Bank exposure to market fear

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Abstract

We find that increases in implied market volatility (a proxy for market fear) have a significant impact on returns of bank stocks, above and beyond systematic risk proxied by the expected excess market return during a bad economic regime. Large bank returns are favorably affected by increases in implied market volatility during the crisis, while small banks are adversely affected by increases in implied market volatility. We attribute the different effects among the size-categorized bank portfolios to the perception that large banks are protected by too-big-to-fail policies. Within the sample of small banks, the adverse share price response to increased implied market volatility is more pronounced for banks that rely more heavily on non-traditional sources of funds, use a high proportion of loans in their assets, have a higher level of non-performing assets, and have a relatively low provision for loan losses. The adverse effect of negative innovations in implied market volatility on small bank returns during the crisis is primarily driven by exposure of their loan portfolio to weak economic conditions.

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1. Introduction

Implied market volatility has received much attention by the financial media, especially when economic conditions are weak. It is viewed as an indicator of market fear and can help to explain the underlying reason for market valuations. In an intertemporal asset pricing framework, innovations or surprises in implied market volatility signal current and future time-varying investment opportunities (Merton, 1973; Campbell, 1993, 1996; and Chen, 2003). Yet, innovations in implied market volatility may offer special implications for commercial banks beyond what is implied by general stock market conditions because they could signal investors' concern about credit conditions that are not necessarily captured within changes in average market returns, such as flow of funds, creditworthiness, access to credit, liquidity, credit premiums, and willingness to lend. Such a signal may be especially meaningful during a financial crisis, when bank managers, investors, and regulators closely monitor shareholder confidence in banks. We investigate how positive shocks (increases) in implied market volatility affect bank valuations. For this purpose, we disentangle the "fear" effect from general changing investment opportunities.

The exposure of stocks to positive innovations (increases) in implied market volatility may vary among banks during a financial crisis. The banking literature has documented that small banks are more exposed to monetary policy (see Kashyap and Stein, 1995, 2000; and Kishan and Opiela, 2000). Also, to the extent that some banks are perceived to receive special protection because they are too big to fail, they could be less exposed to shocks in implied market volatility. Large banks that experience serious financial problems are more likely to be rescued by regulators than small banks (see Uzun and Webb, 2007). Therefore, a rise in implied market volatility is expected to have a more pronounced adverse effect on the valuation of smaller banks. In fact, large banks could even benefit from increases in implied market volatility, because they may possess a competitive advantage over smaller banks under these conditions. They may be more capable of sustaining normal loan operations even when implied market volatility is rising because of implicit regulatory protection, while smaller banks are forced to restrict their lending operations for defensive purposes. Second, smaller banks may be less diversified, and have more limited sources of liquidity (see Fecht, Nyborg, and Rocholl, 2011), which could also increase their exposure to shocks in implied market volatility. Third, small banks may be more sensitive to signals that reflect more uncertainty about market conditions (see Alfonso, Kovner, and Schoar, 2011).

To account for the possible disparate effects of bank size on sensitivity to market fear, we categorize banks by size before measuring the sensitivity of bank portfolios to increases in implied market volatility. Furthermore, we also attempt to identify other firm specific characteristics of banks that could cause banks to be more exposed to positive shocks in implied market volatility than others. To achieve this objective, we measure the sensitivity of each individual bank's returns to positive shocks in implied market volatility, and then conduct a multivariate analysis to determine how this sensitivity is influenced by bank-specific characteristics. Since we anticipate substantial differences in bank sensitivity to large versus small banks, we conduct the multivariate analysis separately for the large and small bank categories.

We find that positive shocks (increases) in implied market volatility have a statistically and economically significant impact on bank stock returns during the crisis regime, beyond the effects caused by general stock market returns. In particular, small bank stock returns are inversely related to shocks in implied market volatility during the crisis regime, while large bank stock returns are positively related to increases in implied market volatility during the crisis regime. Furthermore, our multivariate analysis tests identify other bank-specific factors that influence the degree to which a bank is exposed to shocks in implied market volatility during a period of financial turmoil. Large banks experience relatively weak returns in response to increases in implied market volatility when they rely more heavily on non-traditional sources of funds, use a relatively low proportion of funds for loans, have relatively low capital levels, and rely more on non-traditional services for income. Small banks experience a more pronounced adverse share price response to increases in implied market volatility when they rely more heavily on non-traditional sources of funds, use a high proportion of their funds for loans, have a high level of non-performing assets, and a low provision for loan losses. Thus, the size effect may go beyond whether a bank is too big to fail. Relatively large banks may have better liquidity and options to cope with crisis conditions. The adverse effect of implied market volatility on small banks is primarily conditioned on the exposure of the individual bank's loan portfolio.

The remainder of the paper is organized as follows. The conceptual approach and hypotheses are presented in Section 2. The methodology and sample used in the empirical analysis are covered in Section 3. We disclose results in Section 4. And offer conclusions in Section 5.

2. **Theoretical motivation**

2.1 Asymmetric innovations in implied market volatility as a common risk factor

In the aftermath of the financial crisis of 2007, many studies have attempted to apply asset pricing models to explain the banks' exposure to systemic risk (see Hawkesby et al., 2007; Acharya, 2009; and van den End and Tabbae, 2012). When the investment opportunity set varies through time as precluded by the intertemporal capital asset pricing model (ICAPM) of Merton

(1973), systematic risk premia is a function of the conditional covariances between risky asset returns and innovations in a parsimonious set of state variables driving the dynamics of the investment opportunity set. In further extensions of Merton's ICAPM, Campbell (1993, 1996) shows that risk averse intertemporal investors seek to hedge against unexpected changes in aggregate volatility, which in an ICAPM framework is directly proportional to future expected stock returns. Campbell's framework though does not allow for a direct role for changes in market volatility on expected stock returns as his model is based on the assumption of homoskedasticy. Chen (2003) extends Campbell's model to a heteroskedastic framework, allowing for time-varying covariances and stochastic market volatility. He shows that expected stock returns are a function of market beta, factor loadings on innovations in a parsimonious set of state variables that help to forecast the future market return, and a factor loading on changes in future market volatility. Put simply, during bad economic times forward looking intertemporal risk averse investors will reduce current consumption in order to increase their level of precautionary savings. Hence, implied market volatility serves as an additional "fear" gauge state variable within the ICAPM framework.

