Time-Varying Systematic and Idiosyncratic Risk Exposures of US Bank Holding Companies

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Abstract

We analyze the time-varying risk exposures of US bank holding companies for the period from 1986 to 2012 by decomposing total bank risk into systematic banking-industry risk, systematic market-wide risk, and unsystematic or idiosyncratic bank risk. Banking-industry risk factors are directly related to banks’ intermediation functions, while market-wide risk factors are affecting banks and industrial firms alike. Idiosyncratic bank risk relates to characteristics that are specific to an individual bank. Our empirical results suggest that credit risk is most important in crisis periods, while real estate risk emanates in the context of adverse real estate market conditions. The banks’ interest rate risk sensitivity reverses over the sample period. We provide evidence that banks’ market risk exposure can be explained by asset-wide risk factors such as liquidity, volatility, and foreign exchange risk. Analyzing individual bank risk suggests that differences in risk exposures are directly related to bank characteristics including the equity ratio, loan loss provisions, and real estate loans. In addition, individual bank risk has a strong state-level business cycle component that is not captured by the systematic banking-industry and market-wide risk factors. Our results are robust to alternative risk factor specifications. Overall, our study contributes to understanding the structure and time-variation of banks’ systematic and idiosyncratic risks.

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Keywords: Bank Risk Exposures; Systematic and Idiosyncratic Risk; Financial Crises

JEL Classification: G01; G21

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1. Introduction

The US banking industry has experienced major structural changes and severe crisis periods during the last three decades. Banks have been subject to numerous regulatory reforms and intensified competition within the financial services industry as well as from the recent growth of the shadow banking sector. The repeal of the Glass-Steagall Act in 1999 allowed commercial banks to participate in investment banking activities, while current regulatory initiatives are designed to restrain or even separate bank activities again (Kroszner and Strahan 2011). However, despite extensive regulation and supervision banking crises have frequently occurred. For instance, during the 1987 to 1992 banking crisis as well as the recent 2008 to 2012 financial crisis, a significant number of US banks failed, with far-reaching effects on bank customers and the economy (Aubuchon and Wheelock 2010). These periods are characterized by sudden and significant changes in the quality of bank assets and bank solvency, exacerbating an accurate assessment of bank risk exposures (Flannery et al. 2013). However, understanding the sources of banks’ risk exposures is essential for bank regulators, investors, and bank customers, because individual bank failures may result in contagion effects and systemic risk (Acharya et al. 2010). In this context, the recent financial crisis has stimulated renewed academic research interest in bank risk exposures.

Although there exists an extensive literature on common risk factors in stock returns (Goyal 2012), most research is devoted to the determinants for industrial firms, e.g. by focusing on the Fama and French (1993) three-factor model and its extensions. Empirical evidence for bank risk factors remains rather scarce, because banks are usually excluded from empirical studies due to their inherent differences from industrial firms (Gandhi and Lustig 2013). In fact, banks differ from industrials with respect to their business activities, leverage, regulation, and systemic relevance for the financial system. Moreover, in financial crisis periods there is a threat of bank runs with the potential to increase the probability of bank failures and the likelihood of contagion effects. For analyzing bank risk in detail, it is constructive to distinguish between systematic and idiosyncratic risks. Systematic exposures to the US subprime mortgage market were at the center-stage of bank distress in the recent financial crisis. In contrast, idiosyncratic or individual bank risk primarily affects a single institution and should be negligible in diversified portfolios. However, the failure of an individual bank may also lead to contagion effects when market participants are unsure about the effective exposures in asset portfolios across banks (Bessler and Nohel 2000). Overall, these relationships emphasize the importance of differentiating and analyzing both systematic and individual bank risk exposures in more detail.
We investigate the time-varying systematic and idiosyncratic risk exposures of US bank holding companies for the period from 1986 to 2012. Besides prolonged non-crisis periods, our sample includes several banking and market crises (Berger and Bouwman 2013). We contribute to the literature by assessing bank risk from a capital market perspective and by decomposing bank stock returns into systematic banking-industry risks, systematic market-wide risks, and individual bank risks. The separation of systematic risk into banking-industry and market-wide risks is motivated by banks’ traditional risk transformation activities. The set of systematic banking-industry risk factors includes interest rate risk, credit risk, sovereign risk, and real estate risk. Although these risk factors are relevant for explaining industrial stock returns as well, the economic intuition for these factors differs substantially between banks and non-banks. In contrast, systematic market-wide risks are not special to the banking industry, but affect banks and industrial firms alike. We define market risk as a market-wide rather than a typical bank risk exposure due to the immanent sensitivity of stock returns to movements in the market portfolio. Although these two groups of systematic risk factors explain a substantial fraction of banks’ stock return variance, it is important to further investigate the excess return variation that is unrelated to common risk factors, i.e. the idiosyncratic risk or individual bank risk, using detailed information on bank characteristics and state-level economic conditions.

Our empirical results indicate that banks’ systematic risk exposures are time-varying and well reflected in bank stock returns. The banking-industry risk factors account for a significant share of systematic return variance especially in times of financial stress. Credit risk is an important factor in crisis periods such as the late 1980s and early 1990s, in August 1998, and in the recent financial crisis. Moreover, our analyses identify significant real estate exposures at the beginning of the sample period and during the recent subprime crisis, consistent with banks’ sensitivity to adverse real estate market conditions. Sovereign risk is mostly insignificant, but becomes important over the recent period as a consequence of structural problems in European sovereign debt markets. Interest rate risk sensitivity is characterized by strong time-variation and reverses over the sample period. Individual bank risk is related to several bank characteristics, including the equity capital, loan loss provisions, and loan portfolio composition. In addition, individual bank risk exhibits a strong state-level business cycle

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1 We focus on bank holding companies because the holding company structure is widespread in the US and the majority of commercial banks belong to a bank holding company (Ashcraft 2008). Strategic management decisions usually are made on the holding company level and regulators focus on monitoring the entire institution. Moreover, we require stock market data for our empirical analysis so that US commercial banks would not yield a representative sample for the US banking industry (Berger et al. 2013).
component, suggesting that regional effects play an important role on the individual bank level. Our results are robust to including additional risk factors such as the Fama and French (1993) factors, the term spread and the Treasury Eurodollar Difference (TED) spread. Moreover, we provide evidence that banks’ market risk exposure is explained by different common risk factors in stock returns, making a definite interpretation in the sense of an unambiguous risk factor difficult. In fact, we document illiquidity risk, volatility risk, and foreign exchange risk as significant determinants, besides the Fama and French value factor. Therefore, we support the perspective that market risk represents a mixture of other risk factors that also are relevant for explaining returns on other asset classes such as mutual funds and hedge funds, fixed income instruments, and currencies.

