berger, Demsetz, and Strahan, 1999). Portfolio theory states that diversification will reduce the total level of risk at a given level of return for each banking firm, making the overall financial system more stable (Berger, Molyneux, and Wilson, 2010). Keely (1990) and Deltuvaite (2010) support the concentration-stability argument and claim that banks in more concentrated markets earn higher profits and are also easier to monitor because there are fewer banks to regulate. Beck, Demirgüç-Kunt, and Levine (2006) also support the concentration-stability argument. They propose that highly concentrated banking systems are less likely to experience a systemic banking crisis. Their rationale is that larger banks earn higher profits and have larger capital cushions to protect against adverse economic shocks.

These studies provide evidence that favor a concentrated banking system from the view point of stability, but there are potentially dangerous side effects. While there are

fewer banks to regulate, they are less transparent due to increasingly sophisticated financial instruments, more complex corporate structures, and cause regulatory and market discipline to be less effective (Cetorelli, Hirtle, Peristani, and Santos, 2007). Banks operating in a highly concentrated system may become too large for the regulators to dare let them fail (too big to fail, TBTF), hold too much market power and, consequently, gain too much political power. Additionally, TBTF banks introduce a moral hazard problem because they have an incentive to hold excessive risk resulting in costly government bailouts when they are in danger of failing (Wheelock, 2012).

The concentration-fragility argument claims that financial institutions in highly concentrated markets hold riskier portfolios, thereby decreasing the stability of the financial system. As an example, Boyd and DeNicolo (2005) theoretically show that banks in highly concentrated systems will charge higher rates on loans adversely affecting the borrowers' profit and driving the borrowers to undertake riskier projects in the hopes of realizing a higher profit. Studies by Boyd, DeNicolo, and Jalal (2006) and Shaeck and Cihak (2007) provide empirical evidence that banks in highly concentrated systems do in fact hold riskier portfolios because borrowers are driven to undertake riskier projects in the hopes of realizing a higher profit. In addition, DeNicolo and Kwast (2002) show that despite the benefits arising from diversification, large financial institutions hold riskier portfolios, than smaller institutions, as they become bold and elevate their risk target.

Another risk associated with highly concentrated banking systems is the spillover effect from banks into other financial markets. As previously explained, coupled with

rising levels of banking concentration has been an increase in the interconnection between banks and financial markets. Bilio, Getmansky, Lo, and Pelizzon (2012) show that as banks increase in size and complexity they become overly intertwined with financial markets. Ultimately this phenomenon increases and strengthens the channels for negative shocks to be distributed through the financial system, thereby increasing the level of systemic risk.

Ferguson, Hartmann, Panetta, and Portes (2007) eloquently explain that large complex financial institutions can impact systemic stability in three ways. First, as financial institutions become complex and more exposed to capital markets, it becomes increasingly difficult to liquidate their balance sheets and sell off assets in a time of crisis without disrupting financial markets. When a firm is in danger of failing, the market value of its assets could plummet and lead markets to overshoot and destroy more value than is warranted (Ferguson, Hartmann, Panetta, and Portes, 2007). Second, a highly concentrated system increases the risk of contagion (Ferguson, Hartmann, Panetta, and Portes, 2007). When large banks consolidate, they become increasingly similar and interconnected to each other and are increasingly exposed to similar risks (Hendricks, Kambhu, and Mosser, 2007). The effects of a major bank collapse or shock to financial markets, could more easily spread across the banking and financial system (Hendricks, Kambhu, and Mosser, 2007). Furthermore, as concentration increases, contracts between firms grow in size and complexity increasing the likelihood that a crisis at one firm could spread to other firms and ultimately cause the financial system to collapse (Ferguson, Hartmann, Panetta, and Portes, 2007). Third, concentration impacts the payment system

because the number of participants is reduced and interdependence between firms becomes more complex. Concentration reduces market liquidity because larger firms create an internal capital market for funds and go to external markets only for the balance (Ferguson, Hartmann, Panetta, and Portes, 2007). This could ultimately, disrupt financial markets, and amplify stressful situations.

The majority of financial intermediation in the US is performed through financial markets; classified as a *market-oriented* system (Allen and Gale, 2000). A requirement of market-oriented financial systems is that markets remain liquid (Hendricks, Kambhu, and Mosser, 2007). As previously noted, large banks that consolidate tend become more alike and exposed to similar risks (Cetorelli, Hirtle, Peristani, and Santos, 2007), and employ increasingly similar risk models (Kiff, Kodres, Klueh, and Mills, 2007). During a period of market stress, large banks could simultaneously decide to reduce or suspend financing activities leading to market gridlock, severe reductions in liquidity (Hendricks, Kambhu, and Mosser, 2007), and amplified market volatility (Kiff, Kodres, Klueh, and Mills, 2007).

The effects of banking concentration on financial market stability remain mostly unknown. Cetorelli, Hirtle, Morgan, Peristiani, and Santos (2007) indicate that the relationship between financial market stability and banking concentration is ambiguous and attempt to find a significant link. They do not find any results that indicate that banking concentration has any impact on financial markets stability and conclude that the association between the two remains ambiguous. Their results are disputable, however,

because the model they employ is primitive and does not allow for data of different frequencies.

We identify two potential econometric pitfalls that have inhibited researchers from establishing a statistical link between financial market volatility and banking concentration. First, market volatility is typically measured daily while banking concentration is measured at much lower frequency; quarterly in most circumstances. Until recently, volatility models have not been able to model data of dissimilar frequencies. Second, long lags (3-5 years) may be required to effectively model the gains/consequences of changes in banking concentration (Jones and Critchfield, 2005). Long lag lengths in previous econometric models require a large number of parameters to estimate and may cause the model to be over-saturated.

In this study, we attempt to circumvent the aforementioned econometric obstacles and seek to determine if there is in fact a statistically significant association between banking concentration and financial market stability. To this end, we collect data on daily financial market volatility and seek a direct link to quarterly banking concentration and macroeconomic data. We employ recent developments in Mixed-Data Sampling (MIDAS) models that allow us to split financial market volatility into a short term and long term component allowing us to model data of dissimilar frequencies. An additional benefit of our MIDAS technique, is we can include a considerably long lag structure without estimating a large set of parameters. Additional details are provided in section 3.3. We investigate the links between bank concentration and seven different markets that represent a broad range of financial activity. These include large firm equity (*SP500*),

smaller firm equity (*Nasdaq)*, options (*Options*), investment grade corporate bonds (*Aaa*), speculative grade corporate bonds (*Baa*), treasury bonds (*TB*), and US dollar markets (*Currency)*. The following hypotheses are tested.

H1: *There is no significant relationship between SP500 volatility and banking concentration.*

H2: *There is no significant relationship between Nasdaq volatility and banking concentration.*

H3: *There is no significant relationship between Aaa volatility and banking concentration.*

H4: *There is no significant relationship between Baa volatility and banking concentration.*

H5: *There is no significant relationship between Options volatility and banking concentration.*

H6: *There is no significant relationship between TB volatility and banking concentration.*

H7: *There is no significant relationship between Currency volatility and banking concentration.*

A summary of hypotheses is provided in Table 3-1.

Table 3-1: Hypotheses

	Hypotheses
H1	*There is no significant relationship between SP500 volatility and banking concentration.*
H2	*There is no significant relationship between Nasdaq volatility and banking concentration.*
H3	*There is no significant relationship between Aaa volatility and banking concentration.*
H4	*There is no significant relationship between Baa volatility and banking concentration.*
H5	*There is no significant relationship between Options volatility and banking concentration.*
H6	*There is no significant relationship between TB volatility and banking concentration.*
H7	*There is no significant relationship between Currency volatility and banking concentration.*

Note: This table provides a list of hypotheses tested in chapter 3

3.3 Model and Methodology

Numerous studies examine financial market volatility and macroeconomic variables. Most notably, Schwert (1989) finds that volatility and levels of macroeconomic variables, such as inflation and industrial production, have no significant impact on stock market volatility. A drawback of this study is that daily volatility is pre-filtered so that volatility observations are available at the same frequency as monthly macroeconomic data; a common solution in volatility models (Ghysels, Sinko, and Valkanov, 2007). As a consequence of this treatment of data, a considerable amount of information is lost, and any conclusions derived are rendered incomplete or disputable (Ghysels, Sinko, and Valkanov, 2007).

The findings of Schwert (1989) are challenged by Engle, Gyshels, and Sohn (2013). The latter authors put forward a GARCH-MIDAS model to address the data

frequency issue. This model has two major advantages over other volatility models such as the GARCH (1-1) model. First, GARCH-MIDAS allows daily return volatility data to be modeled directly as a function of lower frequency macroeconomic variables. Second, this specification allows long lags of macroeconomic variables to be incorporated into the analysis without increasing the number of parameters being estimated. In short, Engle, Gyshels, and Sohn (2013) find that levels and volatilities of inflation and industrial production, both measured quarterly, do in fact have a significant relationship with stock market volatility sampled at the daily frequency. Subsequent studies by Asgharian, Hou, and Javed (2013), Girardin and Joyeux (2013), Nieto, Novales, and Rubio (2015), and Conrad and Loch (2014) all conclude that macroeconomic data are very useful in modeling daily financial market volatility and that the GARCH-MIDAS model is superior to GARCH (1-1) in modeling volatility. This model, however, has never been used to model the volatility-concentration relationship

To illustrate the GARCH-MIDAS model, we define $r_{i,t}$ as the return of an asset on day *i* during period *t* which can be a month, quarter, year, etc. For our study, *t* refers to each quarter because banking concentration are available on a quarterly basis. N_t is the number of days in quarter *t.* We assume that daily returns follow a structure defined by equation (1) below, where μ is the average daily return and $\eta_{i,t}$ is a disturbance term distributed normally as: $N\left(0, \sigma_{i,t}^2\right)$. Equation 3.1 can be written as equation 3.2 where $\varepsilon_{i,t}$ is a shock with distribution $N(0,1)$ given all available information up to day i-1 of quarter *t.* The total variance component, $\sigma_{i,t}^2$, can be decomposed into a long term and short term component such that $\sigma_{i,t}^2 = \tau_t \, g_{i,t}$. The intuition behind equation (3.2) is that

the same information, say, poor earnings, may have different effects depending on the state of the economy (Engle, Gyshels, and Sohn, 2013). For example, unexpected poor earnings should have an impact during a period of economic expansion that is different during a recession (Engle, Gyshels, and Sohn, 2013). The component $g_{i,t}$ is assumed to relate to the liquidity concerns that change daily, and possibly other short-lived factors (Engle, Gyshels, and Sohn, 2013). Following Engle, Gyshels, and Sohn (2013), $g_{i,t}$ is assumed to follow a GARCH (1, 1) process. This is a reasonable assumption because GARCH (1, 1) has been shown to be superior in forecasting short term volatility (Hansen and Lunde, 2005). The component τ_t, relates to future expected cash flows and future discount rates. Macroeconomic and/or financial variables are assumed to influence this source of stock market volatility (Engle, Gyshels, and Sohn, 2013).

Since $g_{i,t}$ is assumed to be a mean reverting GARCH (1,1) process, it can be rewritten as equation 3.3 where $\alpha + \beta < 1, \alpha > 0$, and $\beta > 0$. It is worth noting that α and β have the same interpretation here as in the standard GARCH (1-1) model. That is, $\alpha + \beta$ is the persistence of the conditional variance process (Bauwens, Hafner, and Laurent, 2012).

$$r_{i,t} = \mu + \eta_{i,t} \tag{3.1}$$

$$r_{i,t} = \mu + \sqrt{\tau_t \, g_{i,t}} \, \varepsilon_{i,t} \tag{3.2}$$

$$g_{i,t} = \ (1 - \alpha - \beta) + \alpha \frac{\left(r_{i,t} - \mu\right)^2}{\tau_t} + \beta \ \ g_{i-1,t} \tag{3.3}$$

As stated earlier, τ_t is a low frequency component that responds to macroeconomic and financial conditions. In the spirit of MIDAS regressions, τ_t is

assumed to be a smooth measure of past macroeconomic observations and is written as equation 3.4, where *X* is a macroeconomic or financial variable. *K* is the number of lags chosen and is determined by minimizing the Bayesian Information Criterion (BIC). *m* is the mean of the low frequency component and is estimated within the model. θ is the main parameter of interest whose sign and significance determine the relationship between the long run volatility component τ_t and the macroeconomic variable *X*. We follow Engle, Gyshels, and Sohn (2013) and consider the logarithmic formulation described by equation 3.5. By employing $\log \tau_t$, we can estimate the relative effect of macroeconomic variables on volatility. Additionally, as in Engle, Gyshels, and Sohn (2013), we assume that at the beginning of each quarter, the high frequency component is equal to its unconditional expectation. That is, $E_{t-1}(\, g_{i,t}) = 1$. Hence, the low frequency component is given by equation 3.6:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k} \tag{3.4}$$

$$\log \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k} \tag{3.5}$$

$$E_{t-1}\left[\left(r_{i,t} - \mu\right)^2\right] = \tau_t\, E_{t-1}[\, g_{i,t}] = \tau_t \tag{3.6}$$

Finally, $\varphi_k(\omega_1, \omega_2)$ from equation 3.5 is the beta weighting scheme used to determine the weight applied to each individual lag. $\varphi_k(\omega_1, \omega_2)$ is displayed in equation 3.7 below. The values of all weights sum to 1.

