The determinants of bank risks: Evidence from the recent financial crisis

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Abstract

We investigate whether US bank holding company fundamental characteristics are related to bank risk over a period that covers the recent 2007-09 financial crisis. We extend prior studies to consider bank equity risk exposure to market-wide default risk, the structured finance market, and the asset-backed money market in a variance decomposition. Four important results emerge: (1) the risk in bank opaque assets is not accurately priced; (2) banks with lower earnings have higher risk; (3) a positive relationship between non-performing loans and bank risk increased threefold during the crisis and (4) banks with a larger buffer of Tier 1 capital have lower risk and lower exposure to shocks in market-wide default risk and the structured finance market in particular. These results highlight the importance to investors of studying fundamentals, while from a bank regulatory perspective, effective management of regulatory capital may manage risks arising from contagion stemming from structured finance markets and funding illiquidity.

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1. Introduction

While there is ample evidence that bank equity risk is associated with managerial shareholdings (Demsetz et al., 1997; Anderson and Fraser, 2000), the presence of capital adequacy requirements (Konishi and Yasuda, 2004), board structure and CEO power (Pathan, 2009), and franchise value (Keeley, 1990; Demsetz et al., 1997; Anderson and Fraser, 2000), less is known about the role of more fundamental variables in explaining bank risk, particularly during periods of financial crisis.[1] We address this by conducting a comprehensive examination of how fundamental characteristics relate to bank risk before, during and after the 2007-09 financial crisis. Specifically, the objectives of this paper are to study the within-bank relationships between fundamental characteristics and decomposed equity risk, and to investigate the changes in these relationships during the recent crisis. The results have important implications for shareholders and bondholders in the context of investment and risk management and for bank regulators for ensuring the safety of banks and the banking system.

Following prior literature, this paper utilises market-based equity risk as a proxy for bank risk and evaluates the association between fundamental variables, including asset composition and opacity, profitability, credit risk control and funding liquidity, and bank risk during non-crisis and crisis periods.[2] An innovative feature of this study is that we decompose total equity risk into six components: market, interest rate, market-wide default, asset backed structured finance, short term funding illiquidity, and residual risks. Each component is specific to individual banks according to their correlation with the factors, while the time variation is driven by the broader market. The components are designed to reflect bank exposure to the market risk factor and shocks to interest rate risk, market-wide default risk, the structured finance market and asset backed money markets, which are interesting and important in the context of the recent crisis.

This first contribution of this paper is to facilitate an improved understanding of the fundamental determinants of bank risk, and we provide a number of useful implications to a range of

[1] A noticeable exception is Stiroh (2006b) who finds evidence that the operating choice and non-interest generating activities of US banks affected their equity risk over the 1997-2004 period.

[2] See Anderson and Fraser (2000), Stiroh (2006b), Haq and Heaney (2012) and Ellul and Yerramilli (2013) as examples of studies using equity risk.

market participants. We follow Jones et al. (2013) and study whether opaque assets are accurately priced and are perceived to be more risky relative to transparent assets, which may provide important implications for policymakers in limiting systemic risk. Second, we evaluate the relationship between loan portfolio credit quality and risk both before and during the crisis, thus highlighting the importance of effective and timely internal risk and credit control, which may be relevant to both investors and regulators. Third, our investigation provides evidence that some fundamentals are important for explaining bank equity risk and that the relationships became stronger in some cases during the recent crisis, which included a possible 'flight-to-quality' phenomenon. Finally, we extend the literature to identify the fundamental characteristics that are related to bank exposure to decomposed risks. Beyond conventional bank risk factors driven by the market and interest rates, we also capture shocks related to a market-wide default risk, structured finance securities and funding illiquidity, which are particularly interesting and topical given the events of the recent crisis. Our sample includes an interesting period characterised by contagion, funding illiquidity and macroeconomic uncertainty when these three additional risk factors were most prevalent, allowing our results to contribute to debates surrounding regulation, financial stability and prevention of systemic bank failures.

One major feature of the US banking sector that contributed to the recent crisis is the 'shadow' banking system in which there is a maturity mismatch between a bank's issuance of short-term money market instruments (for example, asset-backed commercial papers (ABCP)) and financing of longer-term structured finance securities via off-balance sheet conduits.[3] During the recent crisis, banks were obligated to fund these conduits via credit line facilities and were thus susceptible to substantial funding illiquidity risk. This motivates us to measure bank exposure to widening ABCP yield spreads to determine whether it is an important constituent of bank risk. In parallel, other studies have shown that securitised and structured finance products, such as Collateralised Debt Obligations (CDOs) and subprime Residential Mortgage Backed Securities (RMBS), were responsible for the intensification and severity of the recent crisis.[4] As downgrades of these structured securities spiked in 2007 their prices plunged, while the buy side almost disappeared (for losses on RMBS, see, Merrill et al., 2012). The RMBS market has been shown to be the origin of contagion

[3]See for example Eichengreen (2008), Frank et al. (2008), Brunnermeier (2009) and Acharya et al. (2013).
[4]See in particular Benmelech and Dlugosz (2009), Brunnermeier (2009), Gorton (2009) and Mählmann (2013).

during the crisis and so represented a source of considerable risk for banks relating to increasing risk aversion and market illiquidity (Fender and Scheicher, 2009; Longstaff, 2010). Given the topical nature and importance of these innovative products and markets, we extend prior literature by isolating the risk exposure of banks to shocks from the structured finance market and asset-backed money markets. We achieve this by implementing a variance decomposition procedure to capture individual bank sensitivity to shocks from the structured finance market index as measured by the ABX AAA index and from funding illiquidity measured by the ABCP market.[5] Our findings show that stronger bank fundamentals protected against both conventional systematic risks and these more recent crisis related shocks.

Using a panel of 227 Bank Holding Companies (BHCs) over the period 2006-11, we estimate a pooled weighted least squares (WLS) regression with two-way fixed effects and two-way clustered robust standard errors to control for unobserved heterogeneity across banks and quarters. We consider a number of bank fundamental variables that includes various types of loan assets, earnings, non-interest income, non-performing loans, loan-to-deposit ratios, Tier 1 capital and other control variables. Our goal is to investigate the potential relationships between these fundamentals and various components of bank risk and also to evaluate changes in these relationships during the recent crisis using interaction effects.

Following Jones et al. (2013) closely, we separate total bank loan assets into trading, commercial real estate, residential real estate, other loans, other opaque assets and transparent assets to investigate how these asset types affect equity risk and whether asset opacity is important. Our evidence shows that banks with more trading and loan assets have significantly higher total and residual risks in the non-crisis subsample, a finding that supplements Fahlenbrach et al. (2012) and Acharya et al. (2013) who find that banks with higher exposure to illiquid assets have lower stock returns. We use F-tests of coefficient equality to evaluate whether the impact of opaque and transparent assets on bank risk differs and find little evidence of any significant differences. This suggests that asset opacity is not often priced in bank equity risk, consistent with the conclusion of Jones et al. (2013) that the risk in opaque assets is not sufficiently discounted. Another interesting finding is that the equity risk relating to the asset types become smaller during the crisis, indicating

[5]The ABX AAA index is a benchmark index that tracks the performance of a static portfolio of RMBS.

a possible change in the market perception of the risk of bank lending activities at a time of extreme short term funding constraint.

We also evaluate whether bank fundamental characteristics are related to the various decomposed equity risk and identify any changes in their impacts during the crisis. We find strong evidence that earnings are significantly and negatively related to total risk and three out of the six components of total risk in our baseline model. Consistent with prior studies (for example Cooper et al., 2003; Wei and Zhang, 2006), lower earnings are associated with higher one-quarter ahead return volatilities over the full period 2006-11, a finding that emphasises the importance of fundamentals for investors. When the crisis effect is estimated, the relationship between earnings and the risk components remains qualitatively similar. However, we find no significant crisis interaction effects for earnings, except for market risk, suggesting that the influence of earnings on risk is pervasive rather than crisis-specific. The interesting case for market risk shows that earnings contribute positively to market risk during the non-crisis period. This is consistent with Jones et al. (2013) who find that banks require higher rates of return for opaque investments, in turn leading to higher systematic risk. The relationship reversed during the crisis possibly because the losses from the mispriced risky investments started to be realised. Furthermore, banks with more income arising from non-interest activities have significantly less market risk, signalling more diversified income sources, but this relationship reversed during the crisis as the risks in some non-traditional activities were uncovered.

We examine whether loan asset quality, as a proxy for the effectiveness of credit control, is related to decomposed bank equity risk. We use the proportion of non-performing loans to total assets to measure loan asset quality and examine its association with the decomposed risks. In the baseline model, we find strong evidence that non-performing loans are positively related to total, interest rate, market-wide default and residual risks. When the crisis dummy is included, this positive relationship weakens and is not statistically significant in the non-crisis period. More notably, the positive impact of non-performing loans on total and residual risks increased threefold during the crisis. This result confirms the conclusion by Ellul and Yerramilli (2013) that stronger risk and credit control is related to lower equity risk and we present new evidence that the beneficial effects of stronger risk control was three times more prominent during the crisis.

Regulatory capital has been the focus of debate on financial reform as regulators attempt to strike a balance between maintaining bank profitability and competitiveness, and reducing their exposure to systemic risk. This paper contributes to this debate by examining how capital adequacy (Tier 1 capital ratios) and funding illiquidity (loan-to-deposit ratios) relate to bank exposure to market-wide default risk and shocks from the asset-backed structured finance and asset-backed money markets. Our baseline results show high significance. Higher Tier 1 capital ratios are associated with lower total risk and its components, except for market and ABX risks. The loan-to-deposit ratio is positively related to interest rate risk in line with our expectation. In our crisis model, the findings are remarkably similar, but we find no significant crisis interaction effects for Tier 1 capital ratios. The findings supplement those of Beltratti and Stulz (2012) and provide new evidence that banks with a larger buffer of Tier 1 capital were less susceptible to the adverse shocks throughout the whole sample period, including the crisis. From a supervisory perspective, this paper presents strong evidence that Tier 1 capital is an effective shield for banks against various risks (and maybe systemic risk) and provides empirical justification for the recent rise in the Basel III regulatory capital requirements.

The remainder of the paper is organised as follows: Section 2 discusses our motivation and states our hypotheses; Section 3 explains our data and empirical framework; Section 4 reports our empirical results; Section 5 presents some sensitivity analysis and Section 6 concludes.