Ang, Hodrick, Xing, and Zhang (2006), show that innovations in aggregate volatility are priced in the cross section of average stock returns with a statistically significant market price of aggregate volatility risk of approximately -1% per year. According to the authors, one plausible explanation of the small size of the estimate is the existence of a peso problem; that is, there is a relatively small number of observed spikes in aggregate volatility ex-post compared to the number of spikes expected by the market ex-ante. A peso problem usually is the result of a structural break in the equilibrium relation. They find that stocks that perform poorly during a crisis or bad economic regime (defined by an increasing market volatility) have negatively skewed returns, while stocks that perform relatively well during the status quo or good economic regime (defined by decreasing market volatility) tend to have positively skewed returns. In this regard, Harvey and Siddique (2000) show that stocks that are relatively more sensitive to innovations in market volatility have lower returns because of investors' preference for co-skewness.

The empirical ICAPM used by Ang et al. (2006) does not capture the asymmetric effect that market volatility has on stock returns, whereby negative innovations in stock returns lead to higher future market volatility. Much literature has documented the asymmetric effect in the cross section of stock returns [see Bekaert and Wu (2000) and Wu (2001)]. The controversy in this literature has been about whether the effect is due to a firm-specific effect such as leverage, or a market-wide effect that works through a feedback relation between the variance and drift return equations. Dennis, Mayhew, and Stivers (2006) use a variance decomposition analysis to show that the empirical relation between individual stock returns and innovations in implied idiosyncratic volatility is marginally negative. On the other hand, the negative relation between individual stock returns and aggregate market volatility is statistically significant. Consequently, their results suggest that the asymmetric effect is more related to systematic market-wide effects than aggregation of firm-specific idiosyncratic effects.

We hypothesize that the relation between negative innovations in implied market volatility and bank stock returns might be unique because of the role that banks play as credit intermediaries. In particular, several banking studies discuss the potential contagion effects in the banking industry during the event of a credit crunch or during the bad economic regime when market volatility is relatively high, including those by Aharony and Swary (1983, 1996), Akhigbe and Madura (2001), Hasman and Samarin (2008), Niktin and Smith (2008), Marucci and Quagliarello (2009), Niinamaki (2009), Shleifer and Vishny (2010), Alfonso, Kovner, and Schoar (2011), and Gennaioli, Shleifer, and Vishny (2011). However, none of these studies directly examines the asymmetric effect i.e., whether bank stock returns' sensitivity to shocks in implied market volatility increases during a crisis.

We hypothesize that the stock price response of large bank stocks to positive surprises (increases) in implied market volatility is distinctly different than the stock price response of small bank stocks. One reason for this difference is that small banks are more exposed to monetary policy [see Kashyap and Stein (1995, 2000) and Kishan and Opiela (2000)]. In addition, large banks are more diversified and may be able to reduce their exposure to market conditions (see Boot and Schmeits, 2000). Their diversification benefits may even allow them cushion so that they can engage in risky activities (see Demsetz and Strahan, 1997). Furthermore, regulatory protection affords larger banks with flexibility to grow market share during a financial crisis, while smaller banks may be forced to manage more conservatively in order to reduce their exposure during a crisis. Since large banks may be perceived to have upside potential along with limited downside risk during a crisis, they could benefit in an environment in which market fear is high. We recognize that generalizations about large banks are complicated, because only the largest of the large banks might have been too big to fail. Yet, the regulators might have seriously considered some form of subsidy to facilitate a takeover of any large bank in our sample before its value plummeted. Nevertheless, we also apply our analysis to a more narrowly defined portfolio of the ten largest banks as a test of robustness.

2.2 Bank characteristics that may influence exposure to positive innovations (increases) in implied market volatility

We hypothesize that the bank share price response to positive shocks in implied market volatility is dependent on the following bank-specific characteristics:

Bank Reliance on Deposits. Banks that rely more heavily on deposits have a more permanent source of funds, and should be less exposed to volatile market conditions. They may also have more flexibility during volatile market conditions, so that they can pursue investment opportunities that occur. Conversely, banks that rely more heavily on alternative sources of funds such as commercial paper may have restricted access to credit during volatile market conditions (see Shleifer and Vishny, 2010). Therefore, we expect these banks that rely more heavily on alternative sources of funds to experience a weaker share price response to relatively large changes in implied market volatility.

Bank Cash. Banks that maintain more cash during the crisis may be viewed as more liquid, and should have more flexibility to pursue investment opportunities. Therefore, we expect these banks to experience a more favorable (or less unfavorable) share price response to relatively large changes in implied market volatility.

Bank Loans. Small banks that maintain a high concentration of loans are exposed to credit risk. Their exposure may be especially high during periods of high market uncertainty, as there is a high degree of asymmetric information surrounding the "opaqueness" of their loan portfolios. This effect will be more severe for the small banks that depend heavily on the loan portfolio as a source of profit. In addition, the composition of the loan portfolio may change during the crisis and the changes may be able to explain the sensitivity of big and small banks to increases in market volatility. Fikru (2009) examines the composition of loan portfolio between 2006-2009 and finds that large banks have not significantly changed their portfolio composition while small banks moved from consumer loans to real estate loans during this period.

Thus, we expect that the share price response to relatively large positive shocks in implied market volatility will be worse for small banks. Large banks are in a different position because of less exposure to real estate loans, and to possible protection by a too-big-to-fail policy. In fact, large banks that engage in more lending activities may even be rewarded because of their upside potential to gain market share, while benefitting from downside regulatory protection.

Bank Investment Portfolio. Banks that invest heavily in securities may be less exposed to low levels of market volatility because they may be perceived to have more liquidity. In addition, they may be subject to less credit risk when holding high-grade securities. Therefore, the share price response of these banks to relatively large changes in implied market volatility may be attenuated. However, the influence of the investment in securities on share price response of large banks may be distinctly different if they are perceived to be too big to fail. Large banks that invest heavily in securities are forgoing loans, and are therefore limiting their potential upside, even while their downside may be protected.

The variables representing the bank proportion of loans and investment securities are strongly and negatively correlated. Because including both variables in the multivariate model results in multicollinearity, we only include one of these two variables when applying any multivariate model.