Overall, our empirical findings contribute to the understanding of banks’ systematic risk, its time-variation and particular relevance in crisis periods as well as the determinants of individual bank risk. The remainder of the paper proceeds as follows. In section 2 we review the literature on bank risk. Section 3 discusses the empirical methodology and section 4 details the data. In section 5 we present our empirical results and robustness checks while section 6 concludes.

2. Literature Review

We begin our analysis by providing a detailed review of the literature on bank risk exposures and by outlining the differences between banking-industry risk factors (2.1) and market-wide risk factors (2.2). For identifying and analyzing the risk exposures of banks, numerous factors have been discussed in the literature. Among the four most prominent factors are interest rate risk (Lynge and Zumwalt 1980; Flannery and James 1984; Kane and Unal 1988), credit risk (Demsetz and Strahan 1997; Hess and Laisathit 1997; Dewenter and Hess 1998), real estate risk (Allen et al. 1995; Mei and Saunders 1995; Martins et al. 2012), and foreign exchange risk (Choi and Elyasiani 1997; Chamberlain et al. 1997; Gounopoulos et al. 2013). An extensive study of banks’ risk exposures by Baele et al. (2013) analyzes a total of 12 variables designed to proxy for a large variety of risk factors in bank stock returns. They include interest rate risk, credit risk, liquidity risk, real estate risk, foreign exchange risk, market sentiment risk and market risk as well as the Fama and French (1993) factors. In the context of a Bayesian model averaging technique the authors conclude that three variables are sufficient for explaining bank stock returns: market risk, real estate risk, and the Fama and French (1993) value factor. Surprisingly, little support is found for interest rate risk and credit risk. Bessler and Kurmann (2013) analyze risk factors for European and US banks that are
based on their financial intermediation functions and provide evidence for the significance of seven variables: interest rate risk, low and high credit risk, sovereign risk, foreign exchange risk as well as real estate risk and market risk. Overall, the authors conclude that banks’ risk factors are multi-faceted and time-varying but generally well reflected in bank stock returns.

While these risk factors are derived from the traditional bank functions, they may also explain a significant fraction of industrial stock returns, albeit for different reasons. In fact, the economic intuition for exposures to interest rate risk, credit risk, sovereign risk, and real estate risk differ substantially between banks and industrial firms (Bessler and Murtagh 2004). For the banking industry, these risks represent systematic risk factors because they are directly associated with banks’ risk transformation activities and their asset and liability positions. In contrast, foreign exchange risk and market risk are not specific banking-industry risk factors because they affect banks and industrial firms alike and, therefore, are systematic market-wide risk factors. We discuss this classification in more detail in the subsequent sections 2.1 and 2.2.

2.1. Systematic Banking-Industry Risk Factors

Interest Rate Risk: The banks’ exposure to changes in interest rates is the result of their maturity transformation and their asset-liability management. Changes in interest rates directly affect the value of banks’ financial assets, liabilities, interest income, and consequently the banks’ equity position. Thus, the importance of interest rate increases for banks is driven by a combination of capital losses on long-term assets due to higher discount rates and a lower future interest income due to declining interest margins. These ideas can be conceptualized in terms of weighted durations. An increase in interest rates leads to a decline in the bank’s equity capital when the weighted duration of its assets is higher than the weighted duration of its liabilities. However, this risk can be hedged with financial derivatives. In contrast, for industrials interest rate changes primarily affect their financing costs on loans and bonds. While interest rates change over the business cycle and, therefore, may also have an effect on industrials’ investment decisions, this effect is not uniform across industries. Therefore, interest rate risk rather reflects risk of higher financing costs in the income statement instead of risk stemming from the primary business activities. Moreover, it also represents a general business cycle indicator for industrial firms.

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2 Also see Samuelson (1945) for an application of the duration concept on banks’ balance sheet and Redington (1952) for an application in the context of the immunization for insurance companies.
Credit risk: Based on banks’ traditional risk transformation activity, credit risk measures the probability that bank borrowers default on their loan obligations. Loan defaults directly affect the value of banks’ financial assets and have to be written down and absorbed by their equity capital. For industrials, the relevance of changes in interest rates, either due to changes in yield spreads between different rating classes or due to rating changes, is closely related to the cost of debt and their financing costs. It is usually not directly related to their asset positions. Changes in yield spreads are also used as business cycle indicators, thereby reflecting the probability that customers default on their commitments (Fama and French 1989). In this case, the value of industrial firms’ assets might also be negatively affected by delayed or defaulted payments. However, the effective channel through which a change in yield spreads impacts their equity position, i.e. either through the assets side or the liabilities side, is difficult to disentangle.

Sovereign risk: Historically, banks have traditionally financed government deficits and consequently held exposures to local and foreign government debt facing the risks of write downs and defaults in case of a crisis. In fact, the Latin American crisis during the 1970s and 1980s (Musumeci and Sinkey 1990a, 1990b), the Russian crisis of 1998 (Fahlenbrach et al. 2012), and the recent European crisis (Acharya and Steffen 2013) have provided sufficient evidence that banks are exposed to sovereign risks and that a bank’s solvency can be highly sensitive to governments restructuring or defaulting on their debt. In contrast, for industrials this risk does not directly correspond to a primary business activity. Although their financing conditions are sensitive to local sovereign risk, i.e. market participants incorporate a risk premium reflecting the default probability or rating of the local sovereign, the overall impact of changing credit conditions of foreign sovereigns on industrials is ambiguous (Fontana 2013), although sovereign and financial crises amplify the business cycle and economic activity (Schularick 2013). While some industrials may hold significant exposures to foreign sovereigns due to their business contracts, this exposure is usually not perceived as universal across all types of industries and, therefore, not a systematic risk for industrials.