2. Motivation and hypotheses

2.1. Bank opacity

It is acknowledged in the literature that banks are more opaque than non-banks (Morgan, 2002). The opacity is the result of information asymmetry arising in a number of ways. First, it arises from the relative difficulty in valuing bank assets because, as information sharing coalitions and delegated monitors, they have privileged knowledge of loan credit quality and do not share this information. In addition, banks might understate their losses during worsening financial conditions (Gunther and Moore, 2003) or smooth their earnings (Bhat, 1996; Fonseca and González, 2008). The lack of transparency and potential problems of moral hazard are the fundamental causes of bank opacity. Second, bank opacity arises from the lack of transparency of its trading assets (Jones et al., 2013). Morgan (2002) notes that trading assets are more liquid and may be easier to 'slip' in and out of the financial statements at bank discretion given the mark-to-market accounting treatment. As a result, the wider scope for banks to manipulate the amount of booked trading assets gives rise to opacity. Third, the issuance of opaque securitised financial products, for example Asset-Backed Securities (ABS), Collateralised Mortgage Obligations (CMOs) and CDOs, increased drastically over the past two decades (Weaver, 2008; Brunnermeier, 2009). Since these structured securities are difficult to value and are not transparent even in stable conditions, their pricing became extremely difficult during the crisis, resulting in considerable opacity in bank assets.

Asset composition is a major determinant of bank opacity. Prior evidence shows that bank loans and financial assets generate disagreement amongst bond rating agencies with split ratings more likely for banks, which is consistent with higher opacity (Morgan, 2002; Iannotta, 2006). The underlying argument is that bank investment in opaque assets is harder for analysts or rating agencies to evaluate. Bank opacity may affect bank risk in three major ways. First, Jones et al. (2013) show that bank investment in opaque assets is related to higher systematic risk and lower idiosyncratic risk as a result of inefficient market discipline in pricing risks. We test explicitly the relationship between asset opacity and new components of bank risk. Second, some types of bank assets may be correlated giving a lower degree of diversification than other asset types. For instance, bank tradable assets, including subprime CDOs, are shown in hindsight to be highly correlated across securitised tranches as a result of incorrect actuarial assumptions (Jaffe, 2008; Weaver, 2008) and an over-reliance on rating agencies (Partnoy, 2009). Banks are therefore significantly exposed to risk related to the troubled structured finance and asset-backed money markets.[6] Third, during the recent crisis, banks with more investments in hard-to-value assets may have been prone to rating downgrades and write-offs and were subject to more uncertainties regarding funding illiquidity and insolvency risk. As the risk embedded in the opaque assets was not sufficiently discounted by investors before the crisis (Jones et al., 2013), investors received wake-up calls and systematically sold these bank stocks during the crisis, resulting in tremendous downward price pressure. In that sense, bank opaque assets may have become more relevant to investors during

[6] A competing argument by Flannery et al. (2004) states that bank opacity may not affect return volatilities. They contend that since the impact of changes in true values of the assets on stock returns is only available publicly on a quarterly basis, the price volatilities between information arrival dates should be low.

the crisis as an indicator of risk.

From these motivations, we test three hypotheses centering on the notion of bank opacity and asset composition. Hypothesis 1A asserts that bank asset composition correlates with bank risk. Hypothesis 1B states that bank investment in opaque assets has a stronger impact on bank risk than transparent assets. Hypothesis 1C suggests that the relations between asset composition and opacity on bank equity risk differ across the non-crisis and crisis subsamples.

2.2. The structured finance market and funding illiquidity risk

Brunnermeier (2009) suggests that the 'shadow' banking system and the process of securitisation both contributed to the severity of the recent crisis. In the 'shadow' banking system, banks are incentivised to issue and underwrite excessively complex and opaque structured finance securities using off-balance sheet conduits as a means of transferring risk, raising funds, and regulatory arbitrage (Acharya et al., 2013). The off-balance sheet Structured Investment Vehicles (SIVs) carry the same maturity mismatch feature as in the traditional banking model and usually rely on the issuance of short-term ABCP to finance their purchases of longer term assets, such as ABS and CDOs (Eichengreen, 2008, and Frank et al., 2008). As banks are liable for the credit lines granted to the off-balance sheet conduits, their exposure to funding illiquidity risk was substantial when investors were unwilling to roll over their short-term money market instruments during the crisis.[7]

The vulnerability of banks to the funding illiquidity shocks from the structured finance and asset-backed money markets highlights the importance of effective and prudent liquidity risk management. As defined by Cornett et al. (2011), the four main drivers in modern liquidity management are core deposits, liquid assets, equity capital and exposure to loan commitments. They show that it is the core deposits rather than total deposits that stabilise the supply of liquidity and that core deposits and loan origination increase when liquidity is low. In addition, bank capital plays an important role in liquidity management as it serves as a buffer to protect depositors from liquidity

[7]Acharya et al. (2013) find that the liquidity guarantees on the ABCP were concentrated in the ABCP conduits sponsored by commercial banks. They conclude that banks did not securitise for risk transfer, but rather for regulatory arbitrage purposes, especially banks with less capital. They find that stock returns were lower for banks with higher exposure to the ABCP conduits during the recent crisis and that losses in conduits were borne by banks. The evidence suggests that bank exposure to funding illiquidity risks was at least in part priced in the market.

shocks, thus absorbing risk (Diamond and Rajan, 2000; Berger and Bouwman, 2013). Based on these arguments, we evaluate whether bank characteristics measuring their capital buffer, core deposits and total loans reduce their risk during the non-crisis and crisis periods. We consider total loans to total core deposits to gauge the ability to meet funding demands, and the Tier 1 capital ratio as a measure of bank capital to absorb funding illiquidity shocks. Hypothesis 2A therefore asserts that banks with a better funding position and a larger Tier 1 capital buffer have lower risk. To examine whether their relevance increased during the crisis, Hypothesis 2B suggests that their impact on bank risk strengthened during the crisis when liquidity shocks were extreme. The tests provide evidence as to whether banks with better funding ability and a larger capital buffer are less exposed to systematic risk and, more importantly, to the shocks relating to market default risk, structured finance products and funding illiquidity.

2.3. Profitability, credit risk control and equity risk

There is ample evidence supporting a negative relation between earnings and risk. Wei and Zhang (2006) contend that return on equity and their variance are integral to conditional volatilities and find evidence of both time series and cross-sectional relationships between return on equity and stock return volatility. Similarly, Cooper et al. (2003) study the cross-sectional predictability in US bank stock returns and document strong evidence of predictability from quarterly changes of earning per share and other variables. Given this evidence, we consider bank earnings to total assets in our regression model for decomposed equity risk. Supportive evidence would highlight the importance of fundamentals in predicting future return volatilities. As banks gradually moved towards off-balance sheet financing, their sources of income have become more diversified with the amount of non-interest income increasing substantially (Brunnermeier, 2009). In the context of this recent trend, we evaluate whether banks with non-traditional activities have higher risks, and larger exposure to the various crisis-related decomposed risks.

Ellul and Yerramilli (2013) examine the relation between bank internal risk control and tail risk and show evidence that banks with stronger risk control had lower tail risk, lower non-performing loans and stronger fundamental performance during the crisis. Their findings lend support to a business model explanation for these results, rather than a learning hypothesis, especially given the evidence that banks with worse performance in the previous crisis did not appear to learn and had lower risk control subsequently. This evidence motivates us to consider bank non-performing loans as a proxy for credit risk control for explaining equity risk, allowing us to contribute to the literature in two ways. First, we test whether the relevance of credit risk control increased during the recent crisis, allowing us to quantify, interpret and emphasise the economic significance of the benefit of stronger risk control. Second, we examine the role of credit risk control in explaining bank exposure to shocks from the structured finance and asset-backed money markets.

In summary, we expect that bank profitability and loan portfolio credit quality are relevant for determining their decomposed equity risks, providing important implications for investors and regulators. Hypothesis 3A therefore suggests that profitability (earnings and non-interest income) is negatively related to bank risks, while Hypothesis 4A states that banks with better internal risk control have lower risks.[8] To investigate these relationships in the topical context of the recent crisis, hypotheses 3B and 4B assert that the impacts of bank earnings, non-interest income and non-performing loans on equity risk are significantly different between the non-crisis and crisis periods.

3. Data and empirical approach

Our sample consists of all publicly traded US BHCs with $500 million or more consolidated assets that file FR Y-9C forms with the Federal Reserve over the sample 2006Q1-2011Q4.[9] All quarterly consolidated fundamental and financial data are obtained from the Bank Regulatory database in the Wharton Research Data Services (WRDS) Database. These are merged with the market data from the Center for Research in Security Prices (CRSP) database by PERMCO and RSSD ID and with the linking table provided by the New York Federal Reserve Bank.[10] We screen

[8] Stiroh (2006b) finds evidence that non-performing loans to total assets is positively related to bank total risks. Meeker and Gray (1987) show that the amount of non-performing loans are satisfactory measures of bank asset quality.

[9] Following Anderson and Fraser (2000), we include bank stocks with the following SIC codes: 6021 (National commercial banks), 6022 (State commercial banks) and 6029 (Commercial banks, NEC) from CRSP.

[10] PERMCO is the CRSP unique company identifier while RSSD is the unique bank identifier on the Bank Regulatory database (the variable is RSSD9001). The linking table can be accessed via: http://www.newyorkfed.org/research/banking_research/datasets.html.

out those quarterly observations for which there are missing or unmerged data to leave 227 BHCs and 3,447 bank-quarters. Following Jones et al. (2013), all quarterly balance sheet variables are calculated as the average of the beginning and ending values of a particular quarter, while the income measures are annualised quarterly amounts. Variable names starting with 'LN' are natural log transformed and those ending in '_A' are scaled by total assets. Total assets are adjusted for inflation using a seasonally-adjusted GDP deflator with a base year of 2005. To reduce any potential bias from outliers, all bank variables have been winsorised at the 1^{st} and 99^{th} percentile at each cross-section. To ensure that we are capturing temporal predictive relationships and to help reduce potential endogeneity problems, all independent variables are lagged by one quarter.