Bank Capital. Banks that have more capital scaled by assets may be less susceptible to high levels of market uncertainty because they should be more capable of withstanding economic shocks (see Gennaioli, Shleifer, and Vishny, 2011). Furthermore, the excess capital gives the banks more flexibility should they wish to expand their investment opportunities. Therefore, these banks should experience a more favorable (or less unfavorable) share price response to relatively large increases in implied market volatility.

Bank Non-Performing Assets. Banks that have a larger amount of non-performing assets may be especially vulnerable to higher levels of implied market volatility. When market conditions are very uncertain and in an environment with much asymmetric information, banks with a larger amount of non-performing loans may be subject to a higher level of suspicion by investors. Small banks may be especially vulnerable to relatively large increases in implied market volatility, because they are not protected by regulators.

Bank Provision for Loan Losses. Banks that maintain a higher provision of loan losses should be more prepared for deteriorating economic conditions. Furthermore, they may have more flexibility with their future lending operations if they set aside a sufficient level of reserves for the future. Thus, their share price response should respond more favorably (or less unfavorably) to relatively large increases in implied market volatility. Conversely, banks with relatively low provision for loan losses may need to shift to a much more conservative lending strategy so that their existing loan loss provision is adequate in the future. Therefore, these banks should experience a weaker share price response to relatively increases in implied market volatility.

Bank Reliance on Non-Interest Income. Banks that rely more on interest income may be more exposed to any conditions that signal a general weakness in credit conditions. Thus, they should be more exposed to relatively large increases s in implied market volatility. Conversely, banks that rely more heavily on non-interest (fee) income should be less exposed to a general weakness in credit conditions, and an increase in implied market volatility. However, a counter argument is that banks that generate much of their non-interest income through non-traditional securities activities could be more exposed to systematic risk. While Rogers and Sinkey (1999) suggest that banks that generate more fee income exhibit lower risk, Stiroh (2006) suggests that banks that earn more non-interest income exhibit more risk. Given the opposing arguments, the relationship between reliance on non-interest income and sensitivity to implied market risk among banks deserves to be tested empirically.

Banks Sophistication. It is possible that the sophistication rather than size of the bank drives its sensitivity to increases in market volatility. Large banks may be more sophisticated and as such, they could take advantage of increases in market volatility by using derivatives. To capture the successful/unsuccessful use of derivatives, we use two different measures of bank sophistication. These measures not only vary across banks, but they also vary for a particular bank over time. As our primary measure, we use accumulated unrealized derivative gain/losses. This item is the after-tax amount of unrealized gain/loss on derivative transactions or cash flow hedges. As an alternative measure, we also use derivative gain/losses reported after net income to arrive at total comprehensive income. This is a component of the reconciliation between the company's net income and total comprehensive income and it includes interest rate swap contracts, any adjustment reported in the derivative section, unrealized gains/losses on a derivative contract, hedging gains/losses, net investment hedges and foreign currency forward contracts.

3. Data and methodology

We apply several empirical models to assess whether bank stock returns are generally sensitive to positive shocks in implied market volatility, and to investigate if individual sensitivities of bank stock returns to positive shocks in implied market volatility are driven by bank-specific characteristics.

We build from the partial equilibrium model of Berk, Green, and Naik (1999), in which a firm's returns are a function of: 1) the effects that changing interest rates have on the cash flows produced by the firm's assets in place; 2) book-to-market proxying for the importance of the firm's existing assets relative to its growth opportunities; and 3) changes in the value of the firm’s growth options as a response to changes in interest rates conditional on the relative size of the firm. A bank's assets in place are its loan and investment portfolios. The valuation of these portfolios is directly affected by changes in interest rates. We account for the differential effect that changes in the slope of the term structure of interest rates may have across large and small banks. This effect may be marginal for a large bank that relies less heavily on the net interest margin and has better access to immunization policies.

To check if daily bank stock returns are sensitive to positive shocks in implied market volatility, we run time series ordinary least square (OLS) regressions that include the market return, an asymmetric implied market volatility factor (ASYM), the interest rate level (RATE), and the slope of the term structure of interest rates (TERM). Our focus is on the asymmetric implied market volatility factor, which represents changes in implied market volatility as proxied by the daily change in VIX, derived from S&P 500 index options. Originally developed in 1987, the VIX index is also referred to as the “fear index” and its purpose is to assess the expected market volatility for the next month. The asymmetric factor (ASYM) is calculated following Delisle et al. (2009) as an interaction term between a dummy that is equal to 1 for positive daily changes in the VIX index and 0 otherwise and changes in VIX. VIX index data are obtained from Bloomberg.

The level of interest rate is proxied by the daily 3-month short term interest rate. The term structure of interest rates (see McKown, 1999) is measured as the difference between the 10–year treasury rate (DGS10) and the 3-month Treasury bill (DGS3M). All interest rate variables are obtained from the Federal Reserve of St. Louis, (FRED) database.

The time series stock return equation is specified as:

$$R_p=\alpha+\Theta_1 MKTRET_t+ \Theta_2 ASYM_t + \Theta_3 RATE_t+ \Theta_4 TERM_t + e_t. \quad (1)$$

A legitimate concern arises about the correlation between implied market volatility and market return. If implied market volatility is highly correlated with the market return, then a significant ASYM coefficient may be the result of its high correlation with the market return, and might simply reflect its possible influence on market return rather than an influence on the bank return that is above and beyond the market influence.

Hence, before estimating OLS time-series regressions we run a regression between stock market returns and changes in the asymmetric factor in order to obtain orthogonalized shocks from VIX, which are then used to represent ASYM. By using orthogonalized shocks, we can measure the pure sensitivity of portfolio returns to changes in implied market volatility and/or its asymmetric effect above and beyond the effect of market return.

Our main hypothesis focuses on the idea that small banks and large banks may be exposed to implied market volatility differently. Thus, equation (1) is run separately for small and large banks. We separate the sample into large, small, and medium banks (top 33%, bottom 33% and middle 33%) and analyze the top and the bottom sub-samples. One of the reasons for eliminating the middle sub-sample is because the division between small and large is relatively arbitrary. Comparing the largest banks to the smallest banks presents a clearer picture about any existing differences in the impact of implied market volatility on large banks versus small banks.