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K}\right)^{\omega_1 - 1}\left(1 - \frac{k}{K}\right)^{\omega_2 - 1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{\omega_1 - 1}\left(1 - \frac{j}{K}\right)^{\omega_2 - 1}} \tag{3.7}$$

The parameters $\omega_1$and ω_2 determine the value of the weighting structure that is applied to each lag *k* of the macroeconomic variable being examined. Both $\omega_1$and ω_2 are estimated within the model. Essentially, by employing a beta weighting scheme, regardless of the lag length *K*, the same number of parameters are estimated. The beta specification is very flexible because it can accommodate increasing, decreasing, or hump-shaped weighting schemes (Ghysels, Sinko, and Valkanov, 2008). The model is estimated using the maximum likelihood procedure (MLE). The parameter space $\Theta = (\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2)$ is estimated by maximizing the log-likelihood function described by equation 3.8

$$\log L\left(r_{i,t}{}_{i=1\ldots N_t}^{t=1\ldots T}\right) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\log 2\pi + \log \tau_t\, g_{i,t} + \frac{1}{2}\frac{\left(r_{i,t}-\mu\right)^2}{\tau_t g_{i,t}} \qquad (3.8)$$

As stated earlier, long term market volatility, τ_t is written in its logarithmic form as: $\log \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k}$ where *X* is a macroeconomic or financial variable observed each quarter. Previous studies (e.g. Engle, Gyshels, and Sohn, 2013) typically consider one macroeconomic variable at a time because the parameter space becomes very complex and difficult to estimate as additional control variables are added[72]. However, excluding important control variables could lead to omitted variable bias (Wooldridge, 2010). Therefore, we expand the one variable model outlined above to include two explanatory variables. The two variable model has the parameter space $\Theta =$

[72] For each additional variable, three additional parameters have to be estimated.

$(\mu, \alpha, \beta, m, \theta_1, \theta_2, \omega_1, \omega_2, \omega_3, \omega_4)$ and is defined by equation 3.9. The addition of the second explanatory variable should help to isolate the impact of banking concentration from other macroeconomic or financial phenomenon[73].

$$\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k} \qquad (3.9)$$

The main explanatory variable of interest in the long-term volatility model (equation 3.5) is *Concentration* in the banking industry. This variable is measured by the asset share of the largest ten commercial banks in the US banking system at date *t*[74]. If the coefficient estimate of the *Concentration* variable is positive (negative), we can conclude that increased banking concentration has an amplifying (dampening) effect on financial market volatility. Additionally, we include the Herfindahl–Hirschman Index (*HHI*) as robustness check.

In addition to *Concentration*, we include a number of control variables outlined below. Control variables are estimated one at a time along with *Concentration* in the model described by equation (3.9). As previously explained, we are limited to estimating two variables due to the computationally complex nature of the underlying model. Following Asgharian, Hou, and Javed (2013), we include economic growth (*GDPG)*[75], the difference between the yield on the 10-yr and 3-month treasury bond (*Spread),*

[73] We also consider a three variable model. However, there was difficulty in finding a global optimum and the results were not stable. Therefore, we do not include them in our final analysis.

[74] Data reporting limitations do not allow us to obtain an accurate concentration estimate using bank holding company data. That is, small BHCs are required to provide data bi-annually, as opposed to quarterly for large BHCs. Therefore, we consider commercial banks, which report every quarter, when calculating concentration and feel it is a good proxy for banking concentration.

[75] Asgharian, Hou, and Javed (2013) employ Industrial Production growth.

inflation (*Inflation)*, and strength of the US dollar against other major currencies. Because fluctuations in currency valuation impact financial market volatilities (Asgharian, Hou, and Javed, 2013), we take the log difference of the trade weighted US dollar index (ΔFX)[76]. These control variables represent broad measures of the state of the real and financial economy and can provide information on future cash flows (Asgharian, Hou, and Javed, 2013). For example, greater GDP growth (*GDPG)* is associated with better economic conditions and should reduce uncertainty as a result of greater expected cash flows. Additionally, following Asgharian, Hou, and Javed (2013), we include the log of realized volatility of each market to measure past return volatility; *SP500_RV, Nasdaq_RV, Aaa_RV, Baa_RV, Options_RV, Currency_RV*, and *TB_RV*.

As previously stated, the GARCH-MIDAS model is computationally complex and the inclusion several variables results in convergence problems (Asgharian, Hou, and Javed, 2013). To circumvent this issue, we follow Asgharian, Hou, and Javed (2013) and consider two principal components as additional explanatory variables. The first principal component, *Macro*, is the Chicago Federal Reserve Bank National Conditions index and contains 85 individual macroeconomic indicators. It is constructed such that a positive value indicates that economic growth is above the long term trend and that the economy is in an expansionary period. The second principal component, *Stress*, is the Chicago Federal Reserve Bank Adjusted Financial conditions index and contains 105 individual variables that measure financial conditions, such as risk and leverage in the financial

[76] This is a weighted average of the foreign exchange values of the U.S. dollar against a subset of currencies in the broad index that circulate widely outside the country of issue. Some of the currencies included are the Canadian dollar, British Pound, the Euro, Mexican Peso, and Swiss Franc. For a complete list, see Loretan (2005).

system. By construction, the variation due to macroeconomic variables is removed from *Stress*. A positive value indicates that the financial system is stressed more than under normal circumstances. Both of these principal components incorporate a large amount of information and represent a good measure for macroeconomic activity and financial stress. Additionally, they help control for variation in long term volatility due to the business cycle. A summary of variables is provided in Table 3-2.

Table 3-2: Variable Descriptions

Variable	Description
Concentration x 100 (basis points)	Asset share of ten largest US commercial banks
HHI (basis points)	Herfindahl–Hirschman Index
FStress (basis points)	Chicago Fed Adjusted Financial Conditions Index
Macro (basis points)	Chicago Fed National Activity Index
GDPG (percentage)	GDP growth
Spread (basis points)	Difference between 10-yr and 3-month Treasury bond yields
Inflation (percentage)	Log difference in CPI
Δ ***FX*** (percentage)	Log difference of US rrade weighted dollar index
SP500_RV	Log realized volatility of *SP500*
Nasdaq_RV	Log realized volatility of *Nasdaq*
Aaa_RV	Log realized volatility of *Aaa*
Baa_RV	Log realized volatility of *Baa*
Options_RV	Log realized volatility of *Options*
Currency_RV	Log realized volatility of *Currency*
TB_RV	Log realized volatility of *TB*

Note: This table provides of summary of variables and their description.

3.4 Data and Calculation of Variables

The methods employed to calculate the variables are outlined in this section. The daily return for each asset is calculated by taking the log difference in closing prices between consecutive trading days. For stock market volatility, we use the S&P 500 and Nasdaq index volatilities. For options market, US dollar returns, and US government

bond returns, we use, respectively, the volatilities of the S&P 500 options index, the trade weighted US dollar index and the US 10-year constant maturity bonds. For corporate bond returns, we use two measures; bond yields on Moody's seasoned Aaa index for investment grade bonds, and bond yields on Moody's seasoned Baa index for speculative grade bonds. To calculate the log returns, we follow Nieto, Novales, and Rubio (2015) and apply the following formula:

$$\log\left(r_{bonds,t}\right) = \log\left(\frac{P_t}{P_{t-1}}\right) = \log\left(\frac{N/(1+y_t)^T}{N/(1+y_{t-1})^T}\right) = \log\left(\left(\frac{1+y_{t-1}}{1+y_t}\right)^T\right)$$

y_t is the yield on date t, P_t is the price, *N* is the nominal value (face value), and *T* is the time to maturity[77].

Realized volatility for each market is calculated by summing the squared daily returns within each quarter. The realized variance in a given quarter for market *i* is $RV_i = \sum_{j=1}^{N_t} r_{i,j}^2$, where N_t is the number of trading days. Data for this study come from four different sources; Yahoo Finance, the Chicago Board Options Exchange (CBOE), Saint Louis Federal Reserve Economic Data (FRED), and Wharton Research Data Services (WRDS). Yahoo Finance provides the daily S&P 500 and Nasdaq indices. CBOE provides the S&P 500 options index. Bank concentration data is drawn from the Call Reports provided by WRDS. The remaining data are provided by FRED.

[77] *T* is fixed at 10 years for US government bonds. For corporate bonds, we assume *T* is fixed at 30 years. In calculating the bond yields, Moody's tries to include bonds with remaining maturities as close as possible to 30 years. Moody's drops bonds if the remaining life falls below 20 years, if the bond is susceptible to redemption, or if the rating changes. We also assume *N* is the same for all bonds to simplify the calculations.

3.5 Results

Section 3.5 provides descriptive statistics along with the results of the empirical model. We reserve discussion and economic interpretation of the results until section 3.5.4.

3.5.1 Descriptive Statistics

Our daily financial data cover the time period spanning January 1986 through December 2013. The quarterly data cover the time period 1986:1 through 2013:4 and corresponds to the maximum time span for which all the data is available. Table 3-3 presents descriptive statistics for all variables employed in the model. Panels A and B report the descriptive statistics for the daily volatility returns and quarterly macroeconomic and financial variables respectively. We note that the minimum and maximum return values of each daily financial market are extreme relative to the mean. For example, the S&P 500 has a minimum and maximum return value of -22.9 ad 10.24, respectively, with a mean value of .028. These extreme values are due to events such as the stock market crash of 1987 and the collapse of Lehman Brothers in 2008. Removing these extreme values does not alter the results qualitatively. Therefore, we include all observations to provide more complete results.

Table 3-3: Descriptive Statistics

	Mean	Median	St. Dev	Kurtosis	Skewness	Min	Max	Obs.
Panel A: Daily Market Returns								
SP500	0.028	0.06	1.162	27.052	-1.4	-22.9	10.246	7688
Nasdaq	0.033	0.111	1.419	7.444	-0.298	-12.043	13.255	7688
Aaa	0.021	0.00	1.398	3.344	-0.089	-9.666	11.084	7660
Baa	0.022	0.00	1.354	3.163	-0.335	-11.886	8.063	7659
Options	0.028	0.06	1.162	27.044	-1.399	-22.900	10.246	7583
Currency	-0.003	0.004	0.444	2.985	-0.167	-4.107	2.155	7656
TB	0.008	0.000	0.591	4.730	0.099	-3.646	6.832	7629
Panel B: Quarterly Variables								
	Mean	**Median**	**St. Dev**	**Kurtosis**	**Skewness**	**Min**	**Max**	**Obs.**
Concentration	30.73	30.23	11.16	-1.61	0.12	16.47	47.22	112
HHI	169.01	155.76	113.93	-1.41	0.43	45.60	364.71	112
FStress	-0.05	-0.23	0.72	2.32	1.23	-1.10	3.04	112
Macro	-0.11	0.04	0.73	7.41	-2.33	-3.55	0.88	112
GDPG	0.65	0.70	0.61	4.24	-1.33	-2.14	1.87	112
Spread	1.77	1.75	1.15	-1.12	-0.18	-0.63	3.61	112
Inflation	0.68	0.73	0.50	11.36	-2.06	-2.32	1.71	112
Δ FX	-0.43	-0.10	3.14	0.05	0.19	-5.82	10.35	112
SP500_RV	4.69	4.54	0.90	1.17	0.88	3.01	7.84	112
Nasdaq_RV	4.87	4.67	1.13	-0.35	0.50	2.80	7.77	112
Aaa_RV	5.15	5.20	0.85	-0.32	-0.05	3.37	7.05	112
Baa_RV	5.16	5.18	0.73	0.32	-0.07	3.16	6.91	112
Options_RV	4.69	4.54	0.90	1.17	0.88	3.01	7.84	112
Currency_RV	3.03	3.03	0.59	0.81	0.12	1.46	5.01	112
TB_RV	3.60	3.57	0.57	0.12	0.46	2.34	5.07	112

Note: This table displays descriptive statistics for all variables employed in the model. Panel A presents the daily financial market return variables while Panel B presents the quarterly macroeconomic and financial variables. Realized volatilities are in logarithmic form.