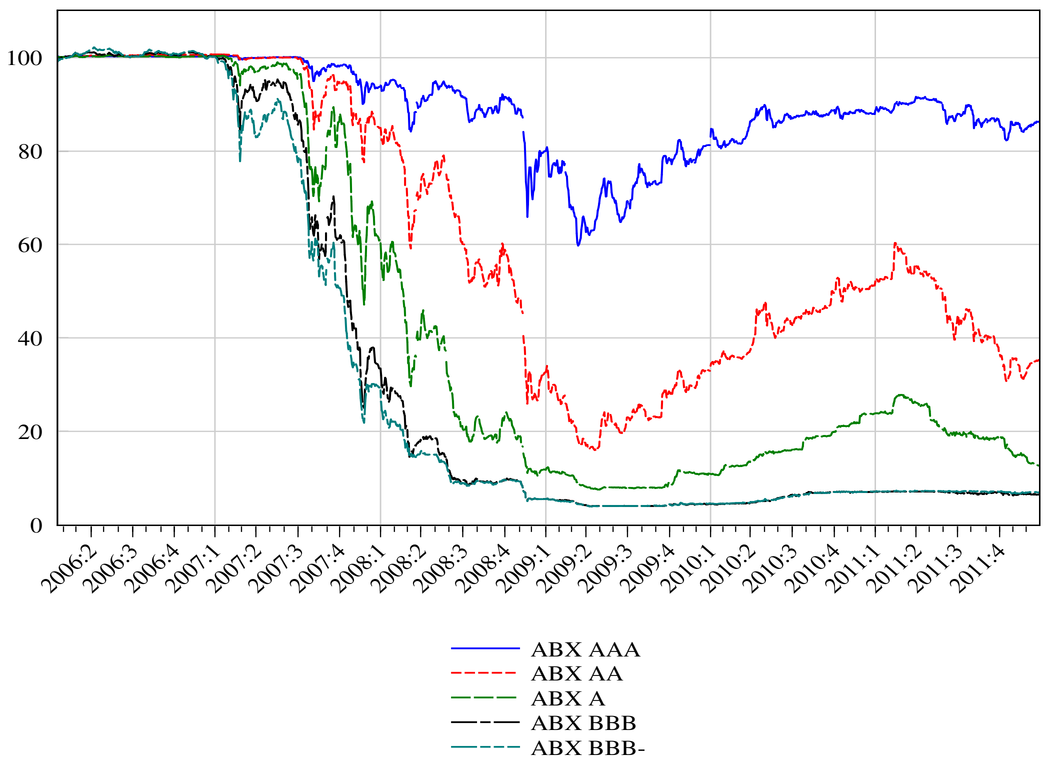
3.1. The ABX indices

Evidence of contagion from the US structured finance market to other US markets has been documented by Longstaff (2010). Fender and Scheicher (2009) also note that the collapse of the structured finance market represented a source of considerable risk during the subprime crisis. To investigate the relative importance of this new crisis-related risk, particularly for banks, we consider a component of bank equity risk that relates to shocks in the ABX index, which tracks the structured finance market. After its inception in 2006, the ABX index family became an important barometer for the subprime RMBS market. Each ABX index, maintained by MARKIT, is an equally-weighted, static portfolio that references 20 subprime RMBS deals. The index serves as a benchmark for the structured finance market in which securities are collateralised by home loans. Five ABX indices, corresponding to the AAA, AA, A, BBB and BBB- credit ratings of the underlying RMBS deals, are included in the family. We include the ABX AAA index of January 2006 vintage, which has the longest history.[11] For comparison, Fig. 1 plots the values of the five ABX indices of this vintage. They started to fall in early 2007 and declined sharply from mid 2007 to mid 2009. Among the five ABX indices, the AAA index outperformed and was the most resilient after the recent crisis, as may be expected given the credit rating.

[11] For a list of constituents, please refer to the Markit website via: http://www.markit.com/en/products/data/indices/structured-finance-indices/abx/documentation.page?#.

Figure 1: The US structured finance market index - the ABX indices

This figure plots the daily closing prices of the ABX.HE.1 indices. The ABX.HE.1 vintage consists of five ABX indices that reference underlying subprime RMBS deals with credit ratings AAA, AA, A, BBB and BBB- (Source: Reuters).



3.2. Decomposing bank risk

Following the variance decomposition approach in the prior literature, we decompose bank equity risk into six components: market, interest rate, market default risk, crisis-related (ABX), funding illiquidity (ABCP), and residual risks.[12] Using this decomposition, we extend the literature to isolate bank crisis-related risks, investigate their relationships with fundamental characteristics, and examine the presence of specific effects relating to the recent financial crisis. We estimate

[12]See for example Anderson and Fraser (2000), Pathan (2009), and Haq and Heaney (2012).

multifactor models for each bank stock using daily returns. To isolate the contribution of each factor in this model, we apply an orthogonalisation to the factors, allowing us to decompose the six risk components. The specifics of our empirical approach are as follows:

1. Using all daily observations in each quarter, we construct orthogonalised factor variables by running the following regressions in order:

$$INT_t = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t}, \tag{1}$$

$$DEF_t = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} + \epsilon_{DEF,t}, \tag{2}$$

$$R_{ABX,t} = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} + \epsilon_{DEF,t} + \epsilon_{ABX,t}, \tag{3}$$

$$ABCP_t = \alpha + \beta R_{MKT,t} + \epsilon_{INT,t} + \epsilon_{DEF,t} + \epsilon_{ABX,t} + \epsilon_{ABCP,t}, \tag{4}$$

   where $R_{MKT,t}$ is the daily excess returns on the value-weighted CRSP market index, INT_t is the daily yield on three-month Treasury bills, DEF_t is the default spread between Moody's AAA and BAA corporate bond yields, $R_{ABX,t}$ is the daily excess returns on the ABX AAA index, and $ABCP_t$ is the daily yield spread of the one-month ABCP above the one-month Treasury bill rates. Importantly, ϵ measures the innovations of each factor, which are orthogonal to the other factors.

   The ordering of factor variables in the orthogonalisation process may be important. We choose this order for two reasons. First, we follow the prior studies that commonly decompose bank risk into market and interest rate risk as the most prominent risks that bank stocks are exposed to (for recent examples see Pathan, 2009, and Haq and Heaney, 2012). Stiroh (2006a) also includes the default spread in the decomposition. Given the importance of MKT_t, INT_t and DEF_t established in these studies, we assign them as the first three variables to be orthogonalised. Second, Longstaff (2010) presents strong evidence of contagion from the ABX indices into the equity market. Given this evidence and that one of our main objectives is to study the fundamental determinants of bank exposure to the shocks from the crisis-related ABX indices, we include ABX_t next. $ABCP_t$ is therefore the last risk factor included and captures the covariance between bank stock returns and innovations in the asset-backed money market factor. The lack of substantial evidence on the effects of ABX_t and $ABCP_t$ mean that the ordering choice of these variables is largely an empirical matter. Our sensitivity analysis in Section 5 considers this ordering more formally.[13]

2. We use the innovations to the factor variables (ϵ) to estimate a multifactor model for the excess returns on the i^{th} BHC:[14]

$$R_t^i = \alpha^i + \beta^i R_{MKT,t} + \gamma_1^i \epsilon_{INT,t} + \gamma_2^i \epsilon_{DEF,t} + \gamma_3^i \epsilon_{ABX,t} + \gamma_4^i \epsilon_{ABCP,t} + \varepsilon_t^i, \tag{5}$$

3. As the factor innovations are orthogonal to each other, the variance decomposition is straightforward:

$$\sigma_i^2 = \beta_i^2 \sigma_{MKT}^2 + \gamma_{i,1}^2 \sigma_{\epsilon_{INT}}^2 + \gamma_{i,2}^2 \sigma_{\epsilon_{DEF}}^2 + \gamma_{i,3}^2 \sigma_{\epsilon_{ABX}}^2 + \gamma_{i,4}^2 \sigma_{\epsilon_{ABCP}}^2 + \sigma_\varepsilon^2, \tag{6}$$

where σ_i^2, σ_{MKT}^2 and σ_ε^2 refer to the variances of the excess returns of the i^{th} BHC, market index and the residuals of equation (5), and $\sigma_{\epsilon_{INT}}^2$, $\sigma_{\epsilon_{DEF}}^2$, $\sigma_{\epsilon_{ABX}}^2$, $\sigma_{\epsilon_{ABCP}}^2$ refer to the variances of the factor innovations of the US interest rate, default spread, ABX index, and ABCP yield spread, based on the daily observations over each quarter.

4. We obtain the quarterly equivalent risk measures for each BHC at each quarter (subscripts t omitted) as follows:

$$\sigma_i^{TOTAL} = \sigma_i \times \sqrt{T}, \tag{7}$$

$$\sigma_i^{MKT} = \sqrt{\beta_i^2 \sigma_{MKT}^2} \times \sqrt{T}, \tag{8}$$

$$\sigma_i^{INT} = \sqrt{\gamma_{i,1}^2 \sigma_{\epsilon_{INT}}^2} \times \sqrt{T}, \tag{9}$$

$$\sigma_i^{DEF} = \sqrt{\gamma_{i,2}^2 \sigma_{\epsilon_{DEF}}^2} \times \sqrt{T}, \tag{10}$$

$$\sigma_i^{ABX} = \sqrt{\gamma_{i,3}^2 \sigma_{\epsilon_{ABX}}^2} \times \sqrt{T}, \tag{11}$$

$$\sigma_i^{ABCP} = \sqrt{\gamma_{i,4}^2 \sigma_{\epsilon_{ABCP}}^2} \times \sqrt{T}, \tag{12}$$

$$\sigma_i^{RESID} = \sigma_{\varepsilon_i} \times \sqrt{T}, \tag{13}$$

where T is the number of daily observations in each quarter. These volatilities are our measures of total, market, interest rate, default spread, crisis-related, funding illiquidity, and residual risks.

[13]We are grateful to an anonymous referee for emphasising the importance of the justification of this ordering and the sensitivity analysis.

[14]We screen out those bank-quarters when there are less than 30 daily observations within any quarters in estimating equation (5).

3.3. Bank variables

The bank variables can be grouped into six categories: loan portfolio asset composition; profitability; loan portfolio asset quality; funding illiquidity; capital adequacy and other control variables.

For bank asset composition, we follow Jones et al. (2013) and compute the proportion of different types of bank assets to total assets as shown in Panel A of Table 1, which describes the construction of all variables. $TRADE\_A$ is the amount of trading assets scaled by total assets, while the total loans variable ($LOAN\_A$) is broken down into three components: commercial real estate ($COMREAL\_A$); residential real estate ($RESREAL\_A$) and all other loans ($OTHLOAN\_A$). The proportion of other assets that are transparent is denoted by $TRANSP\_A$. $OTHOPAQ\_A$ measures the amount of all other opaque assets, which may include ABS (and MBS) and other fixed assets and real estate investments. All other opaque assets are computed as total assets minus trading assets ($TRADE$), total loans ($LOAN$) and transparent assets ($TRANSP$). The six types of assets sum to one for each bank in each quarter by construction.

[Insert Table 1 here]

Bank profitability is measured by both earnings before income taxes and extraordinary items to total assets (EBT_A) and non-interest income to total assets ($NONINT\_A$). Non-performing loans are measured by the sum of total loans that are 90 days or more past due, or are in non-accrual status, and their proportion of total assets (NPL_A) is a gauge of the credit quality of bank loan portfolios. To measure bank funding illiquidity and capital adequacy, we include the ratio of total loans to total core deposits ($LOAN\text{-}TO\text{-}DEPOSIT$) and the ratio of Tier 1 capital to total risk-weighted assets ($TIER1\_CAP$). A higher loan-to-deposit ratio and lower Tier 1 capital ratio mean that the bank has less ability to fund any unforeseen requirements and is more vulnerable to funding illiquidity risk.