In order to validate our results that small and large banks' sensitivity to implied market volatility differs, we also apply a seemingly unrelated regression (SUR) to estimate the coefficients simultaneously. The SUR model facilitates testing whether the sensitivity of bank returns to the implied market volatility is different across bank size classifications. The following 2-equation SUR model is used to assess the sensitivity of each bank portfolio's returns to implied market volatility:

$$R_{p,L}=\alpha+ \Theta_1 MKTRET_t+ \Theta_2 ASYM_t+ \Theta_3 RATE_t+ \Theta_4 TERM_t + v, \text{ and} \quad (2)$$

$$R_{p,S}=\alpha+ \Theta_1 MKTRET_t+ \Theta_2 ASYM_t+ \Theta_3 RATE_t+ \Theta_4 TERM_t + w, \quad (3)$$

where subscripts L and S in the dependent variable represent the samples of large banks and small banks respectively, while v and w represent error terms.

Also, given the methodological discussion in Giliberto (1985) about a potential misspecification problem of running contemporaneous OLS regressions between factors to find orthogonalized residuals, we run a vector autoregression (VAR) model of order 1[1] and use the residuals as independent variables in the SUR regression. Using this method, we can disentangle the market and volatility effects by orthogonalizing all variables with causality flowing from the shocks in the state variables to the market return as required under the ICAPM. We follow the vector autoregression (VAR) approach of Campbell (1996) and write the excess market return *MKT* as the first element of the state vector $z_t = [MKT, ASYM, RATE, TERM]'$, where the rest of the variables *ASYM*, *RATE*, and *TERM* proxy for changes in the investment opportunity set.

The VAR model we use to obtain the residuals that will become independent variables in the SUR regression is:

$$z_t = Az_{t-1} + u_t, \quad (4)$$

where *A* is a matrix of coefficients; and u_t are innovations in the state variables that enter as risk factors into the SUR regression. Notice that unlike Campbell (1996) here we adopt a non-structural first-order VAR.

We acknowledge that one of the main empirical challenges is to identify the shocks in implied market volatility. The interpretation of shocks may vary among investors. As a robustness check, instead of using all increases in VIX as a measure of ASYM, we use a dummy

[1] Campbell and Shiller (1988) show that any high order VAR collapses to its first order (i.e., lag 1) companion VAR.

variable called SHOCK and set it equal to 1 when the increase is in the top decile and 0 otherwise.

Daily bank stock returns for the period 2006-2009 are collected from CRSP. The sample includes commercial and savings banks (NAICS 522110 and 522210 respectively). We form portfolios of bank stock returns for the pre-crisis and crisis period. The sample consists of 420 day-observations for the pre-crisis period, and 124 day-observations for the crisis period. A total of 189 large banks, 190 medium and 189 small banks are identified for a total sample of 568 banks. The regression analysis is separately applied to the pre-crisis period (2006-2007), and the crisis period (Q32008-Q12009).

One of the questions that we would like to answer is if one can identify major events during the 2008 financial crisis using our methodology. Using the timeline of the financial crisis and policy actions that can be found in the website of the Federal Reserve Bank of St. Louis[2] we seek to identify each major event with the volatility shock on that day obtained from the data measured following our methodology.

Next, we attempt to identify bank-specific characteristics that influence the sensitivity of individual bank stock returns to shocks in implied market volatility. In the first stage, OLS regressions (similar to model (1)) are applied but with individual bank returns as the dependent variable. Models are applied to the crisis period in order to estimate the sensitivity of each bank return to the implied market volatility (as measured by theta Θ per bank) for individual banks in the large and small bank samples

In the second stage, we use theta as the dependent variable, and conduct a multivariate analysis to individual banks in the large bank sample to determine if theta is related to bank-

[2] http://timeline.stlouisfed.org/index.cfm?p=timeline.

specific characteristics. We then replicate that multivariate analysis for individual banks within the small bank sample. We use the following bank-specific variables: deposits, cash, loans, investment securities (INVSEC), capital ratio (CAP), non-performing assets (NONPERF), provision for loan losses (PLL), non-interest income (NONINT) and bank sophistication level (SOPHLEVEL). All variables are scaled by total assets (or total revenue in the case of non-interest income) to account for differences in bank size. Each independent variable is measured as the average of quarterly observations over the crisis period. The multivariate model is specified as:

$$\Theta_j = \alpha + \beta_1 DEPOSITS_j + \beta_2 CASH_j + \beta_3 LOANS_j + \beta_4 INVSEC_j + \beta_5 CAP_j + \beta_6 NONPERF_j + \beta_7 PLL_j + + \beta_8 NONINT_{j+} \ \beta_9 SOPHLEVEL + e. \quad (5)$$

In addition to exploring the statistical significance, we also analyze the economic significance of the results by rerunning the model in its log form. These results give us the betas that can be interpreted economically as elasticities.

4. Empirical results

Table 1 presents banks' descriptive statistics before and during the crisis. The major difference in the mean is related to the size of the bank. The mean log of total assets for the small banks is $5.96 billion before the crisis and $6.11 billion during the crisis. The mean log of total assets for large banks is $9.58 billion before the crisis and $9.74 billion during the crisis. Capital ratios are higher for small banks.. The mean ratio of loans to assets is higher for small banks than large banks, and the provision for loan losses is higher during the crisis than before the crisis. Investment securities as a percentage of total assets are similar for the two types of banks and the two periods. Deposits are about 5% higher for smaller banks than for the larger banks. The mean ratio of non-interest income to total revenue is similar for the two types of banks in the pre-crisis period, but higher for small banks during the crisis period.

4.1 Sensitivity of bank portfolio returns

As shown in Figure 1, we can identify major events during the financial crisis with a major spike in aggregate volatility. Looking at the major increases, we can see that they correspond to significant events, such as the creation of the MMIFF and the change in the formula to pay interest rate to banks on their excess reserves. Other major increases correspond to the announcement of TARP and the creation of the Temporary Liquid Guarantee Program, the extension of three liquidity facilities, and the purchase of 4 billion USD in preferred stock of 35 US banks. In addition, increases in implied market volatility seem to correspond to the anticipated collapse of Lehman Brothers and the rescue of AIG. Overall, it seems that increases in VIX signal the trouble within banks but is reduced following major governmental purchases of stocks in banks.

Results from measuring the sensitivity of bank portfolio returns to shocks in implied market volatility are presented in table 2. Large and small bank returns are dependent on the return of the market, as expected. Returns of large banks to stock market conditions are more sensitive than returns of small banks. This is consistent with what has been found in previous studies (see Viale, Kolari, and Fraser, 2009).