Real estate risk: Mortgage loans represent a large share of the banks’ loan portfolio so that changes in their collateral value, i.e. real estate risk, denote a relevant risk for banks. For the last twenty years, Young et al. (2013) document that US banks’ holding of real estate loans remarkably increased, while other loan categories declined on a relative scale, thereby resulting in a higher real estate exposure on banks’ balance sheets. The immanent exposure to real estate risk has been documented during the US real estate crisis in the late 1980s and early 1990s (Hendershott and Kane 1992) as well as the recent subprime and financial crisis
Therefore, real estate price fluctuations directly affect the profitability of mortgage-related bank lending. In contrast, for industrials real estate risk generally has lower immediate relevance with respect to their principle business activities. While it is important for firms operating in the construction industry, this sector generally is considered to be highly cyclical and sensitive to the state of the economy so that real estate risk only denotes one relevant risk factor amongst others. Therefore, we interpret real estate risk for industrials as a common business cycle indicator instead of a specific risk stemming from primary business activities. In fact, real estate prices are closely associated with common leading economic indicators such as housing starts and building permits. The analysis of Allen and Gale (2000) supports this perspective by providing evidence that real estate market problems often precede financial crises.

2.2. Systematic Market-wide Risk Factors

**Foreign exchange risk:** Besides the aforementioned risk factors, foreign exchange risk also is among the commonly used factors for explaining bank stock returns, although the empirical evidence is rather mixed. However, while the aforementioned systematic bank risk factors exhibit a direct influence on the value of banks’ assets, foreign exchange risk is not specific to the banking industry but relevant for other industries as well for the following three reasons. First, although a large strand of empirical literature provides evidence that industrials are significantly exposed to foreign exchange rate variations (Kolari et al. 2008; Bartram et al. 2010; Wei and Starks 2013), Francis et al. (2008) document that financials’ foreign exchange exposure is comparable to that of industrials. Therefore, there is no convincing evidence on the unique importance of foreign exchange risk for banks or even evidence that banks’ foreign exchange exposure differs systematically from that of industrial firms. Second, liquidity conditions in the foreign exchange market strongly correlate with equity market liquidity so that isolating pure foreign exchange risk is quite challenging (Mancini et al. 2013). Third, the well developed derivatives markets allow both, banks and industrials, to effectively hedge their foreign exchange exposure (Hankins 2011; Bodnar et al. 2013). Overall, these findings sug-

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3 Recently, Du (2014) attributes the weak empirical support for foreign exchange risk exposures in stock returns to the relevance of persistent instead of contemporaneous exchange rate movements. Moreover, Du and Hu (2012) underline that the evidence for foreign exchange risk exposure is particularly sensitive to the research design.

4 Foreign exchange risk may represent a relevant risk for banks that are strongly engaged as a market maker in foreign exchange derivatives markets. However, this is only the case for a rather small number of banks and, therefore, not representative for the overall banking industry.
gest that foreign exchange risk represents a market-wide risk rather than an unambiguous type of bank risk and likely shares some common variation with the market risk factor.\(^5\)

**Market risk:** Theoretically well supported by the Capital Asset Pricing Model are factor models, which usually incorporate an aggregate market factor. While the single market factor does not provide a coherent, unambiguous risk measure, its relevance for the construction of any type of multi-factor model is widely acknowledged. For banks, neither theoretical nor empirical evidence so far suggests that their market risk exposure systematically differs from that of industrials. Therefore, the market factor rather represents a systematic market-wide risk exposure that is important for explaining the time series variation of bank stock returns without being directly associated with banks’ primary business activities. More importantly, the market factor itself can hardly be interpreted as a clear and transparent risk factor. Regression evidence in Fama and French (1993) indicates that the market portfolio has significant exposures to both the size and value factors as well as two bond market factors. The authors conclude that the market factor represents a “hodgepodge” of common factors.

### 3. Methodology

Next we discuss the existing statistical techniques for decomposing banks’ systematic risk exposures (3.1), the empirical implementation of the democratic orthogonalization approach (3.2), and the analysis of banks’ idiosyncratic risk determinants in a panel regression framework (3.3).

#### 3.1. Systematic Risk Decomposition

In time series regressions the estimated R-squared represents the portion of bank stock return variance that is explained by the set of systematic risk factors. As discussed before, it is unlikely that the different risk factors are uncorrelated per se so that an orthogonalization is necessary, which serves two purposes. First, it allows estimating the component of a variable that is free of any information embedded in the other variables. Hence, after orthogonalization the correlation between the variables is zero by construction, i.e. the variables are linearly independent. Second, this orthogonalization allows decomposing the systematic variation of bank stock returns with respect to each systematic risk factor. Therefore, the relative im-

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\(^5\) Bessler and Kurmann (2013) focus on differences between foreign exchange risk exposures of European and US banks and consider an explicit foreign exchange risk factor for banks. For European banks, the introduction of the Euro marks a relevant structural break and, as a response, European banks’ foreign exchange risk exposure has declined significantly. For US banks, however, no such evidence is documented. In this paper, we do not focus on differences in risk exposures of European and US banks. Therefore, we do not require foreign exchange risk in our factor set but consider this type of risk to be a market-wide risk for the reasons outlined above.
portance and explanatory power of each variable can be inferred. In empirical applications, this issue is relevant as the magnitude and statistical significance of beta coefficients do not provide any information on this aspect. For instance, in a multi-factor model all factors may be highly significant while their relative importance, i.e. the contribution of each individual factor to the overall R-squared, can differ substantially. In fact, only one factor or a subset of factors can dominate the systematic variance of bank stock returns.

\[ \sigma_{S,B,t}^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \beta_{i,j} \beta_{j,b} \text{Cov}(F^i, F^j). \]

Formally, the systematic time series variation of bank stock returns (\( \sigma_{S,B,t}^2 \)) is denoted in equation 1. It is a linear function of the factors’ beta sensitivities (\( \beta \)) and the factors’ variance-covariance structure (\( \text{Cov} \)). The explanatory power of each individual factor cannot be identified as long as the factors are correlated. These correlations usually are non-trivial because all factors share some common variation with each other. To isolate each factor’s uncorrelated components, the literature has proposed two different techniques. First, a *sequential procedure* that requires a “leading” factor and a particular orthogonalization sequence when more than one regressor is used. The leading factor enters the regression in its original form while the other factors are orthogonalized according to the selected sequence. Second, a *democratic procedure* which neither requires a leading factor nor an orthogonalization sequence. Instead, the technique provides a simultaneous transformation of all regressors to identify the factors’ underlying uncorrelated components.