To measure bank equity liquidity, we compute turnover ratios by dividing the number of shares traded by the number of outstanding shares in each month, following Chordia et al. (2001). We average the monthly turnover ratios over the three months in each quarter and then log transform the ratios. We also include the log market capitalisation to control for size.[15] Other control variables include a proxy for interest rate risk exposure, computed as the absolute value of the difference between short-term assets and short-term liabilities and equity, and bank franchise value, as measured by Keeley's Q.[16]

3.4. Empirical approach

To identify the determinants of bank risk, we estimate pooled WLS regressions with two-way fixed effects as follows:

$$\begin{aligned} LN(\sigma^j)_{i,t} =& \alpha_1(TRADE\_A)_{i,t-1} + \alpha_2(OTHLOAN\_A)_{i,t-1} + \alpha_3(OTHOPAQ\_A)_{i,t-1} \\ &+ \alpha_4(TRANSP\_A)_{i,t-1} + \alpha_5(COMREAL\_A)_{i,t-1} + \alpha_6(RESREAL\_A)_{i,t-1} \\ &+ \alpha_7(EBT\_A)_{i,t-1} + \alpha_8(NONINT\_A)_{i,t-1} + \alpha_9(NPL\_A)_{i,t-1} \\ &+ \alpha_{10}(LOAN\text{-}TO\text{-}DEPOSIT)_{i,t-1} + \alpha_{11}(TIER1\_CAP)_{i,t-1} + \alpha_{12}(INTRISK\_A)_{i,t-1} \\ &+ \alpha_{13}(KEELEY's\ Q)_{i,t-1} + \alpha_{14}LN(TURN)_{i,t-1} + \alpha_{15}LN(MCAP)_{i,t-1} \\ &+ \sum_{i=1}^{227}\gamma_i(BHC)_i + \sum_{t=1}^{24}\psi_t(Quarter)_t + \epsilon_{i,t}, \end{aligned} \tag{14}$$

where i denotes the individual BHC ($i = 1, 2, \ldots, 227$), t denotes the quarterly period ($t = 1, 2, \ldots, 24$) and j denotes the risk measure: TOTAL; MKT; INT; DEF; ABX; ABCP or RESID. α, γ and ψ are the coefficients to be estimated. BHC and $Quarter$ are bank and quarter dummy variables respectively. To control for unobserved heterogeneity across banks and quarters, we use the least squares dummy variables (LSDV) approach with bank and quarter fixed effects. Following Jones et al. (2013), we use bank size as the weight in the pooled regressions and measure size by log market capitalisation ($LN(MCAP)_{t-1}$). While both OLS and WLS regressions yield consistent coefficient estimates, we prefer the WLS approach for its ability to control for heteroscedasticity

[15] As the bank equity risks are market-based, the use of log market capitalisation (which is also market-based) provides better explanatory power than the use of log deflated total assets. Using log deflated total assets as the size measure has no effects on our main results.

[16] Keeley's Q is computed by summing market value and total liabilities, then dividing by book equity value. Keeley (1990) argues that the Q measure is a proxy for franchise value.

related to size and therefore provide more efficient estimates. Since OLS residuals tend to be larger among small banks, using bank size (relative to total market cap) as the weight allows us to control for the heteroscedasticity and attribute proportionately more weight to large-cap bank stocks.[17] In addition, to ensure that our statistical inference is not biased by correlations in variables across firms and time, we cluster robust standard errors by both firm and time dimensions following Cameron et al. (2011).[18] We suppress the intercept terms given that the loan asset composition variables sum up to unity at each cross-section.

To investigate whether the relationships between fundamental variables and bank risks changed during the crisis, we add a crisis dummy variable to each regression and interact it with the asset composition and fundamental variables. The crisis window is defined as 2007Q1-2009Q1 such that the start coincides with Longstaff's (2010) subprime crisis subperiod, while the end date is consistent with Beltratti and Stulz (2012).[19] By focusing on the interaction terms on bank earnings, non-interest income, non-performing loans, loan-to-deposit ratios and Tier 1 capital ratios with the crisis dummy variables, this study reveals the impact of the recent crisis on the relationships between bank fundamental characteristics and equity risk.

4. Empirical results

4.1. Summary statistics

Table 2 reports the full sample and subsample means, medians and standard deviations of the bank variables. Mean inflation-adjusted total bank assets is \$51.7 billion. Loan assets represent the largest proportion of bank assets averaging 69.0% with 14.5% in commercial real estate loans, 17.0% in residential real estate loans and 37.4% in other loans. Other opaque assets, transparent

[17]In unreported results, pooled OLS regressions yield qualitatively and quantitatively similar results, but confirm the size related heteroscedasticity in residuals.

[18]Our regressions contain independent variables that may be correlated within firms, across time, and simultaneously across both firm and time, so two-way clustering of standard errors is helpful in eliminating potential bias (Thompson, 2011).

[19]While a number of empirical studies define the start of the recent crisis as 2007Q3 (see for example Edmonds et al., 2010; Flannery et al., 2013; Olson et al., 2012), we define 2007Q1 as the start of the crisis window because this is precisely when the ABX indices started to decline sharply.

assets and trading assets average 23.7%, 6.4% and 0.7% respectively. In comparison to Jones et al.'s (2013) 2000-06 sample period, banks have noticeably less commercial real estate loan assets on their balance sheets, falling from 27.6% during 2000-06 to 14.5% in 2006-11. In our sample, the proportion of bank commercial real estate loans to total assets declines from 34.1% to 19.8% from the pre-crisis to the crisis period.[20] Total loans to total assets increased from the pre-crisis level of 68.6% to 71.6% during the crisis while trading assets also increased from 0.6% to 0.9%.

[Insert Table 2 here]

For bank profitability, the full sample mean (median) earnings to total assets is 0.1% (0.9%) while the mean (median) non-interest income to total assets is 1.2% (1.0%). The subsample statistics show that the mean earnings to total assets declined from the pre-crisis level of 1.6% to 0.1% during the crisis and to -0.4% during the post-crisis subsample. Bank credit risks heightened during and after the crisis as evidenced by the increases in non-performing loans to total assets from the pre-crisis level of 0.4% to 1.2% during the crisis, and further to 2.9% in the post-crisis subsample. As for bank funding ability, the mean loan-to-deposit ratio increased from 1.42 to 1.50 while the Tier 1 capital ratio declined from 11.5% to 10.8% in the crisis subsample so that banks on average faced a more constrained funding position and had less equity capital as a buffer against liquidity shocks.

All bank risks increased remarkably during the crisis, approximately threefold, and remained at comparatively high levels in the post-crisis subsample. The full sample mean TOTAL risk is 28.46% while the RESID risk represents the second largest risk component with a mean value of 24.26%. The third largest component of equity risk is MKT risk which has a mean value of 10.20%. The full sample mean INT, DEF, ABX and ABCP risks are 2.23%, 2.37%, 2.56% and 2.60% respectively. The percentage increases in mean risks from the pre-crisis to crisis subsamples are considerable, measuring 185.7% for TOTAL risk, 201.43% for MKT risk, 123.4% for INT risk, 216.4% for DEF risk, 221.2% for ABX risk, 184.2% for ABCP risk, and 179.6% for RESID risk.

Table 3 reports the pairwise correlations between the bank variables. The decomposed bank risks are negatively related to earnings, non-interest income, Tier 1 capital, Keeley's Q and log

[20]The statistics are consistent with Cornett et al. (2011) who show that during 2008, US commercial banks received more core deposits and extended more commercial and industrial loans.

market capitalisation, but are positively related to non-performing loans and loan-to-deposits, consistent with our hypotheses. The statistics indicate that the decomposed bank risks are closely related to their fundamental characteristics. The non-performing loans ratio is moderately and negatively correlated with earnings and Keeley's Q while the log turnover ratios are moderately correlated with log market capitalisation.

[Insert Table 3 here]

4.2. Determinants of bank risk - baseline model

Table 4 reports the results of the estimation of equation (14) when either TOTAL, MKT, INT, DEF, ABX, ABCP, or RESID risks are the dependent variables. The model fit of the WLS regressions is satisfactory and yield the following R^2 values: 82% (TOTAL); 65% (MKT); 32% (INT); 32% (DEF); 31% (ABX); 30% (ABCP); and 83% (RESID). F-tests of joint significance of the right hand side variables are significant at the 1% level for all seven risk models, but are not reported for brevity.

Hypothesis 1A, suggesting a relation between asset composition and bank risk, is not supported for most risks. The variables measuring the composition of loan assets are not related to bank risk, apart from in the interest rate risk model. In this particular model, the coefficients on trading assets, other loans and commercial real estate assets are significant and negative. Banks with larger proportions of these types of loan assets are less exposed to risk from the interest rate factor. Hypothesis 1B, which asserts that banks with more opaque assets are more risky, is also not supported according to the significance of coefficient estimates. More interestingly, in addition to the trading assets, other loans and commercial real estate assets, which are all relatively opaque, the proportion of other opaque assets also reduces exposure to the interest rate risk factor. This surprising result suggests that banks with larger proportions of opaque assets have stock returns that are less responsive to short term interest rate shocks. The opacity of assets seems to prevent the accurate pricing of interest rate risk in particular. Aside from the significance of coefficient estimates, F-tests of equality between the estimated coefficients of the five types of opaque and transparent assets confirm this finding for other risk factors. As shown at the bottom of Table 4, the impact of opaque assets on bank risk is more negative than that of transparent assets and this occurs in the majority of risk models and for three types of opaque asset. Therefore, although not always captured by significant coefficients, the F-tests suggest that bank investment in opaque assets translated into lower equity risk. Although apparently counterintuitive, this is consistent with Jones et al. (2013) who conclude that the risks in opaque assets are not priced accurately.