Large and small banks react differently to shocks in implied market volatility. During 2006-2007, a positive shock in implied market volatility does not affect the returns of large or small banks stocks. However, during the crisis regime, the ASYM variable is positively and significantly related to the returns of large banks during the crisis. Conversely, the ASYM variable is negatively and significantly related to the returns of small banks during the crisis, and the coefficient for the market return variable is no longer significant. That is, small bank returns are driven by changes in implied market volatility instead of the market return during the crisis.

Robustness check results from the SUR analysis are presented in table 3. The results confirm our prior conclusions. Small bank returns are not sensitive to increases in market volatility before the crisis but they are sensitive during the crisis. Large bank returns are not sensitive to increases in implied market volatility before the crisis but are sensitive during the crisis.

An alternative SUR model is run for the shocks in the independent variables. To derive the shocks, we run a vector autoregression (VAR) model of lag 1 and use the residuals as independent variables in the SUR regression. Using this method, we can disentangle the market and volatility effects by orthogonalizing all variables with causality flowing from shocks to the market variable. The results are presented in table 4. Again, the asymmetric implied market volatility factor is insignificant before the crisis, and significantly negative during the crisis for small banks. Furthermore, the market return coefficient becomes insignificant during the crisis when applied to the small bank portfolio, suggesting that the market influence is replaced by the influence of implied market volatility (market fear). For large banks, the implied market volatility factor is insignificant before the crisis, and significantly positive during the crisis.

We also perform the Chow test to investigate if the coefficients for the ASYM variable are statistically different between small and large banks. With an F-statistic of 187.57 and a probability of 0.000, we conclude that there is a difference in the coefficients for the ASYM between the small and large banks. Similar to our prior findings, the Chow test serves as additional evidence that small and big banks react differently to increases in implied market volatility.

In addition, we re-assess a portfolio of large banks based on a more restricted criterion in which only the banks in the top ten based on market capitalization are included. Results for this portfolio are disclosed in footnotes that accompany tables 2, 3 and 4. The only difference is that when we only look at top 10 big banks, the ASYM coefficient becomes positive and significant in the pre-crisis period, just like during the crisis. The coefficients for the small banks stay the same.

As a robustness check to our proxy ASYM, we use an alternative measure of the asymmetric shock in aggregate volatility called SHOCK. The results presented in Table 6 are quantitatively and qualitatively similar to the ones found in Table 3. The SHOCK coefficient is insignificant for both big and small banks before the crisis. It is positive and significant for the large banks during the crisis and negative and significant for the small banks during the crisis. The results emphasize our original findings that big and small banks valuations react differently to increases in market volatility during the 2008 financial crisis. Thus, we conclude that the results are robust to an alternative definition of increases in market volatility.

4.2 Multivariate analysis results

To assess if positive shocks in implied market volatility affect returns of banks differently within the sample of large banks or within the sample of small banks, we apply a multivariate model to the sample of large banks, and then re-apply the model to the sample of small banks. The results are presented in table 5. An initial analysis of the independent variables reveals a high negative correlation between investment securities and loans, as they serve as imperfect substitutes. The correlation coefficient is -0.6524 in the pre-crisis period and -0.7173 in the crisis period. To avoid the multicollinearity problem, each model is run twice, including only one of these variables at a time.

During the crisis period, the multivariate models explain between 14.07% and 25.37%

percent of the variation in sensitivity to implied market volatility among banks. Not only do investors appear to rely more heavily on implied market volatility when pricing banks during the crisis period (based on earlier results), but they also discriminate among banks based on their financial characteristics when revaluing banks in response to changes in implied market volatility.

The DEPOSITS variable is positive and significant in all models, which supports the hypothesis that banks relying more heavily on deposits as their source of funds are less exposed to high implied market volatility. The CASH variable is not significant in any of the models. The LOANS variable is positive and significant for large banks, which suggests that within the sample of large banks, the bank share price response to increases in implied market volatility is more favorable for banks that maintain a larger amount of loans. The LOANS coefficient is negative and significant for the small banks, which suggests that small banks with a higher percentage of loans suffer more from an increase in implied market volatility. However, the INVSEC variable is not significant in any of the models. These results suggest that large bank borrowers suffer less as a result of increased market volatility compared to small banks.

The CAP variable is positive and significant in both models in which it was applied for large banks, which supports the hypothesis that banks with larger capital ratios experience a more favorable share price response to changes in implied market volatility. The NONPERF variable is not significant for the sample of large banks, but is negative and significant for the sample of small banks. This result for small banks supports our hypothesis that small banks experience a weaker share price response to increases in implied market volatility when they have a larger proportion of non-performing loans. The PLL variable is not significant for the sample of large banks. However, it is positive and significant for the portfolio of small banks, which supports the hypothesis that small banks that set aside a higher reserve for loan losses are less exposed to increases in implied market volatility. The NONINT variable is negative and significant for the sample of large banks, which suggests that larger banks relying on more non-interest income experience a less favorable share price response to increases in implied market volatility.

We do not find any evidence that bank sensitivity to increases in market volatility is conditioned by the degree of bank sophistication as proxied by the successful/unsuccessful use of derivatives. With coefficients of -0.0121 and -0.0112 for the large banks (respective p-values of 0.853 and 0.862) and -0.4713 and -0.4613 for the small banks (p-values of 0.132 and 0.122), we do not find that large banks are less exposed to increases in market volatility compared to smaller banks or vice versa. The results for the alternative measure of bank sophistication are similar to the main measure and are presented in Table 5, footnote 3.

To offer more insight about the difference in sensitivity of small banks versus large banks to loans during the crisis, we evaluate the composition of loans for the sample of large banks and small banks in the pre-crisis period and in the crisis period. For the large bank portfolio, commercial and industrial loans represent 17.75% of total assets before the crisis and 17.64% during the crisis. Consumer loans represent 10.40% in the pre-crisis period, and 10.80% during the crisis. Real estate loans represent 29.45% in the pre-crisis period, and 28.54% during the crisis. None of these differences are significant.

For small banks, commercial and industrial loans represented 8.2% of total assets before the crisis and 8.5% during the crisis. More importantly, the consumer loans decreased from 12% to 10%, and the real estate loans increased from 40% to 49%. Both of these changes are significant at the 5% level. The differences in loan composition can explain the relative difference in sensitivity of small and large banks to increases in implied market volatility. The market may perceive the predominant real estate lending of smaller banks as riskier, which results in a more pronounced sensitivity of small banks to increases in VIX.