In the context of a small number of regressors, the sequential technique has been widely applied in the empirical literature (Flannery and James 1984; Fraser et al. 2002; Korkeamäki 2011; Knaup and Wagner 2012). These studies, however, focus on the orthogonalization of only one factor instead of addressing the complexity using the sequential procedure for a larger number of variables. Bessler and Opfer (2004) motivate an orthogonalization sequence for five macroeconomic factors based on economic theory and analyze their explanatory power for different industries including banks. The empirical challenge of the sequential technique arises in the context of a relatively large number of factors. For instance, with five (six / seven / eight) regressors the researcher would face a total of 120 (720 / 5,040 / 40,320) possible orthogonalization structures as long as she cannot economically justify a particular sequence. Consequently, the empirical findings are highly sensitive to the orthogonalization choice.
The recently introduced democratic technique does not suffer from this problem because it treats all factors equally (Klein and Chow 2013). The approach conducts a simultaneous orthogonal transformation of the factors to identify their uncorrelated components. This method avoids the pitfalls associated with the sequential orthogonalization and has several attractive features. First, the variances of the orthogonalized factors are identical to the variances of the original (non-orthogonalized) factors, while their covariances are equal to zero. Second, the democratic technique ensures that the orthogonalized factors best resemble the original factors compared to a set of commonly applied orthogonalization approaches. Klein and Chow (2013) demonstrate that the correlations between each possible original/orthogonal factor pair is highest for the democratic procedure while Principal Component Analysis and the sequential approach often identify orthogonal factors that are significantly different from their original counterparts making their economic interpretation difficult. In addition, the deviations between the orthogonalized and original series (Frobenius norm values) are lowest for the democratic orthogonalization. Therefore, other orthogonalization techniques often produce factor series that may become rather unrelated to the information provided by the original factors.

3.2. Democratic Variance Decomposition

Our time series analysis is based on the democratic orthogonalization technique of Klein and Chow (2013). Using the orthogonalized factor series we run OLS time series regressions over the full period as well as over different sub-periods. The linear regression model is presented in equation 2, where \( R_t \), \( \alpha \), \( \beta_k \), \( F^\perp_{k,t} \), and \( \varepsilon_t \) represent the monthly excess return of the value-weighted bank portfolio, a constant term, a vector of beta sensitivities corresponding to the orthogonalized bank risk factors, and the regression residuals, respectively. All standard errors are adjusted for heteroskedasticity and autocorrelation with 12 lags (Newey and West 1987).

\[
R_t = \alpha + \beta_k F^\perp_{k,t} + \varepsilon_t.
\]

The matrix of uncorrelated, variance-preserving factors \( F^\perp_{k,t} \) is estimated with equation 3. Here, \( F_{t\times k} \) and \( S_{k\times k} \) denote the matrix of original, non-orthogonalized factors and the inverse of the correlation matrix between the original and orthogonalized factors, respectively.

\[
F^\perp_{t\times k} = F_{t\times k} S_{k\times k}.
\]
In the variance decomposition analysis we use a rolling window technique with 36 months. The period of three years balances the trade-off between modeling dynamic exposures to the systematic banking-industry and market-wide risk factors while at the same time ensuring statistically reliable estimates.6

3.3. Panel Regression Framework

While the time series analyses allow drawing inferences with respect to the systematic risk in bank stock returns, unsystematic or idiosyncratic risk may constitute a substantial fraction of banks’ stock return variance (Kelly et al. 2012). It represents the portion of total risk that is not attributable to banks’ exposures to systematic risk factors but to the specific risk of an individual bank. The determinants of these individual bank risks should be factors such as the specific business model and risk culture of an individual bank (Fahlenbrach et al. 2012) as well as bank characteristics including the equity capital or leverage ratio, the structure and quality of the loan portfolio as well as the diversification of the income streams. Moreover, empirical evidence indicates that during the late 1980s and early 1990s crisis as well as during the recent financial crisis, the regional, state-level business cycle exposures were significantly related to the individual bank risk (Aubuchon and Wheelock 2010).

In our empirical analysis, idiosyncratic risk is defined as the annualized standard deviation of individual banks’ regression residuals. Similar to the time-varying analysis of systematic risk we use a rolling regression approach with 36 months and calculate idiosyncratic risk in December of each year. We select a set of representative bank-specific variables that reflects the bank size and equity, the composition of the bank’s loan portfolio, its revenue diversification, and profitability. These variables are: the log of total assets (assets), the equity-to-assets ratio (equity), the relative percentages of the loan portfolio dedicated to real estate loans (rel), commercial and industrial loans (cil), and consumer loans (cl), the ratio of non-interest income to total income (nii), the return on assets (roa), and the ratio of loan loss provisions to total loans (pll). The control variables measured in levels represent averages over a three-year rolling window lagged by one year. To control for regional effects we incorporate the growth rates of state-level business cycle indices (buscycle) that are available from the

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6 As a robustness check, we also tested an estimation window of 60 months. With this longer estimation window, we find similar results although the variance shares are more stable over time. Due to the more dynamic inferences drawn from 36-months regressions, we decide to focus on this shorter estimation window for our empirical analysis. The results using the longer estimation window are available from the authors upon request.
Federal Reserve Bank of Philadelphia. As a robustness check, we use the growth rate of labor income (labor) and the relative unemployment rate (unemploy) following the approach of Korniotis and Kumar (2013). State-level labor income growth is obtained from the Bureau of Economic Analysis while state-level unemployment data is provided by the Bureau of Labor Statistics. We use fixed-effects regressions that have the advantage of controlling for the effects of time invariant heterogeneity among individual institutions such as their specific business model and risk culture. The regressions include year dummies and standard errors are clustered at the individual bank level (Petersen 2009).

4. Data

4.1. Bank Holding Companies

Our empirical analysis spans the time period from December 1986 to December 2012. We use monthly stock return data. The sample of bank holding companies is constructed from the quarterly FR Y-9C reports provided by the Federal Reserve Bank of Chicago. To merge the FR Y-9C reports with stock return data from the University of Chicago’s Center for Research in Security Prices (CRSP) we use the CRSP-FRB Link. We identify a total of 1,019 individual bank holding companies, but apply a series of filters by excluding (1) institutions that are not incorporated in the US, (2) banks for which we do not have any valid information on total assets or total deposits, and (3) banks with less than three years (36 months) of available total stock return data. To reduce the probability that our results are biased by market microstructure issues we exclude all institutions with an average share price of less than USD 5.00 and winsorize banks’ return time series at the lower 0.1 percent level and the upper 99.9 percent level. The final sample consists of 857 individual bank holding companies. We calculate value-weighted portfolio returns in excess of the 3-months Treasury bill rate which implies that our time series portfolio analyses implicitly put more weight on the systematic return determinants of larger, systemic institutions in the US banking sector.