[Insert Table 4 here]

In testing our remaining hypotheses, Table 4 shows evidence that bank fundamental variables predict the seven equity risks, lending support to Hypotheses 2A, 3A, and 4A. The estimated coefficients on earnings are statistically significant and negative in the TOTAL, MKT, ABX, and RESID risk models. For an economic interpretation, the estimated coefficients of the log-linear equation mean that a standard deviation increase in earnings (approximately 3.0%) is associated with 3.83% lower TOTAL risk, 3.56% lower MKT risk, 9.77% lower ABX risk, and 3.68% lower RESID risk.[21] While these figures show the percentage change in the risk variables for a meaningful change in earnings, their economic significance is better observed by relating them to the scale of the risk variable as captured by their median values. The coefficients on non-interest income are also significant in the TOTAL and RESID risk models and banks with more income arising from non-traditional activities have less total and firm-specific risks. With regard to internal risk control, the coefficients on the non-performing loans are statistically significant and negative for TOTAL, INT, DEF and RESID risks. These coefficients imply that a standard deviation increase in non-performing loans relative to total assets (2.1%) relates to 6.57% higher TOTAL risk, 20.02% higher INT risk, 11.84% higher DEF risk, and 7.10% higher RESID risk. The evidence confirms that banks with stronger risk control have significantly lower risk. The lower exposure to the adverse shocks in the market-wide default risk, which has not received as much attention as the other more popular TOTAL, MKT, INT and RESID risks, is consistent with Ellul and Yerramilli (2013). The estimated coefficients of the Tier 1 capital ratios are highly significant and negative across all bank risks except MKT and ABX. A standard deviation increase in Tier 1 capital ratios (3.40%) is therefore associated with 6.12% lower TOTAL risk, 12.49% lower INT risk, 14.82% lower DEF

[21] We are grateful to an anonymous referee for highlighting the importance of different methods of interpreting coefficient values. We calculate the change in risk for a standard deviation change in earnings (3.0%) as $Exp(0.030 * (-1.303)) - 1 = -0.0383$, or -3.83%.

risk, 9.01% lower ABCP risk, and 5.80% lower RESID risk.

The evidence in the baseline regressions indicates that bank equity risk is related most strongly to profitability, internal risk control, and regulatory capital. The innovation of these results is that banks with more vulnerable fundamentals are significantly more exposed to risk. In some cases, these adverse effects are found in DEF, ABX, ABCP risks, which can only be observed using our decomposition method. The evidence motivates investors and other market participants to conduct fundamental analysis to help predict bank stock return volatilities, particularly in a sample period characterised by heightening macroeconomic uncertainty and risk aversion. From a regulatory perspective, we find a significant and negative relationship between bank equity capital and risk, a finding that highlights the effectiveness of Tier 1 capital as a buffer against shocks. Good management of bank regulatory capital helps reduce equity risk and may help prevent systemic bank failures in times of funding illiquidity.

4.3. Crisis interaction effects

Table 5 reports the estimation results of our regression models including the crisis dummy and interaction variables. The loan asset composition variables, earnings, non-interest income, non-performing loans, loan-to-deposit ratios and Tier 1 capital ratios are interacted with the crisis dummy variable to allow for shift changes in the slope coefficients measuring the incremental effect on the relationship during the crisis. We report the results of each crisis model for the TOTAL, MKT, INT, DEF, ABX, ABCP, or RESID decomposed risks as the dependent variables. We include bank fixed effects while the standard errors are clustered by both firm and time dimensions.

The estimated coefficients of the crisis dummy variables are significant and positive in the TOTAL, ABCP and RESID risk models. In the crisis period, average TOTAL, ABCP, and RESID risks increase enormously by 8.37, 73.29, and 14.18 times, respectively. Clearly, bank equity risk increased dramatically during the crisis, but the most extreme increase seen in ABCP risk shows the importance of our decomposition for improving our understanding of bank risk exposure, especially in crisis periods. During the non-crisis period, the bank loan asset composition variables contribute significantly and positively to TOTAL and RESID risks, lending some support to Hypothesis 1A. However, we find no significant differences between the impact of opaque and transparent assets on bank risk, inconsistent with Hypothesis 1B, except for INT risk.[22] Analysing the crisis interaction effects in more detail, the estimated coefficients on the interacted loan asset composition variables are in general negative across the risk models, but are only significant for opaque assets and for TOTAL, ABCP and RESID risks. The incremental effect of the crisis was to reduce the relationship between the proportion of opaque assets and these risks. Estimating the crisis models, therefore, uncovers more interesting relationships for the asset composition variables compared to the weak negative relationship documented in the baseline model of Table 4. The evidence, particularly for ABCP exposure, is consistent with the findings of Gatev and Strahan (2006). They show that in times of market-wide funding liquidity stress, banks tend to receive liquidity inflows in the form of deposits, increase their holdings of liquid assets and fund greater proportions of assets with these deposits. These suggest that the increased availability of bank deposit finance to fund loan assets is a natural hedge against funding liquidity shocks as captured by a lower exposure to the ABCP risk. The negative interaction coefficient for ABCP risk is therefore consistent with the negative correlation between spreads and bank funding inflows explained by Gatev and Strahan (2006).

[Insert Table 5 here]

During the non-crisis period, the impact of bank earnings and Tier 1 capital ratios on bank risk remains qualitatively similar to the baseline regression results. The slight differences are that coefficients on earnings are slightly smaller in magnitude with less statistical significance, whilst those on the Tier 1 capital ratio are larger in absolute terms, but also show less statistical significance. An interesting finding for the coefficient on earnings is that in the MKT risk model it becomes positive and significant at the 10% level in the non-crisis period. This is consistent with Jones et al. (2013) who show that investments in opaque assets required higher rates of return and led to higher systematic risk over the 2000-06 period. The crisis interaction term however is strongly neg-

[22]We estimate F-tests of coefficient equality between the coefficients of the opaque and transparent assets in a similar fashion as in the baseline models of Table 4. The F-statistics are insignificant across all bank risk models in the non-crisis and crisis settings, and hence, the results are not reported here. The only exception is for the INT risk model in which we find that the opaque assets relate to lower risk compared to transparent assets, and this occurs during both the non-crisis and crisis periods. Since the results of the INT risk model are qualitatively similar to those of the baseline models, they are not reported for brevity, but are available upon request.

ative for MKT risk showing that during the crisis period the incremental effect on this relationship reversed such that banks with higher earnings were less exposed to MKT risk when the risks and huge losses from opaque assets emerged. Non-interest income shows negative coefficients in the non-crisis period that are much larger compared to the baseline model, but not always statistically significant. Non-interest income is significantly negatively related to MKT and INT risks in the non-crisis period, becoming significant compared to the baseline regression, whereas significance is lost for TOTAL and RESID risks. These findings confirm the importance of decomposing equity risk and modelling the crisis to improve our understanding of risks over this period. The impact of non-interest income on MKT risk is particularly interesting since it shows a large and significant positive incremental effect during the crisis, which offsets the large and significant negative effect in the non-crisis period. This suggests that non-traditional sources of income reduce bank exposure to MKT risk in normal times by diversifying sources of income, but generated a large incremental increase in this risk when such non-interest income suffered in the crisis period. This further confirms the importance of decomposing risk and modelling the crisis effects to interpret the relationships between fundamental variables and risk.

For bank internal risk control, during the non-crisis subsample the coefficients on non-performing loans for all bank risks are considerably lower, sometimes negative, and always insignificant compared to the baseline results. The significant positive relationship identified in the baseline model is in part related to a crisis effect so Hypothesis 4A may not hold unconditionally. The estimated coefficients on the crisis interaction terms for non-performing loans are significant and positive in the TOTAL and RESID risk models. The relation between non-performing loans and TOTAL and RESID risks intensified during the crisis, lending support to Hypothesis 4B. In economic terms, a standard deviation increase in non-performing loans is associated with a change of 7.32% in TOTAL risk and 7.49% in RESID risk in the crisis periods. These marginal effects of non-performing loans on bank risk are approximately three times larger than in the crisis compared to the non-crisis period. Bank equity volatility during the crisis was therefore strongly related to faults in credit risk management. An alternative interpretation is that the benefit of more effective risk control was about three times more prominent when extreme risks were encountered during the crisis. In contrast, the interaction terms on bank earnings and Tier 1 capital ratios are insignificant suggesting no incremental changes in their relation to bank risks during the crisis, rejecting Hypotheses 2B and 3B. However, our evidence shows that bank earnings and Tier 1 capital ratios are significantly associated with bank risk throughout the sample, implying that their significance in predicting risk is present at all times and is not emphasised during the crisis.

Regarding the remaining control variables, log turnover ratios are positively correlated with all risks except ABCP risk, consistent with the prior literature.[23] The positive relationship between trading activity and bank equity risk may arise from a possible 'flight-to-safety' phenomenon, as suggested by Longstaff (2010), where investors switch from bank stocks with poorer fundamentals into safer assets. Keeley's Q has a negative coefficient which is significant at the 1% level across all bank risks except in the ABCP model, indicating that higher franchise value is associated with lower risk, also consistent with prior studies. Finally, we confirm a significant size effect found in the extant literature in which banks with a smaller capitalisation are associated with higher equity risks.

5. Sensitivity analysis

One of the contributions of this paper is the decomposition of bank equity risk into six components, which is of particular interest given the risks that arose during the recent crisis. Crucial to this decomposition is the orthogonalisation of risk factors, which requires the specification of the order of risk factors. In this section, we perform a sensitivity analysis to determine whether this ordering is important. In our baseline model, the order of the factor variables is as follows: MKT_t, INT_t, DEF_t, ABX_t and $ABCP_t$. As many prior studies show that the MKT_t and INT_t are important determinants of bank stock returns, we keep the order of the first two variables. The DEF_t variable is well recognised in the asset pricing literature and combined with the recent evidence of Stiroh (2006a) documenting the importance of this factor for banks prompts us to include it as the next factor in the order. There are few studies to guide us in our choice of whether ABX_t or $ABCP_t$ should come next. Given the evidence of contagion from the ABX market to equity markets demonstrated by Longstaff (2010), we opt for ABX_t to precede $ABCP_t$, but are intrigued to investigate their relative importance empirically. This section performs this sensitivity analysis by re-estimating both the baseline and crisis models to compare Permuatation 1 (P1: ABX_t fol-

[23]For a review on the relationship between price changes and trading volume, see Karpoff (1987).

lowed by $ABCP_t$) and Permutation 2 (P2: $ABCP_t$ followed by ABX_t). For each permutation, we obtain the innovations for ABX_t and $ABCP_t$ and use them to re-estimate equation (5). We obtain the decomposed bank risks using equations (6) - (13) and use them as dependent variables in the crisis WLS regression. Since the measurement of all other risk factors is identical in these two permutations of the orthogonalisation process, only regressions results for ABX and ABCP risks need to be reported. Firm fixed effects are included and the robust standard errors are clustered by firm and time. The results are presented in Table 6.[24]

[Insert Table 6 here]

Comparing P1 and P2, the results are quite similar suggesting that their ordering in the orthogonalisation process has little impact on the results. There are a few cases where the magnitudes of coefficient estimates differ due to the ordering, particularly for the asset composition variables; but for fundamental variables, crisis effects and control variables, the estimates are reasonably similar. In only rare cases does the statistical significance of coefficients differ between permutations. Focussing on these significant coefficients, there seems to be a tendency for Permutation 2 with $ABCP_t$ appearing first to deliver larger (absolute) and more significant estimates (apart from on the earnings to total assets variable). This suggests that our preferred ordering (Permutation 1) may be providing more conservative estimates compared to Permutation 2. Given that the contributions of ABX and ABCP risks to TOTAL risk are relatively small, we are not concerned about relatively minor differences in coefficient estimates between the Permutations and we do not change our conclusions.

