The Association between Financial Market Volatility and Banking Concentration

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Abstract

Research on the association between financial market volatility and concentration of the banking system has been sparse. The relationship is debated by policy makers and regulators, but remains ambiguous. In this study, we seek to determine if banking concentration has a significant relationship with financial market volatility and in what direction. 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. Our sample period runs from 1986:1 to 2013:4. Our results indicate that increased banking concentration is associated with greater volatility in the US stock, options, and corporate bond markets and reduced volatility in the US government bonds market. We do not find evidence suggesting any association between banking concentration and US dollar volatility.

THE ASSOCIATION BETWEEN FINANCIAL MARKET VOLATILITY AND BANKING CONCENTRATION

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[1] (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 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.

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

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.

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. 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 2 contains a literature review of previous research. Section 3 provides details on the GARCH-MIDAS model. Section 4 provides a detailed description of the data and variable calculations. Section 5 provides an analysis of the results. Section 6 provides concluding remarks and recommendations.

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 nontraditional 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. 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 1.

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 1 can be written as equation 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 (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 $\mathrm{g}_{\mathrm{i,t}}$ 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 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).

$$r_{i,t} = \mu + \eta_{i,t} \tag{1}$$

$$r_{i,t} = \mu + \sqrt{\tau_t \, g_{i,t}} \, \varepsilon_{i,t} \tag{2}$$

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{i,t} - \mu\right)^2}{\tau_t} + \beta \; g_{i-1,t} \tag{3}$$

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 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 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 6:

$$\tau_t = m + \theta \ \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k} \tag{4}$$

$$\log \tau_t = m + \theta \ \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k} \tag{5}$$

$$E_{t-1}\left[\left(r_{i,t} - \mu\right)^2\right] = \tau_t \; E_{t-1}[\,g_{i,t}] = \ \tau_t \tag{6}$$

Finally, $\varphi_k(\omega_1, \omega_2)$ from equation 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 7 below. The values of all weights sum to 1.

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K}\right)^{\omega_1 - 1}\left(1 - \frac{k}{K}\right)^{\omega_2 - 1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{\omega_1 - 1}\left(1 - \frac{j}{K}\right)^{\omega_2 - 1}} \tag{7}$$

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 8

$$\log L\left(r_{i,t}{}_{i=1\ldots N_t}^{t=1\ldots T}\right) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t} \log 2\pi + \log \tau_t\, g_{i,t} + \frac{1}{2}\frac{\left(r_{i,t}-\mu\right)^2}{\tau_t g_{i,t}} \qquad (8)$$

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[2]. 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 $\Theta = (\mu, \alpha, \beta, m, \theta_1, \theta_2, \omega_1, \omega_2, \omega_3, \omega_4)$ and is defined by equation 9. The addition of the second explanatory variable should help to isolate the impact of banking concentration from other macroeconomic or financial phenomenon[3].

$$\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k} \qquad (9)$$

The main explanatory variable of interest in the long-term volatility model (equation 5) is *Concentration* in the banking industry. This variable is measured by the

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

[3] 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.

asset share of the largest ten commercial banks in the US banking system at date *t*[4]. 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 (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)*[5]*,* the difference between the yield on the 10-yr and 3-month treasury bond (*Spread),* 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)[6]. 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

[4] 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.

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

[6] 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).

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 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 2.

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[7].

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.

[7] *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.

5 Results

Section 5 provides descriptive statistics along with the results of the empirical model. We reserve discussion and economic interpretation of the results until section 5.4.

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 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.

Tables 4 and 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 5.5.

In Figure 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.

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 5) in Table 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 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[8] 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[9]. 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 $\sqrt{\tau}$).

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

[9] 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 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 5.5.

5.3 Two Variable Model Results

In this section, we extend Engle, Gyshels, and Sohn (2013) by including a second explanatory[10] variable in addition to banking concentration to help filter out the effects of macroeconomic and financial conditions. Tables 8 through 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 appendix A 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.

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

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 8 through 14[11].

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 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

[11] 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.

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[12] negative and positive respectively. Both are significant 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

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

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.

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 : $VR_{X_1} = {Var\left[\log\left(\tau_t^{X_1}\right)\right]} \big/ {Var\left[\log\left(\tau_t^{X_1,X_2} g_t^{X_1,X_2}\right)\right]}$ where X_1 and X_2 refer to given variables such as *Concentration* and *Macro*[13]. 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 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 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

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

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.

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.

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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Table 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.

Table 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.

Statistics

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

ays descriptive statistics for all variables employed in the model. Panel A presents the daily financial market return B presents the quarterly macroeconomic and financial variables. Realized volatilities are in logarithmic form.

Table 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 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.

Table 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.

Table 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.**

Table 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 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 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 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 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 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 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	