7 These indices are designed to aggregate information from the following four variables: the nonfarm payroll employment, the average hours worked in manufacturing, the unemployment rate, and the wage and salary disbursements deflated by the consumer price index.
8 See http://www.chicagofed.org/webpages/banking/financial_institution_reports/bhc_data.cfm.
9 See http://www.newyorkfed.org/research/banking_research/datasets.html.
10 When alternatively using equally-weighted portfolio returns, our empirical results are generally robust. However, the risk exposures naturally are tilted towards medium- and small-sized banks’ exposures. For a detailed analysis of differences in risk exposures of banks in different size categories also see Gandhi and Lustig (2013) as well as Bessler and Kurmann (2013). The results are available from the authors upon request.
4.2. Systematic Risk Factors

For the analysis of systematic risk exposures we include interest rate risk, credit risk, sovereign risk, real estate risk, and market risk. For reasons presented and discussed in section 2.1, we do not employ foreign exchange risk in our factor set. While market risk is considered in the general factor set, we interpret this factor as rather reflecting systematic market-wide risk that is not specific to the banking industry. The factor series are presented in Figure 1.

< Please insert Figure 1 about here >

Interest rate risk (LTB) is measured as the first differences of the yield of 10-year constant-maturity US government bonds\textsuperscript{11}, while credit risk is represented by two spreads, assuming that banks facilitate their lending operations to borrowers with different credit rating classes (default probability). Low credit risk (CORP), i.e. lending to borrowers with a supposedly low default probability, is approximated by first differences of the spread between Moody’s BAA and AAA corporate bond yields. High credit risk (HY), i.e. lending to borrowers with a supposedly high default probability that usually dominate banks’ loan portfolios, is measured by first differences of the yield spread between the Merrill Lynch high yield index and the aforementioned corporate spread. Besides the general composition of banks’ loan portfolios, the importance of HY also is supported by the documented decline in banks’ lending standards leading up to the recent crisis (Dell’Ariccia et al. 2013). Sovereign risk (SOV) is measured by first differences in the spread between the mean of the yields on 7-10 years government bonds for Greece, Italy, Ireland, Portugal, and Spain, and the 7-10 years German government bond.\textsuperscript{12} The exposure to real estate risk (REIT) is measured by the percentage changes of the total return index for US Real Estate Investment Trusts provided by FTSE/NAREIT, while the market factor (MKT) is approximated by the percentage changes of the CRSP value-weighted market index. Both factors are measured in excess of the 3-months US Treasury bill rate.

From these factor series we extract innovations reflecting the unexpected component of the risk factors by estimating a vector autoregressive (VAR) model with one lag. After run-

\textsuperscript{11} We are aware that, besides our long-term interest rate factor also short-term interest rate factors have been applied in the literature. We decided to use the long-term interest rate because it best reflects the interest rate of typically longer-term bank asset positions such as loans.

\textsuperscript{12} We focus on European sovereign risk for three reasons. First, US banks strongly increased their foreign exposure to European countries over the last decades (Cetorelli and Goldberg 2006). Second, during the recent European sovereign debt crisis, US banks show significant stock market reactions in response to European sovereign rating changes (Happ et al. 2014). Moreover, the magnitudes of these reactions line up with US banks’ effective exposures to sovereign debt. Third, other sovereign risk factors are not consistently available throughout our sample period. For instance, yield spreads for Latin American countries are only available from the late 1990s onwards.
ning the VAR model we orthogonalize both, REIT and MKT, with respect to LTB, CORP, HY, and SOV. This sequential procedure is necessary to account for the implicit correlation between the interest rate based factors and both stock market related variables. Although banks are significantly exposed to the real estate market (Huizinga and Laeven 2012; Young et al. 2013), sequentially orthogonalizing REIT also addresses the potential concern that REIT only reflects information associated with the current state of the business cycle as argued with respect to industrials.

4.3. Definition of Different Sub-Periods

The US banking industry has been subject to several regulatory changes and crisis situations over our sample period. Therefore, structural breaks in the return-generating process may lead to significant changes of banks’ risk exposures and inferences drawn from regressions using the full period naturally masks this time-variability. To test for the existence of structural breaks in banks’ return time series we apply the technique proposed by Bai and Perron (1998, 2003) that allows testing for multiple structural breaks with unknown break dates in a linear regression framework.14 We apply the sequential test for the hypothesis of L versus L+1 break dates where L is the number of structural breaks (Acharya and Merrouche 2012).

< Please insert Table 1 about here >

The test results in Table 1 indicate that there are two structural breaks in the return time series. The first break date is identified in November 1999 which corresponds to the time when the Gramm-Leach-Bliley (GLB) Act was signed into law. The GLB Act eliminated the longstanding separation between commercial and investment banking, thereby allowing commercial banks to engage in non-interest generating (investment banking) activities. The economic importance of this breakpoint is well supported by a series of studies examining the effects of the GLB Act on banks’ risk and return characteristics (Stiroh and Rumble 2006). Furthermore, the identified break date also is confirmed in a recent study by Viale and Madura (2013). The second breakpoint coincides with the onset of the recent financial crisis and dates to October 2007. The financial crisis witnessed a period of substantial declines in bank stock prices, increased bank stock return volatility, and a surge in the number of failing banks.

13 Because the yield-based factors (LTB, CORP, HY, SOV) exhibit rather low volatility levels we scale their time series to have the same variance as MKT. This approach ensures a meaningful interpretation of beta estimates.

14 This procedure is preferred to alternative commonly applied structural break tests such as (i) the Chow test which requires the exact break date to be known and (ii) the Quandt Likelihood Ratio (QLR) test that only allows testing for one unknown structural break.
Therefore, the third sub-period represents an ideal setting for analyzing banks’ systematic risk exposures and their changes over time. Further support for these sub-periods is provided by Delis et al. (2014), documenting significant changes in both perceptions and expectations about economic conditions around both break dates. Figure 2 presents the performance of the value-weighted BHC portfolio and the CRSP value-weighted market portfolio over the full period and the different sub-periods.

< Please insert Figure 2 about here >

5. **Empirical Results**

The presentation of our empirical findings is divided into five sections. We first present the descriptive statistics of our sample (5.1). Section 5.2 is divided into two parts. First, the rolling variance decomposition of banks’ systematic risk is discussed (5.2.1) and then the corresponding beta sensitivities over the full period and individual sub-periods are analyzed (5.2.2). The determinants of individual bank risk are analyzed in section 5.3, and robustness checks for our empirical analyses are presented in section 5.4. Finally we discuss the implications of our findings with respect to contagion effects and systemic risk as well as regulatory initiatives and bank supervision (5.5).