Tables 3-4 and 3-5 display the simple correlations for the quarterly macroeconomic and financial variables and daily financial market returns respectively. As expected, there is generally an inverse relationship between stock and bond market returns suggesting a "flight to safety" where investors look for relatively less volatile assets during times of distress (Baele, Bekaert, Inghelbrecht, and Wei, 2014). Markets within the same class of assets (e.g. SP500 and Nasdaq; Aaa and Baa) have significant and positive correlations indicating that returns generally move in the same direction. We also note that the correlation between *Concentration* and realized volatility is positive and highest for the Aaa and Baa markets; .65 and .60 respectively. This could be an indication that there is higher correlation between banks and these two financial markets, compared to the remaining financial markets we consider which have correlations ranging between .04 and .44. We address this in greater detail in section 3.5.5.

In Figure 3-1, we display the value of *Concentration* and *HHI* over our sample period; 1986:1 to 2013:4. The upward trends of the two variables indicate that the series may be non-stationary; failing to correct for such an issue may produce spurious results (Greene, 2003). We provide the results of the Augmented Dickey-Fuller test, as displayed in Table 3-6, to determine if any of the quarterly variables suffer from unit-root issues. The D-F statistics for *Concentration* and *HHI* are -2.762 and -2.32 respectively and indicate the two variables suffer from unit root issues. We take the first difference of *Concentration* and the log difference of *HHI* in our regression attempts to ensure stationarity. None of the remaining control variables contain a unit-root and are not altered.

Table 3-4: Correlation of Quarterly Variables

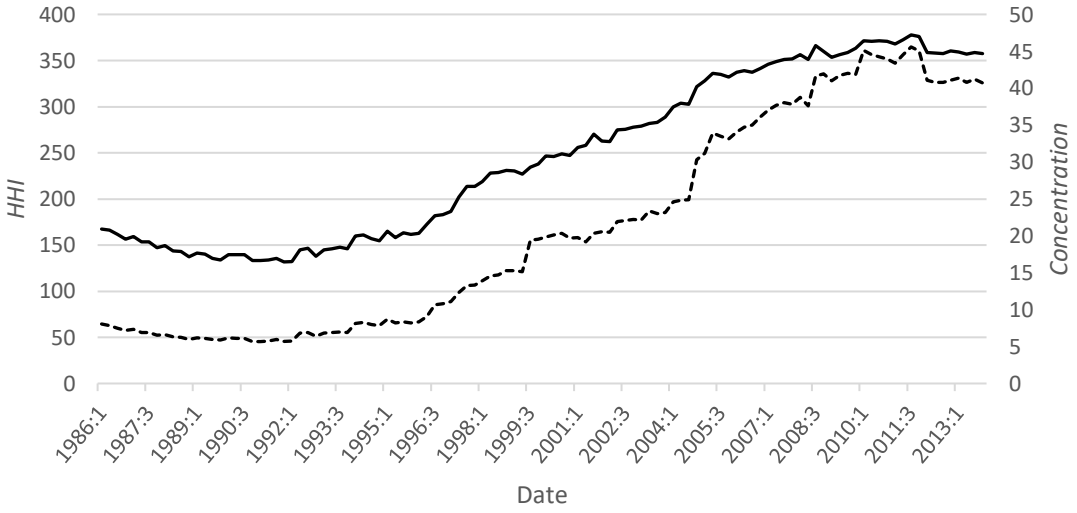
	HHI	*Conc*	*Stress*	*Macro*	*GDPG*	*FX*	*Spread*	*Inflation*	*SP_RV*	*Nas_RV*	*Aaa_RV*	*Baa_RV*	*Opt_RV*	*Cur_RV*	*TB_RV*
HHI	1														
Conc	.99*	1													
Stress	-.02	-.02	1												
Macro	-.31*	-.28*	-.13	1											
GDPG	-.3*	-.27*	-.04	.78*	1										
Δ *FX*	.03	.02	.03	-.14	-.12	1									
Spread	.12	.09	-.19*	-.06	-.03	-.10	1								
Infl	-.25*	-.26*	-.21*	.25*	.21*	-.30*	-.17*	1							
SP_RV	.24*	.26*	.49*	-.48*	-.33*	.04	.07	-.22*	1						
Nas_RV	.38*	.44*	.22*	-.44*	-.27*	.14	.01	-.28*	.76*	1					
Aaa_RV	.64*	.65*	.26*	-.26*	-.15	-.03	.23*	-.36*	.40*	.49*	1				
Baa_RV	.60*	.60*	.17*	-.32*	-.21*	-.05	.34*	-.35*	.38*	.50*	.93*	1			
Opt_RV	.24*	.26*	.49*	-.48*	-.33*	.04	.06	-.22*	.99*	.76*	.40*	.38*	1		
Cur_RV	.23*	.21*	.15	-.41*	-.30*	-.07	.34*	-.23*	.37*	.17*	.22*	.26*	.37*	1	
TB_RV	.05	.04	.38*	-.30*	-.16	-.18*	.39*	-.11	.51*	.28*	.57*	.61*	.52*	.37*	1

Note: This table displays correlations between all quarterly variables. "*" indicates significant at the 10% level or higher.

Table 3-5: Correlations of Daily Market Returns

	SP500	*Nasdaq*	*Aaa*	*Baa*	*Options*	*FX*	*TB*
SP500	1						
Nasdaq	.846*	1					
Aaa	-.103*	-.139*	1				
Baa	-.086*	-.121*	.901*	1			
Options	.998*	.846*	-.103*	-.086*	1		
FX	-.035*	-.024*	.020*	-.003	-.035*	1	
TB	-.089*	-.157*	.810*	.805*	-.089*	-.014	1

Note: This table displays correlations between all daily financial market returns. "*" indicates significant at the 10% level or higher.



Note: This figure displays the trend of banking concentration over the sample period 1986:1 – 2013:4. The asset ratio of the ten largest banks is depicted by the solid line. HHI is depicted by the dashed line.

Figure 3-1: Concentration and HHI Over the Sample Period; 1986:1 – 2013:4

Table 3-6: Augmented Dickey Fuller Test Results

	Functional Form	D-F Statistic	p-value
Concentration	trend	-2.762	0.211
HHI	trend	-2.323	0.4232
FStress		-4.311	.0009
Macro		-3.845	.0025
GDPG		-7.007	.00004
Spread	drift	-2.178	.0157
Inflation		-7.967	.00005
ΔFX		-8.078	.000008
SP500_RV		-5.855	0.00002
Nasdaq_RV		-4.281	0.0005
Aaa_RV		-3.652	0.0048
Baa_RV		-3.799	0.0029
Options_RV		-5.806	0.00002
Currency_RV		-4.915	.00006
TB_RV		-4.638	.0001

Note: This table provides the results of the Augmented Dickey-Fuller test. Failing to reject the null hypothesis indicates the series suffers from unit-root issues and is therefore non-stationary. The second column indicates if the form of the test indicates if a drift or trend term is included in the test.

3.5.2 One Variable Model Results

Following Engle, Gyshels, and Sohn (2013), we first display the results of the one-variable model of market volatility (equation 3.5) in Table 3-7 to establish a baseline relationship between financial market volatility and banking concentration. Panel A displays the results when the asset share of the ten largest banks is employed as the measure of banking concentration (*Concentration*) and Panel B displays the results of the GARCH (1-1) market volatility models with constant long term variance. We provide additional detail on the GARCH (1-1) models below. The results of *HHI* are very similar and are provided in Appendix C for the interested reader. The optimal lag length is determined by minimizing the Bayesian Information Criterion (BIC) and varies between 4 and 28 quarters. We note that altering the lag length does not significantly affect the

Table 3-7: GARCH-MIDAS Parameter estimates with One Exogenous Variable; *Concentration*

Financial Market	μ	α	β	m	θ	ω_1	ω_1	LLF	BIC	LR
Panel A										
SP500	0.05***	0.07***	0.92***	0.11	0.29***	243.67*	189.86	-7708.26	2.71	15.31
Nasdaq	0.08***	0.11***	0.88***	0.54***	0.32**	7.35*	5.01**	-10332.88	3.08	9.42
Aaa	0.03**	0.05***	0.95***	0.67***	0.41**	1.00	1.92	-10972.72	3.28	8.39
Baa	0.03*	0.05***	0.94***	0.56***	0.62***	1.17*	1.52**	-11029.50	3.29	18.79
Options	0.05***	0.08***	0.91***	-0.12	1.12***	8.07**	2.66**	-7740.05	2.71	13.59
Currency	-0.001	0.03***	0.96***	-1.53***	-0.53**	53.49**	99.37**	-2677.53	1.04	8.18
TB	0.01*	0.03***	0.96***	-1.02***	-0.17***	799.78	236.24	-4894.31	1.66	19.18

Panel B	μ	α	β	m	LLF	BIC
SP500	0.05***	0.08***	0.91***	0.18	-7715.91	2.71
Nasdaq	0.08***	0.10***	0.89***	0.61***	-10337.59	3.08
Aaa	0.03**	0.05***	0.95***	0.75***	-10976.91	3.29
Baa	0.03	0.05	0.94	0.71	-11038.90	3.29
Options	0.05***	0.08***	0.92***	0.22	-7746.85	2.71
Currency	0.00	0.04	0.96	-1.66	-2681.62	1.04
TB	0.01*	0.04***	0.95***	-1.06***	-4903.90	1.67

Note: Panel A of this table displays the results of the GARCH-MIDAS model estimated with ML. The specification of the model is $\log \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}$ where X_{t-k} is banking concentration. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". Panel B displays the estimates of the GARCH (1-1) where we restrict $\theta = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 3.84 at 95% confidence.**

value of the main parameter θ. We check for robustness by estimating various lag structures for each specification and find the results to be qualitatively similar. These lag lengths are consistent with the literature (e.g. Engle, Gyshels, and Sohn, 2013; Asgharian, Hou, and Javed ,2013; Conrad and Loch, 2014). We employ robust standard errors to correct for any autocorrelation issues.

θ is the main parameter of interest because it depicts the association between financial market volatility and banking concentration. θ is highly significant in all regressions. Furthermore, we find that θ is positive in the equity markets, options markets, and corporate bond markets indicating that positive changes in banking concentration has an amplifying effect on volatility is these markets. In the remaining markets, US dollar (*Currency*) and US Treasury Bonds (*TB*), θ is negative suggesting that positive changes in banking concentration has a dampening effect on volatility in these markets.

We note that both α and β are both highly significant in all regressions. As previously explained, $\alpha + \beta$ is the persistence of the conditional variance process (Bauwens, Hafner, and Laurent, 2012). Furthermore, the sum of α and β is consistently less than one in all models indicating the long-term shock is persistent, but not explosive (Bauwens, Hafner, and Laurent, 2012). By restricting θ to equal zero, the GARCH-MIDAS model reduces to a GARCH (1-1) with unconditional variance equal to e^m (Conrad and Loch, 2014). Following Conrad and Loch (2014), we perform the likelihood ratio test to determine if the GARCH-MIDAS model has greater explanatory power than the GARCH (1-1) model. The likelihood ratio (LR) is given by $LR = 2 \cdot [L_{UR} - L_R]$

where L_{UR} and L_R are the values of the log-likelihood function of the unrestricted (GARCH-MIDAS) and restricted (GARCH 1-1) models respectively. LR is displayed in the last column of Panel A, Table 3-7, and exceeds the critical value of 3.84[78] in all models. Based on this test, we conclude that the GARCH-MIDAS model with banking concentration as an explanatory variable, is superior to the GARCH (1-1) model with constant long run variance.