Exploring the economic significance of the results, we find that a 1% increase in the deposits held by small banks reduces the sensitivity of those banks to increases in implied market volatility by 1.12%-1.50%, depending on the model. By comparison, large banks that rely on deposits as their main source of funds can reduce their sensitivity to increases in implied market volatility only by 0.7%-0.9% when increasing their deposits by 1%.

As mentioned previously, the effect of loans on the changes in market volatility varies based on the size of the bank. While large banks seem to benefit from an increase in its loan percentage as part of their portfolio of assets, small banks seem to suffer. A 1% increase in the loans held by a small bank results in an increase in the sensitivity to implied market volatility of 1.17%. Interestingly, while large banks appear to statistically benefit from an increase in loans, the economic significance is minuscule; a 1% increase in the loans held by a large bank results in a reduction in sensitivity to increases in market volatility of 0.17%.

The factor that has the most economic impact on the increases in market volatility for small banks is non-performing loans. A 1% increase in the non-performing loans leads to an increase in the sensitivity of small banks to increases in implied market volatility of 8.42%. The provision of loan losses (PLL) is also an important determinant for small banks as a 1% increase in PLL results in a sensitivity reduction of about 2.5%.

5. Conclusions

Intertemporal asset pricing theory suggests that an increase in implied market volatility can affect bank stock prices, especially during the crisis regime. A challenge in testing the effects of shocks in implied market volatility is its high correlation with market movements, which could cause its effects on bank returns to be disguised by market movements. We disentangle the effects of these two variables on bank stock prices, and determine that an increase in implied market volatility has a significant impact on bank returns, above and beyond the impact of general stock market returns.

We also find that the impact of shocks in implied market volatility on large bank returns is distinctly different from the impact on small bank returns. Large bank returns are favorably affected by increases in implied market volatility, while small banks are adversely affected by increases in implied market volatility. The difference in sensitivity could be partially attributed to the ability of large banks to achieve increase substantial diversification benefits. While large banks are subject to a decline in valuation, they are more diversified across geographical and product space than smaller banks. Therefore, they may establish a natural floor valuation; their diversified operations and their capital can cushion the blow if their revenue is weakened by bad market conditions. Yet, they may be able to capitalize on bad market conditions by expanding their market share, as smaller banks retreat from various product and geographic markets. The high sensitivity of small banks may also be attributed to their focus on real estate loans and their increase in concentration of real estate loans at the time the crisis began.

We also attribute the difference in the share price response to increases in implied market volatility to the perception that large banks are protected by regulators. To the extent that large banks are perceived to be too big to fail, they have much upside potential to gain market share during weak economic conditions, while receiving protection against downside risk. Conversely, small banks are not as diversified, and cannot cushion against conditions that weaken revenue. They are more susceptible to losses in market share. They are perceived by the market to be small enough to fail, and therefore are subject to more limitations on accessing and using funds when market fear is high.

Based on our results regarding exposure to implied market volatility, we suggest the following policy implications. First, large banks may be more resilient than small banks because being large allows for economies of scale, diversification, and easier access to funding, even in the absence of a safety net. One particular form of diversification is in loans, as large banks do not concentrate as heavily on real estate loans. Second, while some large banks may be better protected than others, regulators may be willing to provide a subsidy to facilitate a takeover and prevent contagion effects that could result from the failure of a large bank. If the market has a similar perception, it establishes an implicit floor valuation, which can attenuate adverse effects caused by shocks in implied market volatility. Even if regulators establish a clear signal that they will not even partially subsidize the rescue of large banks, we expect that size still helps to insulate against market volatility shocks.

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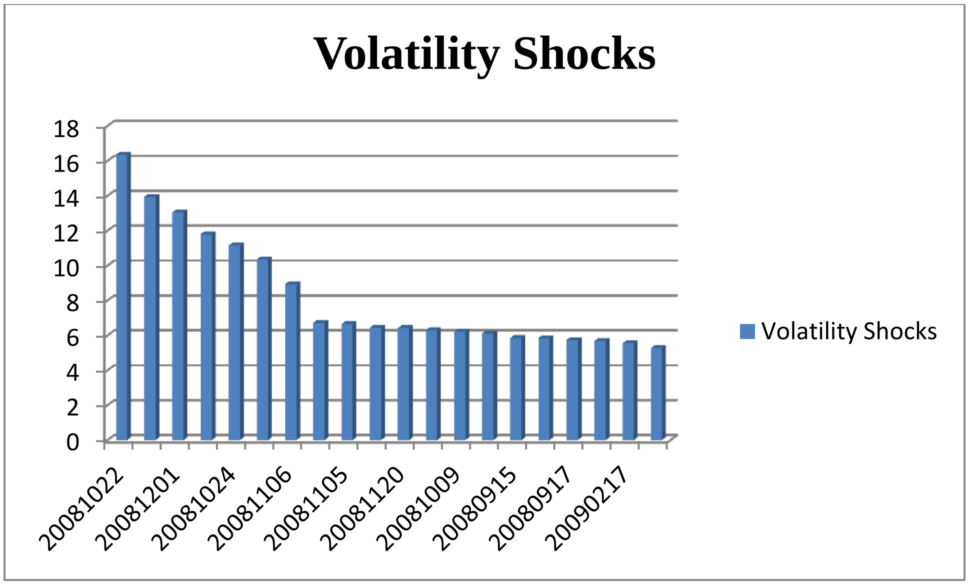

Figure 1. Major Increases in VIX. The graph plots the biggest increases in VIX during the 2008 financial crisis.

Table 1

Panel A: Descriptive Statistics for the firm specific characteristics of small and large banks.