5.1. **Descriptive Statistics**

Over the full period, the value-weighted bank portfolio generates an average return of 0.6 percent per month (Table 2, Panel A) or 7.2 percent per year. The overall positive average performance stems from the continuous upward trend of stock prices in the first sub-period, while bank returns are more volatile and not significantly different from zero in periods subsequent to 1999. The corresponding Sharpe ratios support the performance figures and indicate that banks’ return-to-risk relationship is highest in the first sub-period (0.192). The hypothesis of normally distributed returns is rejected for the full period and the first sub-period. For the individual bank characteristics (Table 2, Panel B) we document for the full period a shift of the relative shares of real estate loans \( (rel) \), commercial and industrial loans \( (cil) \), and consumer loans \( (cl) \). While real estate loans account for an average share of 56 percent of banks’ loan portfolios in the first sub-period, they continuously increase to 75 percent in the third sub-period. Consequently, the relative importance of \( cil \) and \( cl \) declines. This observation is consistent with empirical findings (Young et al. 2013) and supports banks’ increased exposure to the real estate market which was at the center-stage of the recent financial crisis as argued in section 2.1. Banks’ reliance on non-interest income increases over the full period.
as indicated by \( n_i \). Profitability (\( \text{roa} \)) is highest in the first sub-period, and banks’ loan loss provisions (\( \text{pll} \)) almost tripled between the second and the third sub period.

5.2. Systematic Risk Exposures

In this section, we discuss our empirical findings with respect to the banking-industry risk exposures. These results are separated into the rolling variance decompositions (5.2.1) and the factors’ beta sensitivities over the full period as well as the three individual sub-periods (5.2.2). Overall, these results allow drawing inferences on the capital market’s assessment of bank risk in a time-varying setting.

5.2.1. Variance Decomposition

We document that our model explains a major fraction of bank stock returns in Figure 3. The solid line denotes the overall explanatory power of the bank risk factors, while the dotted line represents the performance of the value-weighted bank portfolio. On average, about 70 percent of banks’ total variance is attributable to systematic risk with the following individual variance shares: interest rate risk (10%), credit risk (21%), sovereign risk (4%), real estate risk (12%), and market risk (23%). Although the average figures provide a first indication of the factors’ relevance, detailed insights can be gained from analyzing their time variation. The pronounced dynamics in risk exposures reflect the capital market’s changing assessment of bank risk, underlining that market participants actively incorporate new information in bank stock returns. None of the individual risk dimensions dominates the return-generating process, indicating that banks’ risk exposures are multi-faceted and cannot be captured by standard one-factor or two-factor models.

Interest Rate Risk: The theoretically well-motivated relevance of interest rate risk is predominantly documented for periods of rising stock market valuations. In these periods, economic conditions generally improve, accompanied by a rising demand for goods and services and increasing capacity utilization. For financing consumers’ spending and firms’ investment activities, banks play a central role as financial intermediary by providing access to loans, and managing credit risk. By accepting short term deposits and supplying fixed rate loans to corporations and households, banks usually transform maturities and increase their own exposure to interest rate risk. Market participants generally are aware of the banks’ new profit opportunities but also of the increased risk exposures stemming from maturity transformation as well
as the growing loan portfolio and the higher risk of loan losses during these periods. While banks’ lending operations usually are associated with credit risk that is often accompanied by rapid loan portfolio expansion, it is negligible or of minor relevance in such positive market environments.15

**Credit Risk**: The exposure to credit risk is mainly concentrated in corporate borrowers with a perceived high default probability while **CORP** is of minor relevance. This observation is explained by the well-developed US corporate bond market, because larger corporate borrowers with a relatively low default probability are less dependent on bank credit and have direct access to debt markets. Moreover, it may also reflect banks’ opportunity to effectively hedge their loan portfolio against the credit risk of borrowers with a perceived low default probability in mature and liquid derivatives markets. Interestingly, the capital market perceives **HY** to be particularly relevant for bank risk in three crisis periods. These are (i) the second part of the savings and loan crisis of the late 1980s and the subsequent US recession of the early 1990s, (ii) the Russian default and the Long-Term Capital Management (LTCM) bail-out in 1998, and (iii) the recent financial crisis. During the late 1980s, banks’ substantial exposure to **HY** emanates from the consequences of the savings and loan crisis that was accompanied by a large number of bank failures and the subsequent recession in the early 1990s (Kane and Yu 1996). The economic downturn in the early 1990s led corporate yield spreads to increase sharply, making possible loan defaults and, hence, credit risk exposure, a relevant determinant of bank stock returns. Consequently, the rising importance of credit risk and loan defaults resulted in a substantial decline of banks’ market values and stock prices between 1989 and 1991 (Figure 2). In August 1998, Russia declared a moratorium on servicing its foreign debt and defaulted on its domestic debt, resulting in declining bank stock prices by more than 25 percent between July and August 1998.16 Kho et al. (2000) support this negative relationship and valuation effects empirically by documenting that market values of banks that had significant exposures to Russian debt declined even stronger. Corporate yield spreads widened in 1998, thereby, reflecting market participants’ awareness of potential loan defaults and negative economic effects emanating from this period.

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15 The sudden surge in both, interest rate risk and credit risk during the most recent year may point to the capital market interpreting these risks as being strongly interconnected in the current market environment. Based on the prevailing ultra-low interest rate level, the market may have well anticipated that any expected increase in interest rates leads to pronounced losses on banks’ balance sheets. Moreover, rising interest rates also may increase the likelihood of corporate borrowers defaulting on their contractual interest payments.

16 Besides the negative returns during the recent financial crisis in 2008, August 1998 represents the month with the largest decline of bank stock prices for our sample. While the overall stock market also declined in this month, the percentage loss was less pronounced (16 percent). Hence, the 1998 crisis clearly was more significant for bank stocks than for the overall market.
Fahlenbrach et al. (2012) view the 1998 period as one of the most severe financial crises to date. Interestingly, they document that information on individual bank performance during the 1998 crisis is helpful for predicting their performance and failure probability during the recent crisis. Hence, these banks continue to have some specific characteristics that make them susceptible in times of a financial crisis. Besides their risk culture and business model, effective risk exposures provide a potential rationale for distress of the same banks across crisis periods. In this context, we document a pronounced increase of the capital market’s assessed credit risk in bank stock returns beginning in mid-2007. This result is consistent with banks’ significant exposure to the subprime mortgage market which was at the center-stage of the recent crisis, suggesting that credit risk exposure is an important factor for banks in crisis periods.