Following Engle, Gyshels, and Sohn (2013), we calculate the marginal effect of a 100 basis point increase in the level of *Concentration* (at date *t-k*) on long term volatility (at date *t*) by the following formula: $^{\partial \tau_t}/_{\partial Concentration_{t-k}} = e^{\theta \cdot \varphi_k(\omega)/3} - 1.$ Consider the Nasdaq financial market as an illustrative example. As a result of a 100 basis point increase in *Concentration*, volatility will grow by $e^{.32 \cdot .0084/3} - 1 \approx .0009$, or approximately .09%, in the next quarter. Likewise, the same increase in *Concentration*, volatility will increase by $e^{.32 \cdot .2166/3} - 1 \approx .0237$ or 2.37% in two quarters time[79]. To put this into perspective, consider the Nasdaq long term average annualized volatility (τ) which is approximately .043 or 4.3% (equivalently, the annualized $\sqrt{\tau}$ is .207 or 20.7%). If banking concentration increased by 100 basis points this quarter (for example, from 25% to 26%), next quarter's volatility would rise by .09% from .043 to .04687 in annualized τ (or from .207 to .2071863 in $\sqrt{\tau}$).

[78] Based on 95% confidence with one degree of freedom.

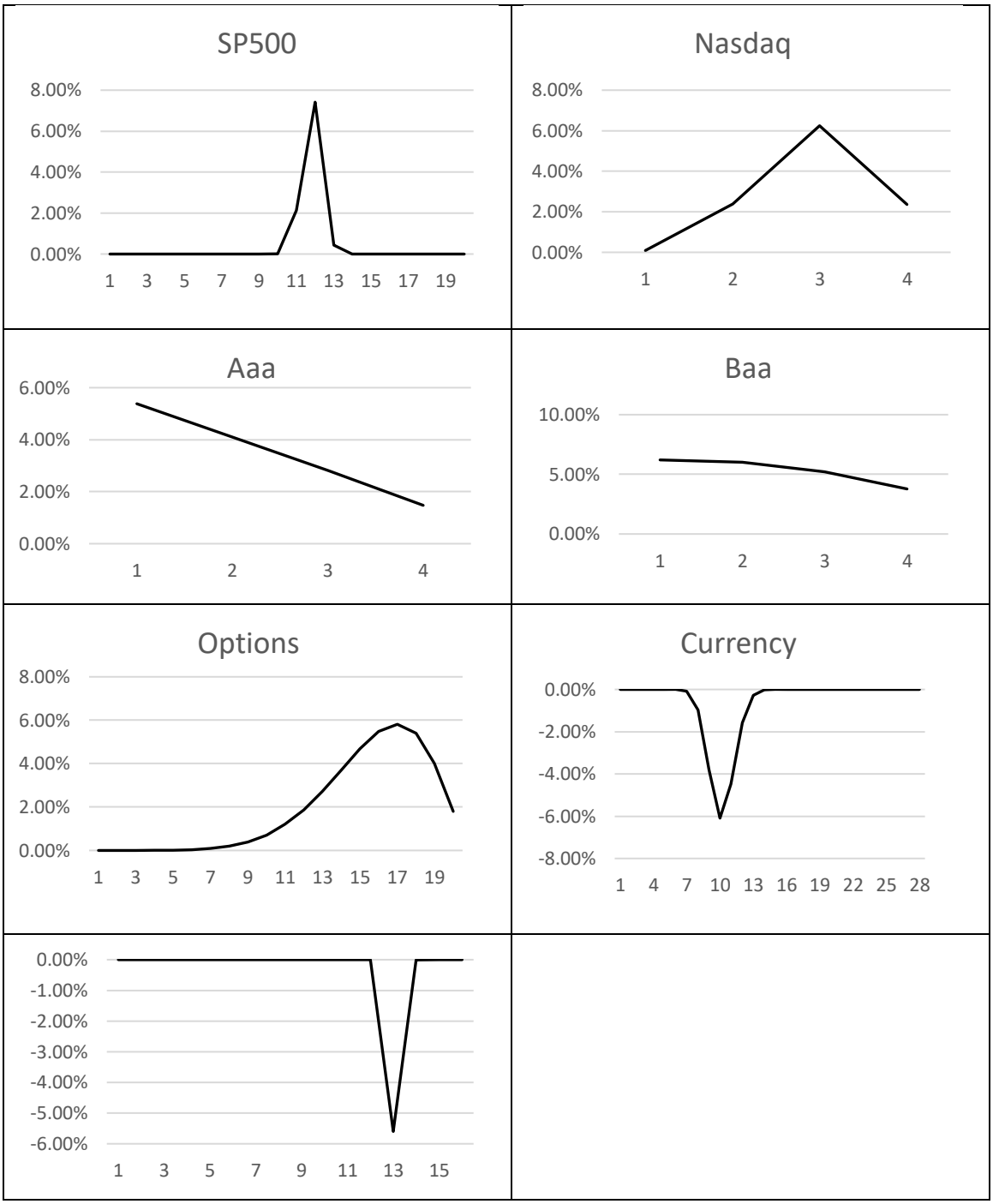
[79] Estimates of $\omega_1$and ω_2 are 7.35 and 5.01 respectively. The value of the beta weighting function at 1 and 2 lags are approximately $\varphi_1 = .0084$ and $\varphi_2 = .2166$.

We provide a summary of the marginal effect of banking concentration on financial market volatility in Figure 3-2. Each graph displays the marginal effect that corresponds to each lag. The lag structure varies across financial markets and is consistent with the literature in both length and shape (e.g. Engle, Gyshels, and Sohn ,2013; Asgharian, Hou, and Javed, 2013); Nieto, Novales, and Rubio, 2015). Changes in banking concentration seems to have the most immediate effect in *Nasdaq*, *Aaa*, and *Baa*. This could indicate that these markets either compete with large banks more than the remaining markets, or are more interconnected with large banks than the remaining markets. For example, smaller firms that raise a portion of their required funds through the Nasdaq market may be more reliant on banks for debt financing. Changes in banking concentration could arguably impact these firms more quickly than larger corporations who could tap into bonds markets for debt financing. We address this interconnection issue in greater detail in section 3.5.5.

3.5.3 Two Variable Model Results

In this section, we extend Engle, Gyshels, and Sohn (2013) by including a second explanatory[80] variable in addition to banking concentration to help filter out the effects of macroeconomic and financial conditions. Tables 3-8 through 3-14 display the results of the two variable model. We focus our discussion on the set of results corresponding to *Concentration* (the asset share of the ten largest banks) and provide the results for *HHI* in

[80] As previously explained, employing three or more explanatory variables produces unstable results.



Note: This table displays the marginal effects of a 100 basis point increasing in *Concentration.* The horizontal axis indicates the quarterly lag of each variable. The optimal lag length varies across markets and is determined by minimizing the BIC. The marginal effect is calculated by $\partial\tau_t / \partial Concentration_{t-k} = e^{\theta \cdot \varphi_k(\omega)/3} - 1$.

Figure 3-2: Marginal Impact Due to a 100 basis Point Increase in *Concentration*

Table 3-8: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *SP500*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.06***	.08***	.91***	-.06	.43**	-.27***	155.14**	117.79**	85.09	595.37	-7703.9	2.71	23.8
GDPG	.05***	.08***	.91***	-.07	1.21***	-.25**	19.84*	9.31**	176.7***	469.4***	-7702.8	2.70	26.2
Spread	.06***	.08***	.9***	.63***	.24***	-.39***	598.5***	480.2***	108.8	304.5	-7690.1	2.71	51.5
Stress	.05***	.07***	.91***	.01	.19**	.56***	593.3***	45.26***	525.24	518.5	-7697.9	2.71	35.9
Inflation	.05***	.07***	.92***	-.19	.39**	.38***	177.83	138.65	483.16	573.0	-7703.6	2.71	24.6
ΔFX	.05***	.08***	.91***	.05	.40**	.06***	176.17*	136.23	405.2***	724.2***	-7703.3	2.71	25.1
SP500_RV	.05***	.08***	.9***	-1.84***	.30***	.38***	574.5***	463.5***	25.9***	336.8***	-7701.8	2.71	28.4
GARCH 1-1	-.001*	.04***	.96***	-1.65***							-7715.9	1.04	

Note: This table displays the results of the GARCH-MIDAS model of the SP500 equity market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table 3-9: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Nasdaq*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.08***	.11***	.88***	.50***	.24***	-.23***	582.6***	243.6***	375.5***	205.5***	-10329.4	3.08	16.3
GDPG	.08***	.11***	.88***	.69***	.18***	-.21***	324.2***	159.2***	857.3***	318.1***	-10330.7	3.08	13.7
Spread	.08***	.11***	.88***	.81***	.26***	-.16***	607.8***	254.1***	785.22	12.27	-10330.4	3.08	14.2
Stress	.08***	.10***	.88***	.55***	.12**	-.30***	445.6***	232.7***	31.67***	34.09***	-10329.3	3.08	16.5
Inflation	.08***	.11***	.88***	.86***	.28**	-.48**	7.66	5.43*	2.63	3.81*	-10329.7	3.08	15.7
ΔFX	.08***	.11***	.88***	.60***	.21**	.07**	52.68	50.63	3.19	4.91	-10330.8	3.08	13.5
SP500_RV	.08***	.12***	.85***	-2.14***	.22**	.52***	7.97	5.89	1.44	2.27	-10317.2	3.08	40.7
GARCH 1-1	.08***	.10***	.89***	.61***							-10337.6	3.08	

Note: This table displays the results of the GARCH-MIDAS model of the Nasdaq equity market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table 3-10: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Aaa*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.03**	.05***	.95***	.70***	.38	-.16*	1.00	2.07	7.52	66.64	-10971	3.28	11.7
GDPG	.03**	.05***	.95***	.83***	.47**	-.22*	1.28	1.91*	99.99***	96.9***	-10969.8	3.29	14.2
Spread	.03**	.05***	.95***	.86***	.41**	-.13*	1.00	1.95	1.04	92.82	-10970.9	3.29	11.9
Stress	.03**	.05***	.95***	.65***	.43**	.06	1.00	1.90	12.41	28.92	-10972.5	3.28	8.6
Inflation	.03**	.05***	.95***	.91***	.22***	-.34***	34.69	84.54	28.35***	64.69***	-10969	3.29	15.7
ΔFX	.03**	.05***	.95***	.64***	.38*	-.01	1.00	1.98	43.47***	1.00***	-10971.8	3.29	10.1
SP500_RV	.03**	.06***	.93***	-2.64***	.29*	.61***	1.00	2.73	1.01	1.00	-10960.3	3.28	33.3
GARCH 1-1	.03**	.05***	.95***	.75***							-10976.9	3.28	

Note: This table displays the results of the GARCH-MIDAS model of the Aaa corporate bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table 3-11: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Baa*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.03*	.05***	.94***	.50***	.70***	-.24**	1.42**	1.63***	66.24***	27.9***	-11026.9	3.29	24.1
GDPG	.03*	.05***	.94***	.62***	.63***	-.12*	1.13*	1.37**	1.01***	99.89	-11027.9	3.29	22.4
Spread	.03*	.05***	.94***	.36*	.60***	.11*	1.20*	1.49**	51.97	85.13	-11027.7	3.29	22.4
Stress	.03*	.05***	.94***	.55***	.64***	.14	1.16**	1.51**	36.95***	85.4***	-11028.4	3.29	21
Inflation	.03*	.05***	.94***	.76***	.57***	-.34	1.12	1.51**	1.22	1.00	-11028.2	3.29	21.5
ΔFX	.03*	.05***	.94***	.57***	.60***	.01	1.11***	1.49***	1.00***	99.5***	-11029.2	3.30	19.3
SP500_RV	.03**	.05***	.92***	-2.4***	.34***	.56***	1.00	1.73	1.29	1.92	-11020.9	3.29	36.2
GARCH 1-1	.03**	.05***	.94***	.71***							-11038.9	3.29	

Note: This table displays the results of the GARCH-MIDAS model of the Baa corporate bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table 3-12: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Options*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.06***	.08***	.91***	-.11	.91***	.81***	30.68*	12.20*	5.47**	1.94**	-7729.70	2.71	34.3
GDPG	.05***	.08***	.91***	-.72***	.80***	.90***	32.78*	12.54*	5.17*	1.84**	-7733.86	2.71	25.9
Spread	.06***	.08***	.89***	.35**	1.00***	-.38***	7.26*	2.27**	22.86	33.48	-7717.54	2.71	58.6
Stress	.06***	.08***	.90***	-.19	.94***	1.18***	1.00	1.48	1.00	1.29*	-7721.89	2.71	49.9
Inflation	.05***	.08***	.91***	-.36	1.15***	.36*	9.04**	2.90**	11.72	100.00	-7736.61	2.71	20.5
ΔFX	.05***	.08***	.90***	-.22*	1.29***	.31***	8.38**	2.41***	4.21**	6.35**	-7731.19	2.71	31.3
SP500_RV	.06***	.08***	.89***	-2.18***	.73***	.42***	16.08	7.94*	5.91*	48.57*	-7730.39	2.71	32.9
GARCH 1-1	.05***	.08***	.92***	.22							-7746.85	2.70	