6. Conclusions

This paper extends prior studies by decomposing bank equity risk into six components: market; interest rate; market default risk; structured finance-related; funding illiquidity; and residual risks. The second objective is to identify the major determinants of the decomposed bank risks based on

[24]For comparison, we also estimate OLS regressions and obtain similar results. We also experiment with six permutations that allow DEF_t, ABX_t and $ABCP_t$ to be re-ordered. We find no evidence that changes in the ordering of these three factors generates any noticeable differences in our results.

a number of fundamental variables, including bank loan asset composition, profitability, loan asset credit quality and funding ability. Our third contribution is the analysis of the impact of the recent crisis, an interesting period characterised by contagion emanating from the structured finance and asset-backed money markets, on these relationships.

In considering asset composition, we evaluate whether bank trading, loan, opaque and transparent assets are related to their equity risk and find that they contribute positively (negatively) to risk during the non-crisis (crisis) period, but rarely significantly. We find no significant difference between the impact of opaque and transparent assets on bank risk during the crisis, suggesting that the risk in their opaque investments was not accurately priced, consistent with Jones et al. (2013). We present significant evidence that more profitable banks, as measured by earnings and non-interest income, have lower risk, a finding that highlights the relevance of fundamental analysis for evaluating bank equity risk. Using non-performing loans as a proxy for bank internal credit risk control, we find strong evidence that banks with better risk control fared better during the crisis. In particular, we present new evidence that the marginal effects of non-performing loans on bank risk increased threefold during the crisis. Finally, we show that banks with a larger buffer of Tier 1 capital have lower risk. Our decomposition shows that Tier 1 capital is associated with lower lower exposure to shocks emanating from market-wide default risk, contagion from the structured finance market and asset-backed funding illiquidity. However, we find no crisis interaction effects for any risk components, which confirms that the importance of bank risk management using Tier 1 capital is not dependent on the crisis.

From an investor's perspective, our findings provide new evidence that bank fundamental characteristics predict bank risk. The identification of the fundamental sources of decomposed bank equity risk thus provides useful implications to investors for investment and risk management. From a regulatory perspective, the evidence of a strong negative relationship between Tier 1 capital and decomposed risk confirms the important role of equity capital in absorbing shocks, and provides justification for the increase in regulatory capital requirements. While the experience of the recent crisis highlights bank vulnerability to funding illiquidity shocks, managing bank equity capital seems to be an effective means of preventing future problems and possible bank failures.

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Table 1: Description of variables

Variables	Description
Panel A: Bank loan portfolio composition	
$TRADE\_A$	Trading assets to total assets.
$LOAN\_A$	Total loans to total assets.
$COMREAL\_A$	Commercial real estate loans to total assets.
$RESREAL\_A$	Residential real estate loans to total assets.
$OTHLOAN\_A$	All other loans to total assets. $OTHLOAN$ is computed as total loans minus the commercial real estate loans and residential real estate loans.
$TRANSP\_A$	All transparent assets to total assets. These include cash, federal funds sold, securities under reselling agreement, guaranteed available-for-sale and held-to-maturity securities.
$OTHOPAQ\_A$	All other opaque assets to total assets. These include available-for-sale or held-to-maturity mortgage-backed-securities (MBS), or asset-backed securities (ABS) that are not guaranteed by a government entity; fixed assets; investments in unconsolidated subsidiaries; and other real estate investments. $OTHOPAQ$ is computed as total assets minus total loans, trading assets and transparent assets.
Note: $TRADE\_A + COMREAL\_A + RESREAL\_A + OTHLOAN\_A + OTHOPAQ\_A + TRANSP\_A = 1$.	
Panel B: Bank fundamental variables	
EBT_A	The earnings before extraordinary items and taxes to total assets (annualised).
$NONINT\_A$	Non-interest income to total assets (annualised).
NPL_A	Proportion of non-performing loans to total assets. We define non-performing loans as the sum of total loans that are 90 days or more past due or are in non-accrual status.
$LOAN\text{-}TO\text{-}DEPOSIT$	Total loans to total core deposits.
$TIER1\_CAP$	Tier 1 capital to total risk-weighted assets.
Panel C: Market and other control variables	
$INTRISK\_A$	The absolute value of the difference between short-term assets and short-term liabilities and equity, normalised by total asset.
$LN(TURN)$	Natural log of the turnover ratio. Turnover ratio is the number of shares traded over the number of shares outstanding in a month. We use the natural log of the monthly average of turnover ratios over the three months in each quarter.
$LN(MCAP)$	Natural log of market capitalisation of bank stock. Market capitalisation is computed as the product of price and number of shares outstanding at the end of each quarter.
$KEELEY's\ Q$	The sum of market value of common equity and book value of liabilities divided by the book value of assets. It is used as a measure of franchise value (see Anderson and Fraser, 2000).

This table provides the description and definition of the bank variables used in this paper. All balance sheet variables are computed as averages of the beginning and ending quarter values while we deflate the total assets using a seasonally-adjusted GDP deflator with a base year of 2005.

Table 2: Summary statistics

Variable	Full sample			Pre-crisis		Crisis		Post-crisis	
	Mean	Median	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Panel A: Bank equity risk (in %)									
σ^{TOTAL}	28.458	21.811	21.946	11.555	4.158	33.007	25.537	30.950	19.649
σ^{MKT}	10.195	6.523	11.529	4.349	3.647	13.109	15.216	9.971	8.799
σ^{INT}	2.230	1.296	3.000	1.109	1.103	2.478	3.153	2.440	3.246
σ^{DEF}	2.365	1.361	3.094	0.941	0.787	2.977	3.734	2.389	2.876
σ^{ABX}	2.560	1.509	3.422	0.955	0.876	3.068	4.178	2.735	3.143
σ^{ABCP}	2.598	1.515	3.319	1.055	1.008	2.998	3.810	2.838	3.285
σ^{RESID}	24.261	17.540	20.135	9.868	3.861	27.589	22.325	26.824	19.540
Panel B: Bank loan portfolio composition									
$TRADE\_A$	0.007	0.000	0.027	0.006	0.027	0.009	0.034	0.005	0.019
$LOAN\_A$	0.690	0.708	0.128	0.686	0.133	0.716	0.129	0.671	0.122
$COMREAL\_A$	0.145	0.039	0.182	0.341	0.163	0.198	0.200	0.030	0.026
$RESREAL\_A$	0.170	0.172	0.089	0.170	0.090	0.164	0.089	0.176	0.088
$OTHLOAN\_A$	0.374	0.394	0.189	0.174	0.090	0.353	0.207	0.464	0.129
$OTHOPAQ\_A$	0.237	0.228	0.110	0.248	0.120	0.225	0.113	0.244	0.103
$TRANSP\_A$	0.064	0.046	0.060	0.059	0.079	0.049	0.052	0.079	0.054
Panel C: Bank fundamental variables									
EBT_A	0.001	0.009	0.030	0.016	0.009	0.001	0.033	−0.004	0.031
$NONINT\_A$	0.012	0.010	0.012	0.014	0.014	0.012	0.011	0.012	0.012
NPL_A	0.018	0.012	0.021	0.004	0.004	0.012	0.015	0.029	0.023
$LOAN\text{-}TO\text{-}DEPOSIT$	1.363	1.242	0.599	1.422	0.893	1.503	0.612	1.228	0.388
$TIER1\_CAP$	0.117	0.114	0.034	0.115	0.029	0.108	0.026	0.125	0.039
Panel D: Market and other control variables									
$INTRISK\_A$	0.150	0.124	0.114	0.162	0.111	0.144	0.105	0.151	0.122
$LN(TURN)$	−0.808	−0.796	1.298	−1.151	0.991	−0.781	1.394	−0.704	1.296
$ASSET$ \$Million	51,700	1,466	246,000	48,000	210,000	56,000	258,000	49,500	249,000
$MCAP$ \$Million	5,504	151	24,500	8,111	32,600	5,960	26,000	4,181	19,000
$LN(MCAP)$	7.780	7.322	2.128	8.506	1.998	7.939	2.042	7.386	2.156
$KEELEY's\ Q$	1.020	1.009	0.064	1.090	0.052	1.027	0.060	0.988	0.046

This table reports the full sample, pre-crisis, crisis and post-crisis subsample means, medians and standard deviations (Stdev) of the bank variables used in this paper. For a detailed description of the variables, please refer to Table 1. The crisis subperiod covers the period 2007Q1 to 2009Q1 as described in Section 3.4.