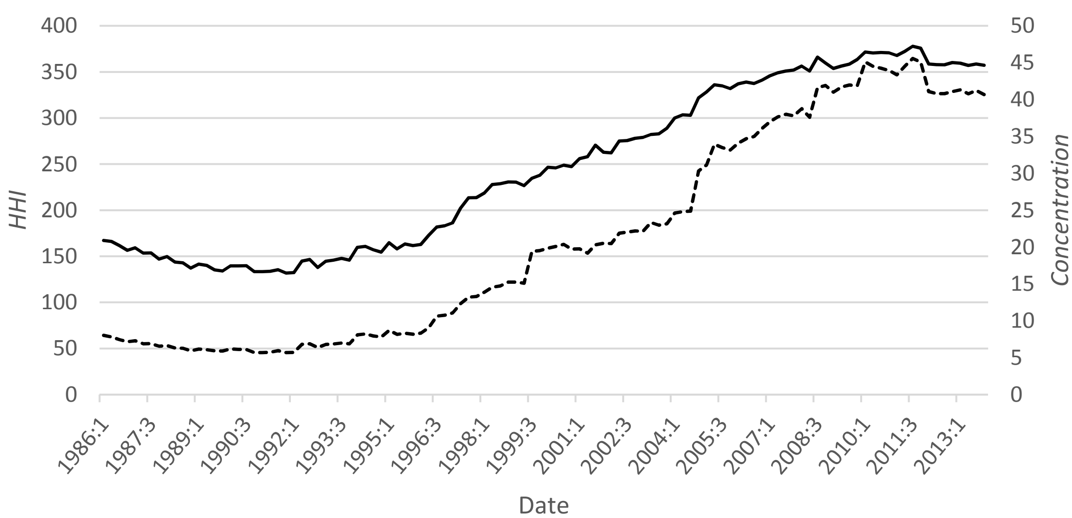
Note: This table displays the results of the GARCH-MIDAS model of the US Treasury Bond market. The specification of the model is $\log \tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{1,t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_3, \omega_4)\, X_{2,t-k}$ where $X_{1,t-k}$ 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.**

Table 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

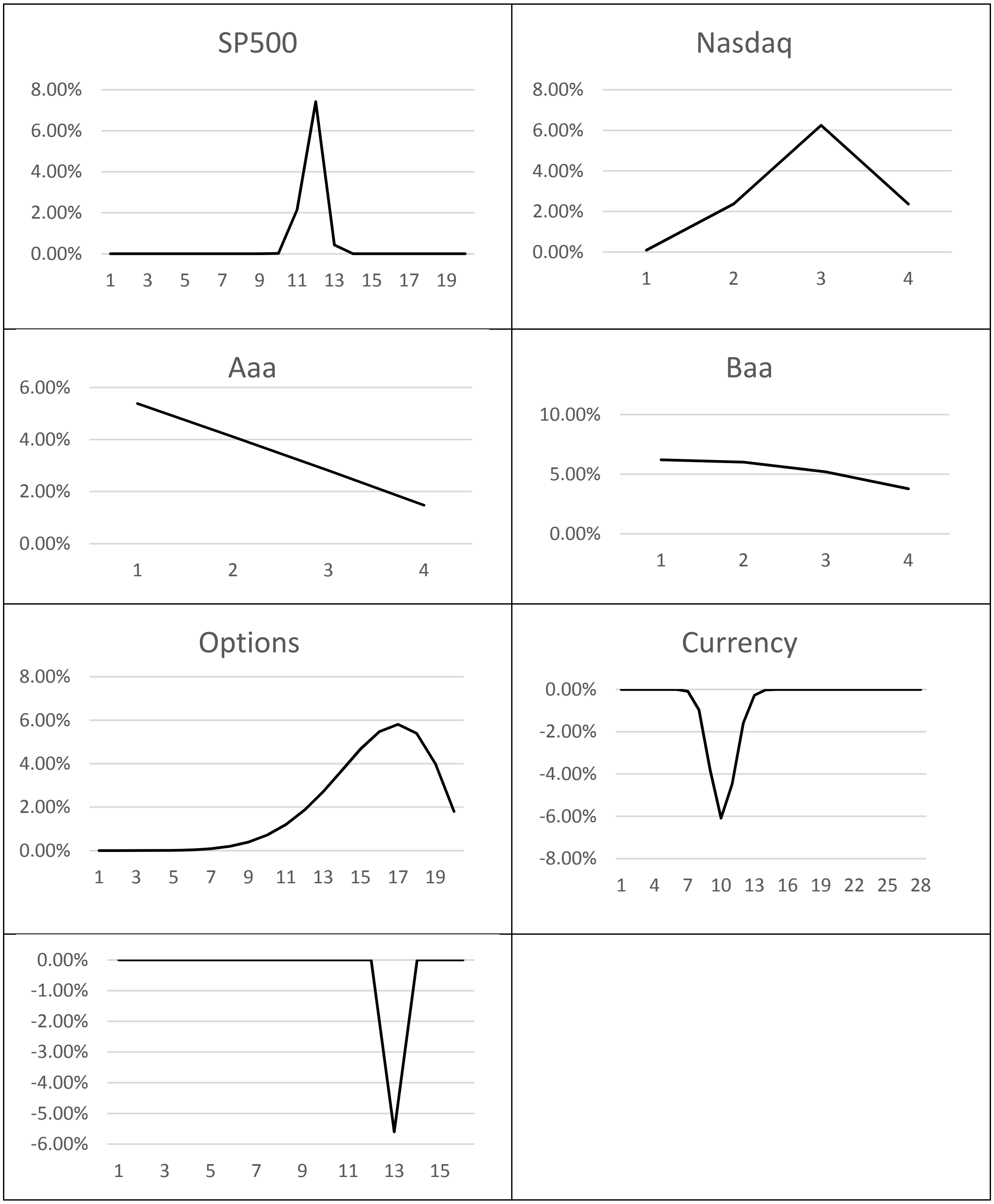
Note: This table displays the amount of volatility (VR) explained by *Concentration, Macro,* and *Stress*. The formula is provided by Engle, Gyshels, and Sohn (2013). $VR_{X_1} = Var[\log(\tau_t^{X_1})] \Big/ Var[\log(\tau_t^{X_1,X_2} g_t^{X_1,X_2})]$. We note that VR for *Concentration* can be calculate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

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



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



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 $\partial\tau_t / \partial Concentration_{t-k} = e^{\theta\cdot\varphi_k(\omega)/3} - 1$.

APPENDIX A
Additional Results

Table 16: 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 17: 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 18: 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 19: 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 20: 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
$\boldsymbol{\Delta FX}$	.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 21: 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
Δ***FX***	.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 22: 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 23: 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.**