Note: This table displays the results of the GARCH-MIDAS model of the Options market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table 3-13: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Currency*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	-.001	.03***	.96***	-1.94***	.61**	.49***	46.26**	43.23**	744.87	220.70	-2668.21	1.04	26.8
GDPG	-.001	.03***	.96***	-2.41***	.50***	.71***	55.65*	7.03*	84.35*	23.20*	-2668.34	1.04	26.6
Spread	-.001	.03***	.96***	-2.66***	1.29***	.28***	26.78*	25.73	179.96	983.99	-2672.89	1.05	17.5
Stress	-.001	.03***	.96***	-1.62***	.07	.40***	731.45	384.88	197.63*	333.17*	-2672.68	1.05	17.9
Inflation	-.001	.03***	.96***	-2.09***	.74**	.28**	38.90**	36.39**	652.53	314.48	-2676.06	1.05	11.1
ΔFX	-.001	.03***	.96***	-1.84***	.50	-.06***	50.63	47.65	137.40	1000.00	-2673.05	1.05	17.1
SP500_RV	-.001	.03***	.96***	-1.37***	-.52*	-.06	56.14*	104.90*	932.70	91.42	-2677.350	1.05	8.54
GARCH 1-1	-.001*	.04***	.96***	-1.66***							-2681.62	1.04	

Note: This table displays the results of the GARCH-MIDAS model of the US dollar market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table 3-14: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *TB*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.01	.03***	.96***	-1.02***	-.15***	.25***	909.46	279.83	850.1***	80.5***	-4888.11	1.67	31.6
GDPG	.01*	.03***	.96***	-1.17***	-.17***	.20**	970.58	301.44	558.66	51.28	-4890.62	1.67	26.6
Spread	.01*	.03***	.96***	-.77***	-.17**	-.14**	622.43	176.52	430.77	615.85	-4890.72	1.65	26.4
Stress	.01*	.03***	.96***	-1.02***	-.21***	-.14	605.59	178.91	355.88	309.13	-4892.30	1.67	23.2
Inflation	.01*	.03***	.96***	-1.23***	-.17***	.27***	867.61	262.66	423.16	150.47	-4889.88	1.67	28.0
ΔFX	.01*	.03***	.95***	-.94***	-.30***	.21***	100.0***	30.77***	3.07	1.67**	-4890.56	1.67	26.7
SP500_RV	.01*	.03***	.95***	.31	-.18**	-.38***	598.01	166.24	611.23	58.13	-4886.25	1.66	35.3
GARCH 1-1	.01*	.04***	.95***	-1.06***							-4903.90	1.66	

Note: This table displays the results of the GARCH-MIDAS model of the US Treasury Bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *Concentration*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

appendix C for the interested reader. In each specification, θ_1 corresponds to banking concentration while θ_2 refers the second explanatory variable considered in that particular regression.

The results of the two variable model are mostly consistent with those of one variable model. That is, *Concentration* (θ_1) is positive and highly significant in the *SP500, Nasdaq, Aaa, Baa,* and *Options* markets. It is negative and highly significant in the *TB* market. Therefore, we reject hypotheses H1-H6, purporting that that financial market volatility and banking concentration are unassociated. We note that in the *Currency* market, the sign of *Concentration* changes signs between the one and two variable models; negative in the former and positive in the latter. This change of signs raises suspicion as to the validity of the results. Therefore, we do not find conclusive evidence of a significant association between US dollar volatility and banking concentration and fail to reject hypothesis H7. We briefly note, that the two variable GARCH-MIDAS model is superior to the GARCH (1-1) model as indicated by the LR statistics displayed in the final column of Tables 3-8 through 3-14[81].

3.5.4 Economic Interpretation

Now that we have established a significant association between financial market volatility and banking concentration, we turn our attention to the channels of the effect and economic interpretation of our results. In the markets where the association is positive (*SP500, Nasdaq, Aaa, Baa*, and *Options*), market volatility could be amplified through the uncertainty introduced by increases in banking concentration through the

[81] In this test, we restrict $\theta_1 = \theta_2 = 0$. The 95% critical value of the LR test is 5.99 with two degrees of freedom is 5.99.

following channels. First, as banks concentrate, they become more complex and highly exposed to capital markets (e.g. securitization) making it increasingly difficult to liquidate their balance sheets in times of distress (Ferguson, Hartmann, Panetta, and Portes, 2007). When a large bank is in danger of failing, the market value of its assets could plummet leading markets to overshoot, destroying more value than is warranted, as a result (Ferguson, Hartmann, Panetta, and Portes, 2007). Investors would, in all likelihood, be aware of this possibility, and would look to sell assets at the first sign of trouble at a major institution.

Second, a highly concentrated banking system increases the risk of contagion. As previously explained, when large banks consolidate, they become increasingly similar and interconnected to one another, they will be increasingly exposed to similar risks, and will use similar risk measurement and risk management models (Hendricks, Kambhu, and Mosser, 2007). As a consequence to this, the effects of a major bank collapse or a shock to financial markets, could more easily spread through the banking and financial system (Hendricks, Kambhu, and Mosser, 2007). Furthermore, as concentration increases, the size and the complexity of the contracts between firms grows considerably, increasing the likelihood that a crisis at one firm could spread to other firms and ultimately cause the financial system to collapse (Ferguson, Hartmann, Panetta, and Portes, 2007).

Third, concentration reduces market liquidity because larger firms create an internal capital market for funds and go to external markets only for the balance (Ferguson, Hartmann, Panetta, and Portes, 2007). Furthermore, large banks that

consolidate tend to become more alike and exposed to similar risks (Cetorelli, Hirtle, Peristani, and Santos, 2007) and employ increasingly similar risk models (Kiff, Kodres, Klueh, and Mills, 2007). During a period of market stress, large banks could simultaneously be reducing or suspending financing and trading activities leading to market gridlock, severe reductions in liquidity (Hendricks, Kambhu, and Mosser, 2007), and amplified market volatility (Kiff, Kodres, Klueh, and Mills, 2007).

Fourth, volatility could also be amplified because of the increased competition between large banks and financial markets. As we previously explained, markets have evolved significantly over the past few decades and have drawn banking customers away (Berger, Molyneux, and Wilson, 2010). In response, banks have further consolidated (Hawkins and Mihaljek, 2001) and have created new products similar those offered by financial markets to maintain market share (Berger, Molyneux, and Wilson, 2010). For example, a bank can provide a back-up line of credit when one of its customers issues commercial paper (Berger, Molyneux, and Wilson, 2010). It is quite plausible that this increase in competition between banks and financial markets has raised uncertainty and, therefore, amplifying market volatility.

Conversely to what we find between concentration and volatility in stock, corporate bonds, and options markets, there appears to be an inverse association between volatility of the treasury bond market (*TB*) and increasing banking concentration. The negative effect could be the result of a *flight to safety* in response to increased stock, corporate bond, and options market volatility due to greater concentration. As banking concentration increases, economic uncertainty increases causing equity and corporate

bond markets to be more volatile. Investors could be willing to sacrifice profits for stability by seeking safer assets, namely treasury bonds, that are less volatile (Kiff, Kodres, Klueh, and Mills, 2007). This principle agrees with Asgharian, Christiansen, and Hou (2015) who find a *flight to safety* effect when macroeconomic uncertainty is high.

The macroeconomic variables, namely macroeconomic conditions (*Macro*) and GDP growth (*GDPG*) are negative and significant coefficients in the *SP500, Nasdaq, Aaa*, and *Baa* markets, indicating that better economic conditions dampen volatility in these markets. The rationale is that better economic conditions stabilize corporate cash flow and reduce uncertainty because firms are able to meet financial obligations (Schwert, 1989). The aforementioned variables are significant and positive in the *Options* and *TB* markets indicating an amplifying effect. The positive relationship of these markets with macroeconomic conditions (*Macro*) and GDP growth (*GDPG*), could be due to investor speculation of increased cash flow when macroeconomic conditions are good. The relationship with macroeconomic conditions (*Macro*) and GDP growth (*GDPG*) is due to investors selling off treasury bonds and shifting to riskier assets when economic times are good and their risk tolerance is enhanced; the inverse of the *flight to safety* argument previously discussed. This relationship is in agreement with Asgharian, Christiansen, and Hou (2015) who find a *flight to safety* effect when macroeconomic uncertainty is high

The financial variables, the treasury yield spread (*Spread*) and financial system stress (*Stress*), are mostly[82] negative and positive respectively. Both are significant

[82] There are occasions where the control variable does not agree with the hypothesized sign. We do not provide an economic explanation because the result could be due to the computational complexity of our

indicating that a larger yield spread has a dampening effect on market volatility, and financial stress has an amplifying effect on financial market volatility. As with the macroeconomic variables, a greater yield spread is associated with reduced uncertainty and less market volatility. Financial stress, however, increases uncertainty in the market because firms are less likely to meet their obligations (Schwert, 1989). The negative and significant sign of *Stress* in the *TB* market supports the flight to quality rationale previously discussed. We note that *Inflation* and changes in US dollar strength (ΔFX) fluctuate between positive and negative across markets indicating that different markets react differently to changes in relative currency strength. Additional research is needed on this topic.

3.5.5 Variance Ratio

Following Engle, Gyshels, and Sohn (2013), we estimate how much of the total volatility is explained by the explanatory variables. To this end, we calculate the variance ratio as the ratio of long term volatility to total volatility. This concept can be formulated as : $VR_{X_1} = {Var\left[\log\left(\tau_t^{X_1}\right)\right]}/{Var\left[\log\left(\tau_t^{X_1,X_2} g_t^{X_1,X_2}\right)\right]}$ where X_1 and X_2 refer to given variables such as *Concentration* and *Macro*[83]. The numerator of VR_{X_1} corresponds to the variance of the long term volatility component of the variable in question. The denominator is the variance of total volatility from the two variable model. We focus our discussion *Concentration, Macro, and Stress* because the latter two variables provide a

model. Instead, we look for the overall pattern across markets and provide an economic explanation for those results.

[83] $g_t^{X_1,X_2}$ is the short term volatility component that changes daily.

very broad representation of macroeconomic and financial conditions. This ratio allows to determine if banking concentration explains a greater proportion of financial market volatility than macroeconomic and financial conditions.

Table 3-15 displays the variance ratios for the aforementioned variables. The contribution by *Concentration* to total volatility varies across markets. *Concentration* is the largest contributor to total volatility in both investment grade (*Aaa*) and speculative grade (*Baa*) corporate bond markets, 4.79 and 14.59 respectively. In both *SP500* and *Nasdaq*, financial stress (*Stress*) is the largest contributor to total volatility. Although we note that the *Nasdaq* variance ratios are similar for all three variables, 2.48, 2.31, and 3.44 for *Concentration, Macro,* and *Stress* respectively. Macroeconomic activity (*Macro*) is the largest contributor to volatility in the *Options*, *Currency*, and *TB* contributing 30.86, 19.44, and 18.27 to total volatility respectively.