Table 3: Pairwise correlations

Correlation matrix

	Variables	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22
V1	$LN(\sigma^{TOTAL})_t$	1.00																					
V2	$LN(\sigma^{MKT})_t$	0.42	1.00																				
V3	$LN(\sigma^{INT})_t$	0.51	0.18	1.00																			
V4	$LN(\sigma^{DEF})_t$	0.53	0.20	0.28	1.00																		
V5	$LN(\sigma^{ABX})_t$	0.52	0.14	0.25	0.29	1.00																	
V6	$LN(\sigma^{ABCP})_t$	0.53	0.19	0.29	0.30	0.29	1.00																
V7	$LN(\sigma^{RESID})_t$	0.96	0.24	0.50	0.52	0.53	0.52	1.00															
V8	$TRADE\_A_{t-1}$	−0.02	0.13	−0.02	−0.02	−0.03	−0.02	−0.09	1.00														
V9	$OTHLOAN\_A_{t-1}$	0.53	0.25	0.26	0.27	0.30	0.30	0.52	−0.11	1.00													
V10	$OTHOPAQ\_A_{t-1}$	−0.18	0.06	−0.11	−0.10	−0.15	−0.13	−0.23	0.06	−0.32	1.00												
V11	$TRANSP\_A_{t-1}$	0.04	0.05	0.04	0.00	0.03	0.05	0.01	0.20	−0.02	−0.13	1.00											
V12	$COMREAL\_A_{t-1}$	−0.42	−0.31	−0.20	−0.18	−0.20	−0.22	−0.35	−0.13	−0.69	−0.22	−0.19	1.00										
V13	$RESREAL\_A_{t-1}$	−0.05	−0.04	−0.04	−0.05	−0.05	−0.04	−0.05	−0.02	−0.21	−0.03	−0.15	−0.18	1.00									
V14	EBT_A_{t-1}	−0.47	−0.11	−0.29	−0.29	−0.30	−0.27	−0.50	0.02	−0.34	0.17	−0.05	0.24	0.05	1.00								
V15	$NONINT\_A_{t-1}$	−0.21	0.10	−0.15	−0.13	−0.16	−0.16	−0.28	0.25	−0.16	0.30	0.00	−0.14	0.15	0.26	1.00							
V16	NPL_A_{t-1}	0.47	0.12	0.30	0.26	0.27	0.25	0.48	−0.05	0.49	−0.18	0.13	−0.42	−0.03	−0.52	−0.17	1.00						
V17	$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	0.13	0.07	0.09	0.10	0.07	0.07	0.13	0.23	0.07	−0.22	−0.02	0.06	−0.09	−0.10	−0.06	0.10	1.00					
V18	$TIER1\_CAP_{t-1}$	−0.20	−0.07	−0.13	−0.16	−0.12	−0.11	−0.20	−0.12	−0.14	0.33	0.22	−0.12	0.04	0.24	0.02	−0.15	−0.23	1.00				
V19	$INTRISK\_A_{t-1}$	−0.13	0.08	−0.06	−0.09	−0.07	−0.07	−0.17	0.03	0.09	−0.13	−0.01	0.07	−0.14	0.06	0.19	−0.05	−0.10	−0.08	1.00			
V20	$Keeley's\ Q_{t-1}$	−0.54	−0.04	−0.31	−0.27	−0.32	−0.30	−0.58	−0.01	−0.52	0.15	−0.08	0.51	−0.09	0.44	0.25	−0.51	−0.09	−0.01	0.11	1.00		
V21	$LN(TURN)_{t-1}$	0.06	0.56	0.07	0.06	−0.01	−0.02	−0.10	0.25	0.08	0.12	0.08	−0.19	−0.08	−0.08	0.21	0.13	0.08	−0.10	0.26	0.03	1.00	
V22	$LN(MCAP)_{t-1}$	−0.32	0.37	−0.18	−0.19	−0.26	−0.23	−0.49	0.50	−0.25	0.30	0.04	−0.02	0.02	0.26	0.48	−0.27	0.05	−0.04	0.27	0.39	0.62	1.00

This table reports the pairwise correlations between the bank equity risk, loan portfolio asset composition, fundamental, market and other control variables used in this study. For a detailed description of the variables, please refer to Table 1.

Table 4: Determinants of bank risk - Baseline model

Dependent Variables:	$LN(\sigma^{TOTAL})_t$		$LN(\sigma^{MKT})_t$		$LN(\sigma^{INT})_t$		$LN(\sigma^{DEF})_t$		$LN(\sigma^{ABX})_t$		$LN(\sigma^{ABCP})_t$		$LN(\sigma^{RESID})_t$	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Loan portfolio asset composition:														
$TRADE\_A_{t-1}$	0.589	(0.635)	0.595	(1.082)	−4.851**	(2.465)	3.807	(4.369)	4.317*	(2.596)	3.243*	(1.658)	0.188	(0.643)
$OTHLOAN\_A_{t-1}$	−0.938	(0.587)	0.113	(0.899)	−4.240***	(1.256)	−2.152	(1.539)	−0.036	(1.739)	−0.080	(1.595)	−0.957	(0.633)
$OTHOPAQ\_A_{t-1}$	−0.229	(0.524)	−0.208	(0.533)	−3.101***	(1.030)	−0.466	(1.417)	−0.082	(1.820)	−0.646	(1.394)	−0.112	(0.562)
$TRANSP\_A_{t-1}$	0.416	(0.389)	−0.058	(0.531)	−0.954	(1.218)	−0.708	(1.357)	1.720	(1.934)	1.341	(1.585)	0.494	(0.380)
$COMREAL\_A_{t-1}$	−0.690	(0.596)	−0.406	(0.879)	−2.886**	(1.194)	−1.446	(1.568)	0.024	(1.731)	−0.450	(1.557)	−0.636	(0.618)
$RESREAL\_A_{t-1}$	−0.375	(0.757)	0.173	(1.122)	−2.588	(1.579)	−0.521	(2.396)	0.757	(1.735)	1.539	(1.957)	−0.291	(0.791)
Fundamental variables:														
EBT_A_{t-1}	−1.303***	(0.374)	−1.207**	(0.503)	−0.606	(1.091)	−1.736	(1.340)	−3.427***	(1.070)	−1.094	(1.235)	−1.249***	(0.374)
$NONINT\_A_{t-1}$	−2.824***	(1.083)	−3.375	(2.171)	−4.833	(3.310)	2.637	(3.788)	0.629	(4.221)	−5.160	(4.216)	−2.831**	(1.263)
NPL_A_{t-1}	3.028**	(1.517)	−3.106	(2.812)	8.691***	(2.538)	5.328*	(3.140)	3.049	(3.129)	−0.654	(4.438)	3.266**	(1.579)
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	0.015	(0.020)	0.037	(0.028)	0.214***	(0.061)	−0.056	(0.077)	−0.016	(0.086)	−0.053	(0.070)	0.007	(0.022)
$TIER1\_CAP_{t-1}$	−1.856***	(0.628)	−2.202	(1.472)	−3.924***	(1.343)	−4.719***	(1.673)	−1.683	(1.506)	−2.777*	(1.557)	−1.757***	(0.640)
Control variables:														
$INTRISK\_A_{t-1}$	−0.008	(0.152)	−0.331	(0.285)	0.232	(0.349)	−0.454	(0.351)	0.592	(0.532)	0.375	(0.522)	−0.037	(0.126)
$Keeley's\ Q_{t-1}$	−0.307	(0.445)	0.945	(0.860)	−0.713	(0.963)	−0.629	(1.182)	0.006	(1.111)	−0.365	(1.234)	−0.554	(0.419)
$LN(TURN)_{t-1}$	0.045	(0.028)	0.219***	(0.063)	0.060	(0.061)	0.051	(0.066)	0.120**	(0.048)	−0.033	(0.051)	0.027	(0.022)
$LN(MCAP)_{t-1}$	−0.248***	(0.042)	0.098	(0.073)	−0.360***	(0.084)	−0.323***	(0.075)	−0.308***	(0.096)	−0.280***	(0.097)	−0.323***	(0.043)
Obs.	3,153		3,153		3,153		3,153		3,153		3,153		3,153	
R^2	0.817		0.652		0.316		0.323		0.314		0.298		0.831	
F-tests														
$TRADE\_A - TRANSP\_A$	0.173		0.653		−3.897*		4.515		2.597		1.902		−0.306	
$OTHLOAN\_A - TRANSP\_A$	−1.354***		0.171		−3.286***		−1.444		−1.756		−1.421		−1.451***	
$OTHOPAQ\_A - TRANSP\_A$	−0.645**		−0.150		−2.147***		0.242		−1.802**		−1.987**		−0.606*	
$COMREAL\_A - TRANSP\_A$	−1.106***		−0.348		−1.932**		−0.738		−1.696		−1.791*		−1.130***	
$RESREAL\_A - TRANSP\_A$	−0.791		0.231		−1.634		0.187		−0.963		0.198		−0.785	

This table reports the results of the pooled WLS fixed effects regressions of bank risk on the loan portfolio asset composition, fundamental and other control variables. The dependent variables are the quarterly-equivalent bank equity risk measures as explained in Section 3.2. The loan portfolio composition variables include the proportion of trading assets ($TRADE$), other loans ($OTHLOAN$), other opaque loans ($OTHOPAQ$), transparent assets ($TRANSP$), commercial real estate loans ($COMREAL$) and residential real estate loans ($RESREAL$) to the quarterly average total assets ($ASSET$) respectively. The loan asset composition variables sum up to unity at each cross-section, and hence, the intercept terms are suppressed in the regressions. The fundamental and market variables include: earnings to total assets (EBT_A), non-interest income to total assets ($NONINT\_A$), non-performing loans to total assets (NPL_A), loan-to-deposit ratio ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratio ($TIER1\_CAP$), interest rate risk ($INTRISK\_A$), Keeley's Q, log turnover ratios ($LN(TURN)$) and log market capitalisation ($LN(MCAP)$). Two-way bank and quarter fixed effects are accounted for in the WLS regressions with robust standard errors clustered by both firm and time dimensions. Following Jones et al. (2013), the WLS regressions are weighted by relative bank size, as measured by log market capitalisation. The F-tests of coefficient equality on the loan asset composition variables are reported in the lower panel. Superscripts '***', '**' and '*' denote statistical significance at the 1%, 5% and 10% level respectively.