**Sovereign Risk:** In contrast to interest rate risk and credit risk, banks’ exposure to sovereign risk is negligible for the most part of our sample period, supporting the regulator’s traditional perspective that government bonds are virtually risk-free. As presented in Figure 1, the spreads between the German government bond and sovereign bonds of other European countries substantially narrowed toward the end of the 1990s, signaling the increased likelihood of the introduction of a common currency in Europe. Subsequent to the introduction of the Euro in 1999, a particularly low volatility of spreads is observed. Hence, for a prolonged period the capital market did not perceive European sovereign bonds to be riskier than investments in the German Bund. However, when the European sovereign debt crisis began to unfold, banks’ exposure to European sovereign debt were suddenly perceived as risky, possibly resulting in significant losses. Figure 3 indicates that the capital market began to reassess banks’ exposure to SOV in 2009, reflecting that capital market participants became aware of the inherent riskiness associated with holdings of European sovereign debt. By 2010, the sovereign risk exposure appears to have declined. Reasons for this observation are (i) that banks already have written down the value of these bonds or sold a portion of their sovereign debt holdings with losses, (ii) that banks effectively hedged their positions with futures contracts or by purchasing credit default swaps, and (iii) the strenuous efforts on implementing bail-out programs for individual European countries have reduced the risk of default. However, the continued exposure to sovereign risk through the end of our sample period is consistent with US banks again increasing their holdings of sovereign debt when spreads started to decline and market values rebounded in 2011-2012.¹⁷

**Real Estate Risk:** Most exposure to the real estate market is concentrated in the late 1980s and early 1990s as well as in the recent financial crisis. During the 1980s, the real estate market experienced an unprecedented boom that came to a sudden halt in the late 1980s. Due to several regulatory reforms promoting competitive pressures in the banking system and the attractive real estate lending environment, banks’ underwriting standards for real estate loans loosened significantly throughout the 1980s (Hendershott and Kane 1992). As a consequence of the savings and loan crisis, hundreds of insolvent thrift institutions were closed that formerly represented an important funding source for real estate. When the real estate market collapsed, banks heavily engaged in real estate lending experienced significant losses on their loan portfolio which is consistent with the exposure in Figure 3.

As discussed before, credit risk is also well reflected in stock prices during these periods, supporting the strong interconnection of both risk dimensions and their association with business cycle movements. For the recent financial crisis, we identify a significant reassessment of real estate exposure following the decline in HY. This result suggests that capital market participants recognized the threat of real estate losses in excess of banks’ subprime exposure. The full scale of losses on real estate loans were likely to emerge after the subprime mortgage market had collapsed so that the capital market perceived banks to be sensitive to real estate risk even after the 2007 to 2008 period.

**Liquidity Risk and Risk Aversion:** While our results clearly provide evidence that the proposed factors explain a significant fraction of bank stock returns, yield spreads such as CORP, HY, and SOV implicitly reflect time-varying liquidity conditions of the underlying assets (Acharya et al. 2013; Monfort and Renne 2013). Moreover, changes in market participants’ risk tolerance likely affect market prices in financial crises (Hoffmann et al. 2013). This link suggests that the strong time-variation of bank risk exposures during crisis periods may be a composite of fundamental changes in the value of banks’ assets affected by the systematic banking-industry risk factors and general variations in liquidity and risk aversion. In fact, during the recent financial crisis, the dynamics in the capital market’s perceived riskiness of banks are most pronounced between 2008 and 2009 when credit risk, real estate risk, and sovereign risk account for a major and dynamic share of banks’ systematic risk exposure. This period lines up with the Federal Reserve initiating several emergency liquidity programs designed to stabilize the financial system and reduce stress in the banking sector (Helwege et al.
Moreover, the Troubled Asset Relief Program (TARP) allowed regulators to infuse equity into troubled institutions and purchase illiquid and opaque bank assets. Importantly, all these programs were aimed at providing sufficient liquidity and equity to troubled banks, minimizing their insolvency risk, and at the same time promoting investor confidence and reducing investors’ risk aversion. The documented changes in banks’ risk exposures during the crisis, especially the strong decline in HY exposure, should be interpreted with reference to these regulatory initiatives. This perspective on the Federal Reserve’s actions is consistent with recent empirical findings, showing that crisis lending programs led to significant bank stock price reactions (Cyree et al. 2013). Similar findings are reported by Ng et al. (2011) for banks that participated in the TARP Capital Purchase Program (CPP). Hence, market participants incorporated information associated with a banks’ access to either one of the programs into bank stock prices and revalued the underlying risk exposures. Overall, the interconnection of liquidity conditions and risk aversion contribute to banks’ dynamic risk exposures in the crisis periods, but disentangling these dimensions is challenging and left for future research.

5.2.2. Beta Sensitivities

So far, the variance decomposition analysis has provided convincing evidence that banks’ systematic risk exposures are time-varying and well reflected in bank stock returns. We proceed by analyzing the underlying beta sensitivities and their time variability, thereby directly relating the dynamic variance shares to the magnitude and variations of factor coefficients. Table 3 (Panel A) presents the empirical results for the full period and the three individual sub-periods defined in section 4.3.

For the full period, the six-factor model explains, on average, two-thirds of banks’ stock return variation. Hence, a significant fraction of return variance is associated with changes in systematic risk factors. Their relevance is more pronounced during the first and third sub-periods when banks were particularly exposed to a wide set of risk factors consistent with the variance decomposition analysis. The lower systematic risk between November 1999 and September 2007 coincides with a period when bank stocks outperformed the overall mar-

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18 The specific programs are the Primary Dealer Credit Facility (PDCF), the Term Auction Facility (TAF), and the Term Securities Lending Facility (TSLF).

19 Importantly, these inferences cannot be drawn in a rolling regression setting due to overlapping observations. However, beta sensitivities from rolling regressions are available from the authors upon request.
ket and fared particularly well during the dot.com bubble period and the 2001 recession (Figure 2). Schuermann (2004) attributes this fact to banks’ strong profitability and relatively low levels of non-performing loans. Compared to the significant decline of bank stock prices in the early 1990s as well as during the recent financial crisis, the 2001 crisis period was less of a concern for banks than for industrials.