Table 3-15: Variance Ratios

Financial Market/Variable	***Concentration***	***Macro***	***Stress***
SP500	3.66	6.38	20.97
Nasdaq	2.48	2.31	3.44
Aaa	4.79	1.26	0.52
Baa	14.59	8.37	1.85
Options	14.93	30.86	21.63
Currency	9.36	19.44	17.73
TB	8.29	18.27	4.54

Note: This table displays the amount of volatility (VR) explained by *Concentration, Macro,* and *Stress*. The formula is provided by Engle, Gyshels, and Sohn (2013). $VR_{X_1} = Var\left[\log\left(\tau_t^{X_1}\right)\right] \Big/ Var\left[\log\left(\tau_t^{X_1,X_2} g_t^{X_1,X_2}\right)\right]$ **. We note that VR for *Concentration* can be calculate from either the *Concentration-Macro,* or the *Concentration-Stress* models. Both models produce very similar results.**

The variance ratio explained above could be an indication that there is a greater connection between banks and corporate bond markets than the other markets tested. As previously explained, increasing concentration of the banking sector has also led to greater interbank competition between the largest banks and reduced profit margins. To compensate, large banks that have better access to technology and can take better advantage of scale economies (Mester and Hughes, 2011), have increasingly turned to capital markets to raise funds which are less costly than traditional deposits (Berger, Molyneux, and Wilson, 2010). For example, securitization allows banks to originate loans to firms with funds often raised in bond markets (Vives, 2016). Because these products are well diversified and often carry the highest rating possible (Vives, 2016), they could be drawing investors away from and reducing liquidity in the corporate bond markets. For example, a BB quality borrower in the corporate bond market could potentially get AAA rates by obtaining banks funds raised through securitization. However, securitization has also led to an over expansion of credit that led to the crisis of 2008 (Vives, 2016). The opacity of these instruments obstructed an accurate risk assessment and led to an underestimation of the systemic risk that had been built up (Vives, 2016). The increase in bank concentration might have reduced the number of market participants in the bond markets (Hendricks, Kambhu, and Mosser, 2007) and might have reduced market liquidity further and amplified volatility more than in the equity markets.

3.6 Conclusion

Research on the association between financial market volatility and banking concentration has been sparse leaving much room for debate among researchers, policy makers, and regulators. This is an important topic because over the past few decades, the US banking sector has concentrated considerably and has become more interconnected with financial markets, making it difficult for regulators to isolate bank risks from market risks (Berger, Molyneux, and Wilson, 2010). Proponents of highly concentrated banking systems claim the larger more complex financial institutions are able to better diversify risks across product lines, consequently improve the risk-return frontier in their own favor (Berger, Demsetz, and Strahan, 1999), and make the overall financial system more stable (Berger, Molyneux, and Wilson, 2010). However, opponents of highly concentrated banking systems claim that the presence of large complex financial institutions increase the risk of contagion, reduce market liquidity, and disrupt financial markets in times of trouble (Ferguson, Hartmann, Panetta, and Portes, 2007).

This study adds to the debate by establishing an empirical relationship between financial market volatility and banking concentration. To this end, we employ the recently developed GARCH-MIDAS model that has two major advantages over other volatility models; 1) it allows high frequency daily volatility to be modeled as a function of lower frequency quarterly variables; and 2) it allows long lag lengths to be employed in the model without adding an excessive number of parameters. We gather daily data from seven US financial markets covering equities, corporate bonds, treasury bonds, the US dollar. We also gather quarterly data on banking concentration and various

macroeconomic and financial indicators. We focus on the time period spanning January 1, 1986 to December 31, 2013; the maximum time span our data allow.

Our results indicate that positive changes in banking concentration amplify volatility in the stock, options, and corporate bond markets. We include multiple exogenous variables in the GARCH-MIDAS model to help isolate the effects of changing levels of banking concentration. Additionally, we include two principal components that represent macroeconomic activity and financial stress, that to eliminate any bias that may result from omitted variables. Our results also indicate that positive changes in banking concentration dampen volatility of US treasury bonds possibly due to a flight to quality effect. We do not find sufficient evidence that banking concentration as a significant impact on US dollar volatility. Additionally, we find that banking concentration explains more of the volatility, in the corporate bond market, than macroeconomic and financial conditions explain. In the remaining markets, US equity and US treasury bonds, macroeconomic and financial conditions explain more of the variation in volatility than does banking concentration.

Prior to this study, the relationship between financial market volatility and banking concentration was ambiguous. These results are important to policy makers and regulators because it adds vital insight into the effects of banking concentration and the presence of excessively large complex financial institutions.

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APPENDIX A
POISSON MODEL DETAILS

Exposure Variables

The standard model for analyzing count data is the Poisson model (Cameron and Trevedi, 2013) and is defined as $P(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!}$, where $E(X) = \lambda$. A link function is required to equate the expected value, λ, to a set of regressors, X. For the Poisson model, the standard link function is the logarithm such that, $\log \lambda = \beta X$ where β is a vector of coefficients estimated by the model (Cameron and Trevedi, 2013). Two of the underlying assumptions of this model are that the dependent variable is a non-negative integer, and that the expected value, $E(Y)$, is equal to its variance, $Var(Y)$. That is, $E(Y) = Var(Y) = \lambda$.

Often the researcher is interested in measuring the number of events in relation to some proportion. Normalizing the dependent variable may lead to non-integer values which violates one of the Poisson model assumptions. Introducing an exposure variable allows the researcher to normalize the dependent variable while maintaining the count data assumption (Cameron and Trevedi, 2013).

To illustrate, consider the following link function where the log of *Failures* is a function of vector *X* and β is a vector of coefficients to be estimated. Assume the variable *Failures* is strictly positive and each observation is an integer. Since the number of failures is proportional to the number of *Banks* in the system, we can normalize *Failures* by dividing it by the number of *Banks*. The resulting variable,

$\left({Failures}/{Banks}\right)$ is a value between zero and one. The resulting link function can be described as:

$$\log\left({Failures}/{Banks}\right) = \beta X \qquad \text{(A.1)}$$

The Poisson model with (A.1) as the link function cannot be estimated as is because the left hand side variable is not an integer. However, if the variables are rearranged such that *Banks* is moved to the right-hand-side and the coefficient is restricted to one, the resulting link function produces the same β. Rewrite equation (A.1) as follows:

$$\log Failures - \log Banks = \beta X \qquad \text{(A.2)}$$

When *Banks* is moved to the right hand side, the link function becomes.

$$\log Failures = \beta X + (1) \log Banks \qquad \text{(A.3)}$$

The parameter estimates β in equation (A.3) is identical to the parameter estimate in equation (A.1). By introducing log (*Banks*) and restricting the coefficient to equal 1, the model allows for a normalized dependent variable without violating the assumptions of the model (Cameron and Trevedi, 2013).

Autoregressive Poisson Model

There is no standardized method to include lagged terms of the dependent variable when working with count regression models (Cameron and Trevedi, 2013). Instead, researchers have a number of methods to choose from depending on the analysis being performed (Cameron and Trevedi, 2013). The model of Zegar and Qaqish (1988) has some advantages over other models. In this model, the lagged terms enter directly

into the equation, making estimation of the parameters and variance of the Poisson model straightforward. Moreover, this procedure is easy to implement and interpretation of the results are straightforward.

To understand this model, first consider adding p lagged values of the logarithm of the failure rate[84]. When the failure rate is zero, as it is during multiple periods, including lagged logarithm terms is problematic. Zegar and Qaqish (1988) propose a transformation of $Failure\ Rate_{t-i}$. To this end, define $Failure\ Rate_t^* = \max(Failure\ Rate_t, c)$ where $0 < c < 1$. c is chosen so that values where $Failure\ Rate_t = 0$ can be approximated. An obvious weakness is the transformation of observed zeroes. However, the transformed values are close enough to zero, that inference can still be drawn from the results. For this study, c is chosen to equal .00001 because it less than any actual value of *Failure Rate* that is not equal to zero. It also provides an approximation near zero so that potential singularities are avoided.

Determining the correct number of lags for an autoregressive count model is similar to the process for linear autoregressive models. Bryant and Williams (2001) state that the standard autocorrelation (AC) and partial autocorrelation (PAC) tests can be applied in determining the lag length. When applied to the data in this study, the AC and PAC tests indicate that two autoregressive lags (AR2) should be included in the model.

Overdispersion

As stated earlier, a requirement of the Poisson model is that the expected value of the dependent variable be equal to its variance. This requirement is often violated in real-

[84] The logarithm of *Failure Rate* is employed because the link function, $\ln(\lambda) = \beta X$, equates the logarithm of the dependent variable to the underlying regressors.

life data (Cameron and Trevedi, 2013). Overdispersion occurs when the actual variance of the dependent variable exceeds its expected value. Failing to correct for overdispersion will lead to inaccurate standard errors (Cameron and Trevedi, 2013).

Cameron and Trevedi (1990) propose the following test to determine if overdispersion is present.

1. Perform the Poisson regression and obtain the fitted values $\hat{\mu}$.
2. Calculate $z = \frac{(y_i - \hat{\mu}_i)^2}{\mu_i\sqrt{2}}$
3. Regress z on a constant with OLS.

If the parameter estimated in step (3) is significant, the data suffer from overdisperion. There are multiple techniques that can correct for overdispersion bias. Palmer, Losilla, Vives, and Jimenez (2007) show that estimating the parameters with robust standard errors is a good solution to correcting overdispersion bias.

APPENDIX B
ENDOGENEITY AND INSTRUMENT SUITABILITY TESTS

Endogeneity Tests

To test for endogeneity, we apply the following tests where applicable; the Hausman test as proposed by Hausman (1978); the WU-Hausman test as proposed by Wu (1973); the *C*-test as proposed by Hayashi (2000); and the Davidson-MacKinnon test as proposed by Davidson and Macinnon (1993). A rejection of the null hypothesis in any of these tests suggests that there are statistical differences between the IV and non-IV estimates and that IV techniques are preferred. If the null hypothesis is not rejected, then there is no significant difference between the estimates, and the bias from endogeneity is either non-existent or is too small to warrant use of an IV model. In this situation, it is better to treat the supposed endogenous variables as exogenous. The Davidson and MacKinnon test is applied only to panel data.

Instrument Suitability Tests

To test for the validity and strength of instruments, we apply the following tests where applicable. The *J* test, as proposed by Hansen (1982), tests the joint hypothesis that the instruments are uncorrelated with the error term and that they are properly excluded from the regression. It follows a chi-squared distribution under the null hypothesis that the excluded instruments are uncorrelated with the error term and are properly excluded from the model. Failing to reject implies that the instruments are valid. The *F* test of excluded instruments, as proposed by Angrist and Pischke (2009), determines if the

instrument(s) are strongly correlated with the supposed endogenous variable. As explained by Bound, Jaeger, and Baker (1995), if the excluded instruments are only weakly correlated with the supposed endogenous variables, then IV estimates may not reduce the bias from endogeneity. The bias of the IV estimates relative to OLS is approximately the inverse of the *F*-statistic from the first-stage regression (Angrist and Pischke, 2009). An *F*-statistic below 10 suggests that the instruments are only weakly correlated with the supposed endogenous variable and that it is better to perform a regression without IVs. The Sanderson-Windmeijer *Chi-squared* test, as proposed by Sanderson and Windmeijer (2016), determines if the IV model is identified and partials out linear projections of the remaining endogenous regressors. Under the null hypothesis, the model is unidentified indicating that the instruments are only weakly correlated with the endogenous regressors. The Sanderson-Windmeijer *Chi-squared* test is applied when multiple endogenous variables are jointly evaluated.

The *C-D,* test as proposed by Cragg and Donaldson (1993), is an *F* test that accesses strength of the correlation between the excluded instruments and the supposed endogenous variables. Stock and Yogo (2005) present critical values of the *C-D* test for the maximum amount of bias the author is willing to accept. For this study, we accept only the strictest level of bias which is 5%. Large values of the test statistic reject the null hypothesis and suggest that the instruments are strong. Because we consider only the strictest level of bias, each of the IV estimators has at most, 5% bias. The Kleibergen-Paap *F* test as proposed by Kleibergen and Paap (2006), is a version of the *C-D* test applied to panel data models.