Table 5: Determinants of bank risks - Crisis model

Dependent Variables:	$LN(\sigma^{TOTAL})_t$		$LN(\sigma^{MKT})_t$		$LN(\sigma^{INT})_t$		$LN(\sigma^{DEF})_t$		$LN(\sigma^{ABX})_t$		$LN(\sigma^{ABCP})_t$		$LN(\sigma^{RESID})_t$	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Loan portfolio asset composition:														
$TRADE\_A_{t-1}$	1.903	(1.352)	−0.160	(2.036)	3.152	(3.881)	3.929	(4.875)	3.501	(3.957)	8.266**	(3.620)	2.659*	(1.400)
$OTHLOAN\_A_{t-1}$	1.609**	(0.649)	1.338	(1.429)	−2.122	(1.515)	0.844	(1.639)	2.324	(2.107)	2.821	(1.911)	1.991***	(0.661)
$OTHOPAQ\_A_{t-1}$	0.981*	(0.568)	0.118	(0.859)	−2.106	(1.400)	0.363	(1.664)	0.437	(2.209)	1.128	(1.721)	1.396**	(0.601)
$TRANSP\_A_{t-1}$	1.348*	(0.740)	0.249	(1.032)	−0.542	(1.792)	−0.199	(1.641)	1.942	(2.449)	2.168	(1.893)	1.578**	(0.718)
$COMREAL\_A_{t-1}$	0.765	(0.678)	−0.861	(1.612)	−2.941**	(1.472)	−0.010	(1.563)	2.081	(1.990)	1.215	(1.889)	1.381**	(0.642)
$RESREAL\_A_{t-1}$	0.338	(0.808)	−0.641	(1.553)	−2.386	(1.736)	−0.078	(2.473)	1.113	(2.196)	2.111	(1.879)	1.121	(0.780)
Fundamental variables:														
EBT_A_{t-1}	−0.548	(0.764)	2.433*	(1.330)	1.201	(1.318)	−2.512*	(1.289)	−2.875**	(1.237)	−1.851	(1.664)	−1.327*	(0.686)
$NONINT\_A_{t-1}$	−3.385	(2.176)	−7.238**	(3.633)	−6.946**	(3.460)	6.178	(4.046)	1.860	(4.950)	−3.899	(4.313)	−2.195	(1.942)
NPL_A_{t-1}	−1.611	(2.586)	−5.359	(4.471)	4.787	(3.112)	−1.579	(3.563)	1.098	(2.942)	−5.426	(4.310)	−1.975	(2.290)
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	−0.051	(0.035)	−0.066	(0.055)	0.141**	(0.062)	−0.099	(0.082)	−0.146	(0.113)	−0.084	(0.073)	−0.036	(0.033)
$TIER1\_CAP_{t-1}$	−2.054*	(1.185)	−1.523	(2.144)	−3.346**	(1.490)	−6.160***	(1.988)	−2.976*	(1.733)	−2.357	(1.921)	−2.480**	(1.052)
Crisis dummy and interaction variables														
$CRISIS_t$	2.238**	(1.038)	0.608	(1.261)	2.105	(1.877)	1.473	(2.296)	1.306	(1.418)	4.308**	(1.963)	2.720***	(0.975)
$CRISIS_t \times$														
$TRADE\_A_{t-1}$	−1.306	(1.020)	1.132	(0.990)	−7.112**	(3.007)	−0.148	(2.226)	0.702	(2.830)	−6.008**	(2.747)	−2.419**	(0.961)
$OTHLOAN\_A_{t-1}$	−1.766*	(1.030)	−0.009	(1.300)	−1.027	(1.943)	−1.340	(2.155)	−0.930	(1.562)	−3.338*	(1.786)	−2.228**	(0.955)
$OTHOPAQ\_A_{t-1}$	−2.022*	(1.107)	−0.798	(1.299)	−1.521	(1.917)	−1.156	(2.394)	−0.420	(2.104)	−3.638**	(1.788)	−2.472**	(1.064)
$TRANSP\_A_{t-1}$	−1.914	(1.177)	−1.067	(1.580)	−0.664	(1.973)	−1.423	(2.784)	−0.376	(2.086)	−1.382	(2.173)	−2.161*	(1.142)
$COMREAL\_A_{t-1}$	−2.598**	(1.129)	−0.421	(1.440)	−1.856	(1.879)	−2.160	(2.125)	−1.739	(1.630)	−4.141***	(1.578)	−3.096***	(1.029)
$RESREAL\_A_{t-1}$	−1.777*	(1.041)	−0.336	(1.363)	−1.737	(1.751)	−0.586	(2.155)	−0.461	(1.775)	−2.421	(1.719)	−2.289**	(0.948)
EBT_A_{t-1}	−0.940	(1.133)	−5.320***	(1.882)	−3.322*	(2.013)	0.024	(1.625)	−0.710	(1.780)	2.037	(2.017)	0.064	(0.968)
$NONINT\_A_{t-1}$	1.482	(2.332)	8.160**	(3.765)	−0.247	(5.179)	−8.296	(5.709)	3.896	(6.112)	−7.482	(5.239)	−0.784	(2.050)
NPL_A_{t-1}	4.973**	(2.058)	1.252	(4.240)	−2.400	(3.840)	1.120	(4.080)	3.840	(2.989)	0.835	(3.389)	5.415***	(1.943)
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	−0.059	(0.046)	−0.011	(0.081)	−0.078	(0.107)	−0.058	(0.121)	0.048	(0.105)	−0.143	(0.120)	−0.083*	(0.048)
$TIER1\_CAP_{t-1}$	0.020	(0.018)	0.016	(0.028)	0.002	(0.032)	0.048	(0.037)	−0.007	(0.037)	−0.024	(0.031)	0.022	(0.015)
Control variables:														
$INTRISK\_A_{t-1}$	0.308	(0.212)	0.173	(0.345)	0.676	(0.427)	−0.300	(0.361)	0.842	(0.608)	0.741	(0.561)	0.190	(0.175)
$Keeley's\ Q_{t-1}$	−2.938***	(0.910)	−2.130	(1.366)	−2.463**	(1.042)	−1.899	(1.239)	−4.629***	(1.301)	−2.492*	(1.481)	−2.991***	(0.779)
$LN(TURN)_{t-1}$	0.145***	(0.042)	0.329***	(0.064)	0.152**	(0.069)	0.194**	(0.091)	0.224***	(0.052)	0.056	(0.059)	0.121***	(0.038)
$LN(MCAP)_{t-1}$	−0.271***	(0.065)	0.065	(0.108)	−0.374***	(0.099)	−0.332***	(0.085)	−0.270***	(0.102)	−0.295***	(0.103)	−0.347***	(0.060)
Obs.	3,153		3,153		3,153		3,153		3,153		3,153		3,153	
R^2	0.683		0.576		0.274		0.271		0.281		0.260		0.741	

This table reports the results of the pooled WLS fixed effects regressions of bank risk on the loan portfolio asset composition, fundamental and other control variables. To capture the crisis effect, we include a crisis dummy variable (crisis period: 2007Q1-2009Q1) and interact it with the bank fundamental and loan asset composition variables. The dependent variables are the quarterly-equivalent bank equity risk measures as explained in Section 3.2. The loan portfolio composition variables include the proportion of trading assets ($TRADE$), other loans ($OTHLOAN$), other opaque loans ($OTHOPAQ$), transparent assets ($TRANSP$), commercial real estate loans ($COMREAL$) and residential real estate loans ($RESREAL$) to the quarterly average total assets ($ASSET$) respectively. The loan portfolio composition variables sum up to unity at each cross-section, and hence, the intercept terms are suppressed in the regressions. The fundamental and market variables include: earnings to total assets (EBT_A), non-interest income to total assets ($NONINT\_A$), non-performing loans to total assets (NPL_A), loan-to-deposit ratio ($LOAN\text{-}TO\text{-}DEPOSIT$), Tier 1 capital ratio ($TIER1\_CAP$), interest rate risk ($INTRISK\_A$), Keeley's Q, log turnover ratios ($LN(TURN)$) and log market capitalisation ($LN(MCAP)$). Firm fixed effects are accounted for in the WLS regressions with robust standard errors clustered by both firm and time dimensions. Following Jones et al. (2013), the WLS regressions are weighted by relative bank size, as measured by log market capitalisation. Superscripts '***', '**' and '*' denote statistical significance at 1%, 5% and 10% level respectively.

Table 6: Sensitivity analysis

Dependent Variables:	$LN(\sigma_t^{ABX})$		$LN(\sigma_t^{ABCP})$		$LN(\sigma_t^{ABX})$		$LN(\sigma_t^{ABCP})$	
	$P1$	$P2$	$P1$	$P2$	$P1$	$P2$	$P1$	$P2$
Asset composition:								
$TRADE\_A_{t-1}$	4.317*	6.911***	3.243*	1.076	3.501	6.205*	8.266**	5.562*
$OTHLOAN\_A_{t-1}$	−0.036	−0.131	−0.080	−0.294	2.324	2.209	2.821	3.305*
$OTHOPAQ\_A_{t-1}$	−0.082	−0.347	−0.646	−0.707	0.437	0.593	1.128	1.866
$TRANSP\_A_{t-1}$	1.720	1.037	1.341	1.082	1.942	1.771	2.168	2.768
$COMREAL\_A_{t-1}$	0.024	−0.709	−0.450	−0.676	2.081	1.775	1.215	2.054
$RESREAL\_A_{t-1}$	0.757	−0.360	1.539	2.006	1.113	0.206	2.111	3.272**
Fundamental variables:								
EBT_A_{t-1}	−3.427***	−3.263***	−1.094	−1.243	−2.875**	−2.513*	−1.851	−2.203
$NONINT\_A_{t-1}$	0.629	−0.070	−5.160	−2.597	1.860	0.641	−3.899	−1.378
NPL_A_{t-1}	3.049	1.454	−0.654	−0.474	1.098	0.510	−5.426	−4.590
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$	−0.016	−0.017	−0.053	−0.064	−0.146	−0.131	−0.084	−0.107
$TIER1\_CAP_{t-1}$	−1.683	−2.266	−2.777*	−3.317**	−2.976*	−3.875**	−2.357	−3.257*
Crisis dummy and interaction variables								
$CRISIS_t$					1.306	1.820	4.308**	5.673***
$CRISIS_t\times$								
$TRADE\_A_{t-1}$					0.702	0.273	−6.008**	−6.007**
$OTHLOAN\_A_{t-1}$					−0.930	−1.729	−3.338*	−4.650**
$OTHOPAQ\_A_{t-1}$					−0.420	−1.347	−3.638**	−5.035**
$TRANSP\_A_{t-1}$					−0.376	−1.653	−1.382	−3.190
$COMREAL\_A_{t-1}$					−1.739	−2.613*	−4.141***	−5.879***
$RESREAL\_A_{t-1}$					−0.461	−0.899	−2.421	−3.969*
EBT_A_{t-1}					−0.710	−0.959	2.037	2.799
$NONINT\_A_{t-1}$					3.896	3.858	−7.482	−6.370
NPL_A_{t-1}					3.840	4.173	0.835	2.753
$LOAN\text{-}TO\text{-}DEPOSIT_{t-1}$					0.048	0.060	−0.143	−0.171*
$TIER1\_CAP_{t-1}$					−0.007	0.010	−0.024	−0.012
Control variables:								
$INTRISK\_A_{t-1}$	0.592	0.476	0.375	0.117	0.842	0.625	0.741	0.479
$Keeley'sQ_{t-1}$	0.006	−0.387	−0.365	0.004	−4.629***	−4.314***	−2.492*	−3.010*
LN_TURN_{t-1}	0.120**	0.102**	−0.033	0.006	0.224***	0.180***	0.056	0.097
LN_MCAP_{t-1}	−0.308***	−0.314***	−0.280***	−0.283***	−0.270***	−0.262***	−0.295***	−0.274**
N	3,153	3,153	3,153	3,153	3,153	3,153	3,153	3,153
R^2	0.314	0.323	0.298	0.300	0.281	0.299	0.260	0.257

This table reports the results of our sensitivity analysis for the ordering of factor variables that go into the orthogonalisation process during our variance decomposition procedure. As explained in Section 3.2, the factor variables are orthogonalised in the following order in the baseline results (subscripts t omitted): MKT, INT, DEF, ABX and ABCP. To check the importance of the ordering on our results, we alternate the order of ABX and ABCP in the orthogonalisation process. There are two possible permutations, P1: ABX followed by ABCP and P2: ABCP followed by ABX. We re-estimate pooled WLS regressions for both the baseline and crisis models and report the results for ABX and ABCP risks in the table. The independent variables are identical to those used previously. The intercept terms are suppressed as the loan portfolio composition variables sum to unity in each cross-section. Firm fixed effects are accounted for in the WLS regressions with robust standard errors clustered by both firm and time dimensions. Following Jones et al. (2013), the WLS regressions are weighted by relative bank size, as measured by log market capitalisation. The estimated coefficients are reported with superscripts '***', '**' and '*' denoting statistical significance at 1%, 5% and 10% level respectively.