	Before Crisis Small Banks Mean/Median (SD)	Crisis Small Banks Mean/Median (SD)	Before Crisis Large Banks Mean/Median (SD)	Crisis Large Banks Mean/Median (SD)
Size (Log of Total Assets)	5.96/6.10 (0.506)	6.11/6.128 (0.4271)	9.58/8.89 (0.788)	9.74/8.95 (1.698)
Capital Ratio I	12.44% /12.56% (0.040)	10.89%/12.41% (0.088)	9.56%/9.8 (2.927)	10.50%/9.57% (2.351)
Cash	3.39% /2.70% (0.027)	3.73%/2.47% (0.026)	3.61%/2.23% (0.0203)	5.10%/5.5% (0.089)
Loans	71.96% /73.76% (0.134)	71.02%/73.53% (0.138)	65.60%/67.73% (0.144)	64.87%/66.12%(0.314)
Investment Securities	18.11% /16.75% (0.113)	18.36%/16.12% (0.133)	18.47%/19.12% (0.337)	18.59%/19.2 (0.032)
Deposits	74.20%/77.28% (0.086)	74.05%/74.80% (0.100)	68.28%/58.14% (0.122)	68.92%/60.40% (0.300)
Provision for Loan Losses	1.025% /0.9% (0.452)	3.12%/2.75% (0.705)	2.24%/2.5% (0.804)	5.42%/4.55% (1.140)
Non-Interest Income (as % of total revenue)	60.85% /55.12% (0.384)	62.17%/54.85% (0.663)	62.89%/63.14% (0.617)	51.52%/55.18% (0.998)

Notes: The sample represents firms. Pre-crisis corresponds to 2006-2007 and crisis corresponds to 2008Q3-2009Q1.All variables are scaled by total assets, or net income in the case of provision for loan losses and non-interest income. All numbers represent averages across quarters for the respective period of concern.

Panel B: Correlations between variables included in the model, $R_p = \alpha + \Theta_1 MKTRET_t + \Theta_2 ASYM_t + \Theta_3 RATE_t + \Theta_4 TERM_t + e_t$.

	MKTRET	VIX (ASYM)	RATE	TERM
MKTRET	1.0000			
VIX (ASYM)	-0.8385	1.0000		
RATE	0.1777	-0.1676	1.0000	
TERM	-0.0033	-0.0152	-0.0408	1.0000

Notes: ASYM is derived based on the daily changes in VIX.

Table 2
Sensitivity of bank portfolio returns to changes in implied market volatility.

Panel A: Large Banks[3]

Variable	Pre-crisis	Crisis
Intercept	-0.0009232 (0.021)**	.0050555 (0.755)
MKTRET	1.3698 (0.000)***	1.5419 (0.000)***
ASYM	.0006 (0.531)	.0061 (0.030)**
RATE	-.0001 (0.949)	-.0012 (0.961)
TERM	-.0003434 (0.732)	-.0015 (0.840)
Adj. R-squared	0.7432	0.5145
Sample size	496	187
F-statistic	211.93 (0.000)***	25.34 (0.0000)

Panel B: Small Banks

Variable	Pre-crisis	Crisis
Intercept	.0000396 (0.793)	.0017593 (0.917)
MKTRET	.05242 (0.062)*	.1233 (0.049)**
ASYM	-.00024 (0.396)	-.0075 (0.071)*
RATE	-.00023 (0.695)	.0097 (0.394)
TERM	-.00048 (0.156)	.0009 (0.896)
Adj. R-squared	0.0568	0.3685
Sample size	496	187
F-statistic	3.32 (0.0107)**	3.96 (0.0041)***

Notes: Large bank and small bank portfolios are built for pre-crisis and crisis periods. The regression equation is $R_p=\alpha+\Theta_1 MKTRET_t+ \Theta_2\, ASYM._t + \Theta_3 RATE_t+ \Theta_4 TERM_t + e_t$. Rp is the return on portfolios of large and small bank stocks. ***, ** and * represents significance of 1%, 5% and 10% respectively.

[3] We have also used only the top ten largest banks as an alternative sample of the too-big-to fail with the following results: during the crisis large banks ASYM coefficient of 0.0117 (p-value of 0.000) and pre-crisis the ASYM coefficient for large banks is 0.0005 (0.312).

Table 3
Large and small bank return sensitivity to changes in implied market volatility using seemingly unrelated regression (SUR).

Panel A: Large Banks[4]

Variable	Pre-crisis	Crisis
Intercept	-.0009232 (0.012)	.0017593 (0.911)
MKTRET	*1.369813 (0.000)****	*1.541863 (0.000)****
ASYM	.0005566 (0.281)	*.0065112 (0.000)****
RATE	-.0001159 (0.940)	-.0010155 (0.961)
TERM	-.0003434 (0.621)	-.0015389 (0.805)
"R-sq"	0.7432	0.5145
Sample size	496	187
Chi-square	1435.69 (0.000)	198.19 (0.000)

Panel B: Small Banks

Variable	Pre-crisis	Crisis
Intercept	.0000396 (0.789)	.0050555 (0.647)
MKTRET	*.052419 (0.010)***	-.1233139 (0.160)
ASYM	-.0002452 (0.237)	*-.0074698 (0.000)****
RATE	-.0002389 (0.698)	.0096716 (0.501)
TERM	*-.0004796 (0.086)**	.0009679 (0.824)
"R-sq"	0.0568	0.3685
Sample size	496	187
Chi-square	29.86 (0.000)	109.11 (0.000)

Notes: The regression equation is: $R_{p,L}=\alpha+ \Theta_1 MKTRET_t+ \Theta_2 ASYM_t + \Theta_3 RATE_t+ \Theta_4 TERM_t + v$ and $R_{p,S}= \alpha+ \Theta_1 MKTRET_t+ \Theta_2 ASYM_t + \Theta_3 RATE_t+ \Theta_4 TERM_t +w$. R_p is the return on portfolios of small and large bank stocks. ***, ** and * represents significance of 1%, 5% and 10% respectively.

[4] We have also used only the top ten largest banks as an alternative sample of the too-big-to fail with the following results: during the crisis large banks ASYM coefficient of 0.0031 (p-value of 0.000) and small banks ASYM coefficient of -0.0083 (p-value of 0.000). Pre-crisis large banks have an ASYM coefficient of 0.0011 (0.007) and small banks -0.0001 (0.497).

Table 4
Large and small bank sensitivity to changes in implied market volatility using an alternative application of seemingly unrelated regression.