APPENDIX C
ADDITIONAL TABLES

Table C-1: Failures Equation Estimates: Single Equation Poisson

Variable	Three	Five	Ten	HHI
$\log Failure\ Rate\ *_{t-1}$	0.2**	.238**	.214**	.211**
$\log Failure\ Rate\ *_{t-2}$	.301***	.271***	.28***	.263**
$Concentration_t$	-.379***	-.166*	-.274***	-.01
$Concentration_t^2$	.013***	.005**	.006***	.00004**
CER_{t-1}	-.488**	-.618**	-.603***	-.687***
ROA_{t-1}	.139	.006	.036	.08
$GDPG_t$	.123	.063	.077	.085
ΔIR_t	.227**	.258**	.28***	.253***
$Inflation_t$	-.193***	-.203**	-.219***	-.193**
$Unemployment_t$	.099	.135*	.127*	.117*
$Insurance_t$	2.991	6.955	4.418	8.561*
$Constant$	.934	-.219	2.058	-1.21

Note: This table reports single equation estimation results for the *Failures* equation. All variables are treated as exogenous. The top row indicates the measure of concentration employed for each regression. "Three" indicates that regression employed the share of deposits held at the largest three banks; "Five" for the largest five banks; "Ten" for the largest ten banks; "HHI" indicates the Herfindahl–Hirschman Index is the measure of concentration. The numbers listed in each column are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels.**

Table C-2: Stressed Bank Equation Estimates: Single Equation Poisson

Variable	Three	Five	Ten	HHI
$\log Stressed\ Rate_{t-1}$	.609***	.598***	.61***	.603***
$\log Stressed\ Rate_{t-2}$	.259**	.214***	.242**	.278**
$Concentration_t$	-.067*	-.08**	-.067*	-.001
$Concentration_t^2$	.003***	.002***	.001***	.00001
ROA_{t-1}	-.115*	-.143**	-.139**	-.136*
$GDPG_t$	-.042	-.045	-.049	-.057
ΔIR_t	.012	.017	.019	.014
$Inflation_t$	.062	.071	.066	.061
$Unemployment_t$	-.014	-.013	-.017	-.025
$Insurance_t$	-3.866***	-4.552***	-4.417***	-3.722
$Constant$	.925**	1.185**	1.402**	.655*

Note: This table reports single equation estimation results for the *Stressed Banks* equation. *Inflation* and *Unemployment* are treated as endogenous. The top row indicates the measure of concentration employed for each regression. "Three" indicates that regression employed the share of deposits held at the largest three banks; "Five" for the largest five banks; "Ten" for the largest ten banks; "HHI" indicates the Herfindahl–Hirschman Index is the measure of concentration. The numbers listed in each column are the coefficient estimates. *, **, and * represents significance at the 10%, 5%, and 1% levels.**

Table C-3: Fixed Effects Estimation Results, Concentration measured by C10 Ratio

Regressors/ Dependent Variables	***Z-score*** ***(1)***	***CER*** ***(2)***	***ROA*** ***(3)***	***Volatility*** ***(4)***
Concentration	7.54***	1.08***	-0.07***	-0.11***
$\boldsymbol{Concentration^2}$	-0.13***	-0.02***	0.001***	0.002***
Concentration*Size	-0.66***	-0.07***	0.01***	0.01***
$\boldsymbol{Concentration^2 * Size}$	0.01***	0.001***	-0.0001***	-0.0002***
CER			-0.002***	0.03***
ROA		-0.11***		0.13***
Volatility		0.46***	0.04***	
OBS	-14.24***	3.42***	0.50***	0.31***
Illiquidity	-16.69***	-2.40***	-0.02*	0.30***
Inefficiency	36.15***	2.28***	-1.82***	-0.23***
Diversification	-27.42***	0.13	0.47***	0.55***
Insurance	-77.64***	-2.67***	0.56***	1.74***
Stress	-1.39***	0.07***	0.02***	0.04***
GDPG	2.65***	0.02***	-0.02***	-0.06***
Inflation	-2.09***	0.04***	-0.02***	0.05***
FX	0.09***	0.00	0.00***	0.000
YR	-1.15***	-0.05***	-0.01***	0.02***
Crisis	3.51***	0.04**	0.11***	-0.09***
Recession	-5.53***	-0.09***	-0.12***	0.13***
GLBA	4.00*	-0.25	0.15***	-0.06*
GLBA*Size	-0.29*	0.010	0.00*	0.00
Size	3.94***	-0.75***	-0.08***	-0.13***
Constant	12.02	16.92***	2.88***	-0.79***
Number of Observations	582,619			
Number of Banks	13,743			

Note: This table presents results from the fixed effects IV model when the concentration is measured as the percent of assets held by the largest ten banks. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table C-4: Fixed Effects Estimation Results, Concentration measured by HHI

Regressors/ Dependent Variables	***Z-score*** ***(1)***	***CER*** ***(2)***	***ROA*** ***(3)***	***Volatility*** ***(4)***
Concentration	0.45***	0.03***	-0.005***	-0.01***
$\boldsymbol{Concentration^2}$	-0.001***	-0.0001***	0.00001***	0.00002***
Concentration*Size	-0.04***	-0.0012**	0.00043***	0.00***
$\boldsymbol{Concentration^2 * Size}$	0.0001***	0.00001***	-0.000001***	-0.000002***
CER			-0.0021***	0.03***
ROA		-0.12***		0.13***
Volatility		0.46***	0.04***	
OBS	-12.22***	3.43***	0.42***	0.31***
Illiquidity	-16.98***	-2.39***	-0.03**	0.31***
Inefficiency	35.79***	2.26***	-1.81***	-0.23***
Diversification	-26.86***	0.12	0.44***	0.55***
Insurance	-72.28***	-2.74***	0.21***	1.69***
Stress	-1.52***	0.09***	0.02***	0.05***
GDPG	2.68***	0.03***	-0.02***	-0.06***
Inflation	-1.94***	0.04***	-0.03***	0.05***
FX	0.10***	0.003***	-0.004***	-0.001***
YR	-1.06***	-0.09***	-0.01***	0.01***
Crisis	3.61***	0.00	0.10***	-0.09***
Recession	-5.31***	-0.06***	-0.12***	0.12***
GLBA	-5.58**	-0.81***	0.26***	0.10***
GLBA*Size	0.50***	0.05***	-0.01***	-0.01***
Size	-2.74***	-1.58***	-0.02***	-0.04***
Constant	83.91***	29.11***	2.42***	-1.82***
Number of Observations	582,619			
Number of Banks	13,743			

Note: This table presents results from the fixed effects model when the concentration is measured as the HHI. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table C-5: 2SLS Estimation Results, Concentration measured by C10 Ratio

Regressors/ Dependent Variables	***Z-score*** ***(1)***	***CER*** ***(2)***	***ROA*** ***(3)***	***Volatility*** ***(4)***
Concentration	41.56***	6.78***	-0.05**	-0.45***
$\boldsymbol{Concentration^2}$	-0.59***	-0.09***	0.001**	0.006***
Concentration*Size	-3.20***	-0.54***	0.01***	0.03***
$\boldsymbol{Concentration^2 * Size}$	0.04***	0.01***	-0.0001***	-0.0004***
CER			-0.01***	0.03***
ROA		-2.33***		0.59***
Volatility		2.67***	0.30***	
OBS	-4.53**	1.26***	0.02	0.12***
Illiquidity	-21.30***	-6.03***	-0.20***	0.31***
Inefficiency	58.19***	-3.03***	-1.69***	0.06*
Diversification	-53.38***	-3.46***	0.55***	0.56***
Insurance	-148.47***	-8.78***	0.05	1.67***
Stress	-1.75***	0.01	0.02***	0.03***
GDPG	2.47***	0.05***	-0.03***	-0.03***
Inflation	-2.04***	-0.09***	-0.03***	0.05***
FX	-0.21***	-0.03***	-0.01***	0.01***
YR	-0.82***	-0.15***	-0.02***	0.04***
Crisis	0.33	0.29***	0.10***	-0.08***
Recession	-5.85***	-0.55***	-0.15***	0.18***
GLBA	-65.39***	-10.92***	0.26***	0.54***
GLBA*Size	5.62***	0.95***	-0.02***	-0.05***
Size	49.70***	8.14***	-0.16***	-0.46***
Constant	-541.43***	-75.56***	7.47***	3.15***
Number of Observations	582,296			
Number of Banks	13,436			

Note: This table presents results from the 2SLS model when the concentration is measured as the percent of assets held by the largest ten banks. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table C-6: 2SLS Estimation Results, Concentration measured by HHI

Regressors/ Dependent Variables	*Z-score* *(1)*	*CER* *(2)*	*ROA* *(3)*	*Volatility* *(4)*
Concentration	1.45***	0.27***	-0.005***	-0.01***
$\boldsymbol{Concentration^2}$	-0.003***	-0.0006***	0.00001***	0.00003***
Concentration*Size	-0.12***	-0.02***	0.0005***	0.00083***
$\boldsymbol{Concentration^2 * Size}$	0.0003***	0.00005***	-0.000001***	-0.000002***
CER			-0.01***	0.03***
ROA		-2.36***		0.59***
Volatility		2.68***	0.30***	
OBS	-3.84*	1.21***	0.01	0.13***
Illiquidity	-21.00***	-6.00***	-0.20***	0.30***
Inefficiency	58.18***	-3.05***	-1.68***	0.05*
Diversification	-53.35***	-3.50***	0.55***	0.55***
Insurance	-94.29***	-6.76***	0.30***	0.76***
Stress	-1.27***	0.04***	0.02***	0.02***
GDPG	2.74***	0.09***	-0.02***	-0.03***
Inflation	-2.05***	-0.11***	-0.03***	0.06***
FX	-0.002	-0.01***	0.00***	0.003***
YR	-1.75***	-0.22***	-0.03***	0.06***
Crisis	1.96***	0.33***	0.11***	-0.11***
Recession	-6.04***	-0.54***	-0.15***	0.19***
GLBA	-45.48***	-8.18***	0.34***	0.25***
GLBA*Size	4.01***	0.70***	-0.02***	-0.03***
Size	7.83***	1.06***	-0.06***	-0.05***
Constant	-28.94***	11.56***	3.33***	-2.36***
Number of Observations	582,296			
Number of Banks	13,436			

Note: This table presents results from the 2SLS model when the concentration is measured as the HHI. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table C-7: Pooled OLS Estimation Results, Concentration measured by C10 Ratio

Regressors/ Dependent Variables	*Z-score* *(1)*	*CER* *(2)*	*ROA* *(3)*	*Volatility* *(4)*
Concentration	8.45***	1.47***	-0.06***	-0.09***
$\boldsymbol{Concentration^2}$	-0.14***	-0.02***	0.001***	0.002***
Concentration*Size	-0.69***	-0.11***	0.01***	0.01***
$\boldsymbol{Concentration^2 * Size}$	0.01***	0.00***	0.000***	-0.0001***
CER			-0.004***	0.02***
ROA		-0.50***		0.33***
Volatility		0.85***	0.09***	
OBS	-4.58**	1.93***	0.03*	0.20***
Illiquidity	-20.99***	-5.71***	-0.12***	0.23***
Inefficiency	58.31***	-0.75***	-1.94***	-0.45***
Diversification	-53.18***	-3.55***	0.80***	0.73***
Insurance	-84.88***	-4.71***	0.61***	1.58***
Stress	-1.51***	0.05***	0.02***	0.04***
GDPG	2.77***	0.05***	-0.02***	-0.06***
Inflation	-2.09***	0.01**	-0.03***	0.05***
FX	0.03**	-0.01***	0.00***	0.001***
YR	-1.55***	-0.09***	-0.01***	0.02***
Crisis	2.35***	0.10***	0.12***	-0.09***
Recession	-6.01***	-0.14***	-0.12***	0.16***
GLBA	4.53**	0.28	0.15***	-0.042
GLBA*Size	-0.30*	-0.02	-0.004**	-0.001
Size	8.78***	1.00***	-0.10***	-0.08***
Constant	-52.08***	2.97**	3.27***	-1.19***
Number of Observations	582,619			
Number of Banks	13,743			

Note: This table presents results from the Pooled OLS model when the concentration is measured as the percent of assets held by the largest ten banks. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table C-8: Pooled OLS Estimation Results, Concentration measured by HHI

Regressors/ Dependent Variables	***Z-score*** ***(1)***	***CER*** ***(2)***	***ROA*** ***(3)***	***Volatility*** ***(4)***
Concentration	0.52***	0.08***	-0.0036***	-0.01***
$\boldsymbol{Concentration^2}$	-0.001***	0.00***	0.00001***	0.00002***
Concentration*Size	-0.04***	-0.01***	0.0004***	0.0003***
$\boldsymbol{Concentration^2 * Size}$	0.0001***	0.00001***	-0.000001***	-0.000001***
CER			-0.0041***	0.03***
ROA		-0.51***		0.33***
Volatility		0.86***	0.09***	
OBS	-4.05**	1.93***	0.01	0.21***
Illiquidity	-21.07***	-5.72***	-0.12***	0.24***
Inefficiency	58.16***	-0.77***	-1.93***	-0.45***
Diversification	-53.04***	-3.56***	0.79***	0.73***
Insurance	-78.41***	-4.94***	0.24***	1.57***
Stress	-1.64***	0.06***	0.02***	0.04***
GDPG	2.81***	0.07***	-0.02***	-0.06***
Inflation	-2.03***	0.01**	-0.03***	0.05***
FX	0.06***	0.00	0.00***	0.00***
YR	-1.48***	-0.13***	-0.01***	0.02***
Crisis	2.49***	0.05**	0.10***	-0.09***
Recession	-5.81***	-0.10***	-0.12***	0.16***
GLBA	-6.49***	-0.68**	0.26***	0.09**
GLBA*Size	0.58***	0.05**	-0.02***	-0.01***
Size	1.98***	-0.17***	-0.05***	-0.02***
Constant	26.25***	18.89***	2.86***	-1.99***
Number of Observations	582,619			
Number of Banks	13,743			