Panel A: Large Banks[5]

Variable	Pre-crisis	Crisis
Intercept	.0000955 (0.734)	.003764 (0.142)
MKTRET	*1.434603 (0.000)****	*1.534027(0.000)****
ASYM	.0013603 (0.900)	*.0064091(0.000)****
RATE	.0008198 (0.425)	.0002125 (0.960)
TERM	.0005887 (0.665)	-.0009561 (0.888)
"R-sq"	0.7574	0.5135
Sample size	496	187
Chi-square	1551.40 (0.000)	197.36 (0.000)

Panel B: Small Banks

Variable	Pre-crisis	Crisis
Intercept	-.0000523 (0.652)	-*.0035453 (0.048)***
MKTRET	*.0607179 (0.0040)****	-.1059917 (0.221)
ASYM	-.0001684 (0.430)	-*.0073403(0.000)****
RATE	.0001413 (0.739)	-.0046395 (0.118)
TERM	-.000322 (0.565)	-.0029826 (0.530)
"R-sq"	0.0600	0.3700
Sample size	496	187
Chi-square	31.75 (0.000)	109.84 (0.000)

Notes: To derive the shocks, we run a VAR of lag 1 and use the residuals as independent variables in the SUR regression. Using this method, we can disentangle the market and volatility effects by orthogonalizing all variable to the market variable. The regression equation is: $R_{p,L}=\alpha+ \Theta_1 MKTRET_t+ \Theta_2 ASYM_t + \Theta_3 RATE_t+ \Theta_4 TERM_t + v$ and $R_{p,S}=\alpha+ \Theta_1 MKTRET_t+ \Theta_2 ASYM_t+ \Theta_3 RATE_t+ \Theta_4 TERM_t + w$. R_p is the return on portfolios of small and large bank stocks. ***, ** and * represents significance of 1%, 5% and 10% respectively.

[5] We have also used only the top ten largest banks as an alternative sample of the too-big-to fail with the following results: during the crisis large banks ASYM coefficient of 0.0080 (p-values of 0.000) and small banks ASYM coefficient -0.0051 (0.020). Pre-crisis large banks have an ASYM coefficient of 0.0042 (0.063) and small banks -0.00089 (0.318)

Table 5
Cross-sectional analysis of large and small banks during the crisis.

Variable	Large Banks Model I	Large Banks Model II	Small Banks Model I	Small Banks Model II
Intercept	-.0994 (0.407)	.1327 (0.167)	.1821 (0.115)	-.0357 (0.653)
DEPOSITS	*.5437 (0.037)***	*.4492 (0.084)**	*.9652 (0.029)***	*.9137 (0.047)***
CASH	.0562 (0.921)	.5931 (0.298)	-.3481 (0.546)	-.4086 (0.521)
LOANS	*.3667 (0.003)****		*-.3044 (0.030)***	
INVSEC		-.0160 (0.922)		-.1494 (0.467)
CAP	*.0200 (0.013)***	*.0156 (0.040)***	.0005 (0.941)	.0021 (0.814)
NONPERF	-.6598 (0.676)	.0054 (0.997)	*-3.871 (0.000)****	*-4.072 (0.000)****
PLL	.4890 (0.863)	2.0485 (0.465)	*9.9592 (0.003)****	*9.7532 (0.020)***
NONINT	*-4.8454 (0.009)****	*-6.4165 (0.000)****	.1667 (0.918)	.11977 (0.941)
SOPHLEVEL[6]	-0.0121 (0.853)	-0.0112 (0.862)	-0.4713 (0.1320)	-0.4613 (0.122)
Sample size	125	125	129	129
Adjusted R-squared	0.2537	0.2059	0.1705	0.1407
F-Statistic (p-value)	4.63 (0.0001)	2.83 (0.0092)	3.28 (0.0031)	3.06 (0.0053)

Notes: Individual ASYM sensitivity coefficients derived during the crisis period are regressed on bank-specific characteristics based on the equation $\Theta_j=\alpha+\beta_1 DEPOSITS_j +\beta_2 CASH_j+\beta_3 LOANS_j+\beta_4 INVSEC_j +\beta_5 CAP_j+\beta_6\ NONPERF_j + \beta_7 PLL_j + \beta 8NONINT_j+ \beta 9SOPHLEVEL+e$. ***, ** and * represents significance of 1%, 5% and 10% respectively. Because of the high correlation between LOANS and INVSEC, the model has been run twice, using only one of the two highly correlated variables at a time. The independent variables are averages of all quarters in the crisis period.

[6] The alternative measure of bank sophistication yields the following results: Large Banks I (0.0011 (0.991)), Large Banks II (-0.0009 (0.993)), Small Banks I (-0.2781 (0.374)), Small Banks II (-0.2564 (0.428)).

Table 6

Large and small bank return sensitivity to changes in implied market volatility using seemingly unrelated regression (SUR).

Panel A: Large Banks

Variable	Pre-crisis	Crisis
Intercept	0.0001 (0.967)	-0.0019 (0.492)
MKTRET	*1.3361 (0.000)******	*1.4230 (0.000)******
SHOCK	0.0009 (0.345)	*0.0531 (0.000)******
RATE	0.0006 (0.513)	0.0007 (0.860)
TERM	0.0006 (0.345)	-0.0009 (0.892)
"R-sq"	0.7544	0.5201
Sample size	496	187
Chi-square	1523.51 (0.000)	202.66 (0.000)

Panel B: Small Banks

Variable	Pre-crisis	Crisis
Intercept	-0.0000 (0.928)	-0.0009 (0.674)
MKTRET	*0.0730 (0.000)******	*0.2335 (0.005)******
SHOCK	-0.0004 (0.264)	-0.0245 (0.004)***
RATE	0.0001 (0.694)	-0.0048 (0.147)
TERM	*-0.0002 (0.610)*	0.0097 (0.065)*
"R-sq"	0.0606	0.2108
Sample size	496	187
Chi-square	32.02 (0.000)	49.95 (0.000)

Notes: We use an alternative measure of increases in market volatility as a robustness check. We use a dummy variable called SHOCK and set it equal to 1 when the increase is in the top decile and 0 otherwise The regression equation is: $R_{p,L}=\alpha+ \Theta_1 MKTRET_t+ \Theta_2\, SHOCK_t + \Theta_3 RATE_t+ \Theta_4 TERM_t + v$ and $R_{p,S}= \alpha+ \Theta_1 MKTRET_t+ \Theta_2\, SHOCK_t + \Theta_3 RATE_t+ \Theta_4 TERM_t +w$. R_p is the return on portfolios of small and large bank stocks. ***, ** and * represents significance of 1%, 5% and 10% respectively.