Note: This table presents results from the Pooled OLS model when the concentration is measured as the HHI. Column (1) contains results for the *Z-score* model. Columns (2), (3), and (4) contain results for the *CER, ROA,* and Volatility models respectively. '*', '**' , and '*' indicate significance at the .01, .05, and .1 levels respectively.**

Table C-9: GARCH-MIDAS Parameter estimates with One Exogenous Variable; *HHI*

Financial Market	μ	α	β	m	θ	ω_1	ω_1	LLF	BIC	LR
Panel A										
SP500	0.05***	0.07***	0.92***	0.07	0.06***	414.02***	336.46***	-7703.84	2.71	24.2
Nasdaq	0.08***	0.11***	0.88***	0.56***	0.03***	51.57	49.57	-10332.31	3.08	10.6
Aaa	0.03**	0.05***	0.95***	0.71***	0.03	2.65	5.29	-10974.61	3.29	4.6
Baa	0.03*	0.05***	0.94***	0.61***	0.08***	1.53**	1.73**	-11031.83	3.29	14.1
Options	0.05***	0.08***	0.91***	-0.27	0.21***	7.72*	3.32*	-7736.78	2.71	20.1
Currency	0.00	0.03***	0.96***	-1.6***	-0.04*	189.53	377.30	-2675.29	1.04	12.7
TB	0.01*	0.04***	0.95***	-1.0***	-0.03***	372.54	596.41	-4897.86	1.66	12.1

Panel B	μ	α	β	m	LLF	BIC
SP500	0.05***	0.08***	0.91***	0.18	-7715.91	2.71
Nasdaq	0.08***	0.10***	0.89***	0.61***	-10337.59	3.08
Aaa	0.03**	0.05***	0.95***	0.75***	-10976.91	3.29
Baa	0.03	0.05	0.94	0.71	-11038.90	3.29
Options	0.05***	0.08***	0.92***	0.22	-7746.85	2.71
Currency	0.00	0.04	0.96	-1.66	-2681.62	1.04
TB	0.01*	0.04***	0.95***	-1.06***	-4903.90	1.67

Note: Panel A of this table displays the results of the GARCH-MIDAS model estimated with ML. The specification of the model is $\log \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}$ where X_{t-k} is banking concentration. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". Panel B displays the estimates of the GARCH (1-1) where we restrict $\theta = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 3.84 at 95% confidence.**

Table C-10: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *SP500*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.06***	.08***	.91***	-.24	.13**	-.31***	65.15	50.14	90.29	646.76	-7698.3	2.71	35.2
GDPG	.05***	.08***	.90***	-.11	.24***	-.53**	11.94**	8.04**	5.59	27.49	-7698.1	2.71	35.5
Spread	.06***	.08***	.89***	.29**	.16***	-.38***	4.63**	2.07**	21.01	36.49	-7683.1	2.70	65.4
Stress	.05***	.07***	.91***	-.31***	.17***	.53***	12.27**	9.23**	534.4***	527.3***	-7688.1	2.71	55.6
Inflation	.05***	.07***	.92***	-.18	.08***	.28*	125.20*	98.89*	148.6***	740.1***	-7701.5	2.71	28.8
ΔFX	.05***	.08***	.91***	-.01	.09***	.06***	113.49**	89.16*	331.46	592.60	-7698.6	2.71	34.6
SP500_RV	.05***	.08***	.90***	-2.27***	.09***	.45***	103.74*	81.66*	2.61	21.53	-7693.1	2.71	45.7
GARCH 1-1	.05***	0.08***	0.9***	0.18							-7715.9	1.04	

Note: This table displays the results of the GARCH-MIDAS model of the SP500 equity market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table C-11: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Nasdaq*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.08***	.11***	.88***	.45***	.06***	-.38***	6.70**	4.87***	1.00	1.21	-10324.7	3.07	25.7
GDPG	.08***	.11***	.88***	.80***	.06***	-.49***	6.72***	4.80***	6.90	4.01*	-10322.9	3.07	29.3
Spread	.08***	.11***	.88***	.81***	.06***	-.17***	6.84**	4.80***	41.97***	1.09***	-10327.9	3.07	19.3
Stress	.08***	.10***	.89***	.55***	.02*	-.29***	25.47***	21.21***	44.03	46.44	-10328.2	3.08	18.7
Inflation	.08***	.11***	.88***	.73***	.04**	-.27**	7.46**	5.54**	70.17	68.77	-10329.5	3.08	16.2
ΔFX	.08***	.11***	.88***	.60***	.04***	.07**	89.18	87.45	4.25	7.06	-10328.9	3.08	17.3
SP500_RV	.08***	.12***	.85***	-2.16***	.03**	.52***	8.65	6.66	1.63	2.68	-10316.2	3.08	42.8
GARCH 1-1	.08***	.10***	.89***	.61***							-10337.6	3.08	

Note: This table displays the results of the GARCH-MIDAS model of the Nasdaq equity market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table C-12: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Aaa*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.03**	.05***	.95***	.73***	.03	-.17*	2.67	5.39	15.00	100.00	-10972.8	3.29	8.2
GDPG	.03**	.05***	.95***	.84***	.03	-.17***	4.31	7.80	95.43***	57.52***	-10971.3	3.29	11.2
Spread	.03**	.05***	.95***	.93***	.03**	-.14**	27.61***	65.85***	1.01***	100.0***	-10972.8	3.29	8.3
Stress	.03**	.05***	.95***	.77***	.03	.05*	2.92	5.77	3.32	4.08	-10972.7	3.28	8.4
Inflation	.03**	.05***	.95***	.81***	.03	-.17**	3.41	7.33	5.44***	100.0***	-10972.1	3.29	9.7
ΔFX	.03**	.05***	.95***	.69***	.03	-.01	2.79	5.30	83.18***	19.02***	-10973.9	3.29	6.12
Aaa_RV	.03**	.06***	.93***	-2.68***	.03**	.62***	2.81	6.08	1.05	1.00	-10962.2	3.29	29.5
GARCH 1-1	.03**	.05***	.95***	.75***							-10976.9	3.28	

Note: This table displays the results of the GARCH-MIDAS model of the Aaa corporate bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table C-13: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Baa*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.03*	.05***	.94***	.57***	.08***	-.20**	1.70***	1.78***	65.10	27.39	-11030.07	3.30	17.7
GDPG	.03*	.05***	.94***	.68***	.08***	-.14**	1.48**	1.53**	13.65	94.30	-11029.66	3.30	18.5
Spread	.03*	.05***	.94***	.71***	.08***	-.05	1.58**	1.75***	55.34	22.89	-11031.56	3.30	14.7
Stress	.03*	.05***	.94***	.60***	.08***	.10	1.48**	1.67**	26.34	56.36	-11031.08	3.30	15.6
Inflation	.03**	.05***	.94***	.75***	.07***	-.27	1.52**	1.74**	1.60	1.00	-11031.04	3.30	15.7
ΔFX	.03*	.05***	.94***	.59***	.08***	-.01	1.43**	1.59**	43.63	68.90	-11031.29	3.30	15.2
Baa_RV	.03**	.05***	.92***	-2.53***	.04**	.58***	1.10	1.94	1.16	1.76	-11022.40	3.29	33
GARCH 1-1	.03**	.05***	.94***	.71***							-11038.90	3.29	

Note: This table displays the results of the GARCH-MIDAS model of the Baa corporate bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table C-14: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Options*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.06***	.08***	.90***	-.26*	.18***	.60***	11.94**	6.10**	8.94	2.21	-7727.54	2.71	38.6
GDPG	.06***	.08***	.90***	-.69***	.18***	.61**	11.02**	5.65**	8.65	1.92	-7731.39	2.71	30.9
Spread	.06***	.08***	.89***	.27*	.16***	-.36***	5.47**	2.14***	25.10	38.13	-7715.44	2.71	62.8
Stress	.05***	.07***	.90***	-.23*	.14***	.54***	7.77	3.69	70.52	68.61	-7721.62	2.71	50.5
Inflation	.05***	.08***	.91***	-.94**	.26***	.76*	7.87**	3.19**	13.40	18.19	-7734.15	2.71	25.4
ΔFX	.05***	.08***	.91***	-.24	.19***	.20**	7.82*	3.16	3.53	6.93	-7733.17	2.71	27.4
Options_RV	.05***	.08***	.89***	-2.30***	.14***	.43***	9.59**	6.11**	4.76	37.67	-7726.93	2.71	39.8
GARCH 1-1	.05***	.08***	.92***	.22							-7746.85	2.70	

Note: This table displays the results of the GARCH-MIDAS model of the Options market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*.The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table C-15: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *Currency*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	-.001	.03***	.96***	-1.70***	-.02**	.41***	387.4***	782.3***	671.63	198.53	-2668.31	1.04	26.6
GDPG	-.001	.03***	.96***	-2.28***	.02	.69***	376.18	147.63	100.87*	27.47*	-2672.06	1.05	19.1
Spread	-.001	.03***	.96***	-1.13***	-.03***	-.32**	365.4***	737.9***	3.97	4.54	-2671.35	1.05	20.5
Stress	-.001	.03***	.96***	-1.51***	-.07**	.38***	51.56	100.00	59.85	100.00	-2671.62	1.05	20
Inflation	-.001	.03***	.96***	-1.21***	-.03*	-.60***	228.11	454.94	926.3***	90.1***	-2665.68	1.04	31.8
ΔFX	-.001	.03***	.96***	-2.02***	.15***	-.12**	12.05**	3.03***	87.85*	32.08*	-2672.89	1.05	17.5
Currency_RV	-.001	.04***	.96***	-2.33***	.05	.18	6.51	40.10	786.80	118.35	-2677.66	1.05	7.92
GARCH 1-1	-.001*	.04***	.96***	-1.66***							-2681.62	1.04	

Note: This table displays the results of the GARCH-MIDAS model of the US dollar market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**

Table C-16: GARCH-MIDAS Parameter Estimates with Two Exogenous Variables; *TB*

Variable	μ	α	β	m	θ_1	θ_2	ω_1	ω_2	ω_3	ω_4	LLF	BIC	LR
Macro	.01*	.03***	.96***	-1.00***	-.03**	.28***	64.55	100.00	100.00	10.69	-4890.44	1.67	26.9
GDPG	.01*	.04***	.95***	-1.21***	-.04***	.28***	64.86	100.00	100.00	10.30	-4892.98	1.67	21.8
Spread	.01*	.04***	.95***	-.69***	-.03***	-.21**	64.54	100.00	2.33	1.07	-4894.59	1.67	18.6
Stress	.01*	.04***	.95***	-1.00***	-.04***	.26***	64.55	100.00	48.78	100.00	-4893.89	1.67	20.0
Inflation	.01*	.04***	.96***	-1.24***	-.03***	.30***	379.95	609.53	622.11	224.27	-4893.05	1.67	21.7
ΔFX	.01*	.04***	.96***	-1.00***	-.03***	.04**	229.79	364.89	67.39	698.51	-4894.05	1.67	19.7
SP500_RV	.01	.04***	.95***	.40	-.02**	-.41***	562.08	150.22	601.45	102.43	-4889.97	1.67	27.9
GARCH 1-1	.01*	.04***	.95***	-1.06***							-4903.90	1.66	

Note: This table displays the results of the GARCH-MIDAS model of the US Treasury Bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ is *HHI*. The optimal lag length varies with each financial market and is determined by minimizing the BIC. A significance level p < .01 is indicated by "*", p < .05 is indicated by "**", and p < .1 is indicated by "*". In the GARCH (1-1) row, we restrict $\theta_1 = \theta_2 = 0$. The final column titled "LR" displays the likelihood ratio statistic that compares the GARCH-MIDAS and GARCH (1-1) models. The critical value for the LR test is 5.99 at 95% confidence.**