The respective beta sensitivities all have the expected signs with credit risk and sovereign risk being negatively and real estate risk being positively related to bank stock returns. Consistent with the variance decomposition results, high credit risk is the dominant return determinant besides real estate risk throughout all sub-periods while sovereign risk becomes highly significant during the recent European sovereign debt crisis. The exposure to interest rate risk is insignificant for the full period which is attributable to its pronounced time-variability and its changing sign over the individual sub-periods. In earlier studies, several authors have documented that banks’ exposure to interest rate changes are negative due to their balance sheet composition and maturity transformation activities (Flannery and James 1984; Madura and Zarruk 1995). We document the expected negative sign for the first sub-period, but the coefficient significantly increases after 1999. While Faff and Howard (1999) discuss potential explanations by referring to changes in banks’ business activities and their involvement in derivatives and securitization markets, they do not explicitly test these hypotheses. The recent work by Young et al. (2013) provides empirical evidence in this respect. Consistent with our findings, they document (i) that US banks’ exposure to interest rate risk is insignificant over the 1990 to 2009 period, and (ii) that the interest rate coefficient significantly changes over the sample period. The authors relate these differences to changes in the composition of banks’ loan portfolios and particularly emphasize the strong growth of real estate loans on banks’ balance sheets accompanied by opportunities for trading rather illiquid assets such as long-term loans in capital markets.

As documented in section 5.1, the dominant share of real estate loans in banks’ loan portfolios is confirmed for our sample. While real estate loans naturally are longer-term assets, Young et al. (2013) argue that the effective times to maturity of real estate loans – which are a function of the time to re-pricing – may have decreased over the sample period. Their argument is based on several regulatory and policy changes during the 1990s that were designed to increase market opportunities for bank loans and were encompassed by the substan-
tial growth in securitization and secondary loan markets.\textsuperscript{20} In fact, Gande and Saunders (2012) support this increased commoditization of bank loans through the emergence of active secondary markets over the last two decades. They conclude that these developments also have altered the nature of bank specialness by combining their traditional role as information producers and monitors as well as their importance for creating an active secondary market for bank loans. Moreover, the prolonged decline in interest rates over our sample period likely accelerated mortgage prepayments. Krishnamurthy and Vissing-Jorgensen (2011) argue that the duration of a typical 30-year mortgage-backed security is about seven years which is comparable to a 10-year bond. In the context of declining interest rates and higher prepayment probabilities, the effective maturity of these instruments may have been even shorter, which is in line with the aforementioned argument of Young et al. (2013).

5.3. Individual Bank Risk

While the previous analyses have provided convincing evidence that the systematic risk factors explain a substantial portion of total bank variance, these exposures do not allow drawing inferences with respect to idiosyncratic or individual bank risk. According to portfolio theory, idiosyncratic risk should be negligible in diversified portfolios, i.e. company-specific risk is diversifiable. Although this should apply for banks as well, problems at one bank may significantly affect the valuation of other banks, suggesting that idiosyncratic bank risk becomes highly positively correlated during crises periods. Therefore, understanding the individual bank risk is relevant not only for bank regulators, banks’ customers, banks’ large shareholders, but even for well-diversified investors.

In Table 4, we present empirical results on the question which bank characteristics are directly related to individual bank risk. Our baseline regression in column 1 includes variables that effectively control for the general characteristics of a typical bank by incorporating assets, equity, nii, roa, and pll. In addition, we control for a non-linear relationship between risk and banks’ reliance on non-interest income by including niisq, the squared ratio of non-interest income to total income (Baele et al. 2007). We find that individual bank risk is negatively correlated with capitalization and profitability but increases with the ratio of loan-loss provisions. The results suggest that the capital market perceives well-capitalized banks to have less individual bank risk which is consistent with equity representing a means for absorbing potential losses. The negative relation between profitability and individual bank risk

\textsuperscript{20} The authors refer to the 1992 Federal Housing Enterprises Financial Safety and Soundness Act (FHEFSSA), the 1995 Community Reinvestment Act (CRA), the 1999 GLBA, and the encouragement of the Department of Housing and Urban Development (HUD) to stimulate the market for mortgages and mortgage-backed securities.
is expected while the positive coefficient on loan-loss provisions is consistent with Docking et al. (1997) who find that announcements of higher loan loss provisions denote a negative signal to stock market investors. We document that individual bank risk generally declines with \textit{nii} but increases once the exposure to non-traditional activities exceeds a certain threshold as shown by the significantly positive coefficient on \textit{niisq}. Consistent with Baele et al. (2007), asset size is insignificant and, therefore, does not denote a reliable indicator for individual bank risk.

As documented in section 5.1, the composition of banks’ loan portfolio has significantly changed over the sample period. Therefore, we incorporate information on real estate loans in column 2. The results indicate that the share of real estate loans has a positive and highly significant effect on banks’ idiosyncratic risk while the remaining variables retain their signs and significance levels. In columns 4 and 5 we conduct robustness tests for our baseline regression (column 1) by alternatively controlling for the relative portion of commercial and industrial loans and consumer loans.\textsuperscript{21} While commercial and industrial loans are insignificant (column 4) the ratio of consumer loans (column 5) is negatively associated with individual bank risk, however, the other coefficients again remain strongly robust. Due to the increasing share of real estate loans on banks’ balance sheets and their immanent exposure to adverse real estate market conditions documented before, we proceed by augmenting the model of column 2.

We control for regional effects with the growth rates of state-level business cycle indices (column 3). We find that individual bank risk increases with deteriorating state-level business cycle conditions as indicated by the significantly negative coefficient on \textit{buscycle}. In columns 6 to 8, we conduct robustness checks with respect to the inferences drawn for regional effects on individual bank risk. Instead of state-level business cycle indices, we consider the state-level relative unemployment rate and the state-level growth rate of labor income. In column 6, we include \textit{unemploy} and document a significantly positive coefficient that is consistent with an increasing level of individual bank risk in light of worsening business cycle conditions. In column 7, we alternatively control for the state-level growth rate of labor income. Similar to the relative unemployment rate, \textit{labor} also is significant and has the expected negative sign. When controlling for \textit{unemploy} and \textit{labor} simultaneously, we find that both variables remain significant. Therefore, the robustness checks for regional effects indi-

\textsuperscript{21} Due to the significant correlations we do not incorporate more than one of these variables in the regression simultaneously. The correlation structure is available from the authors upon request.
cate that unemployment and labor support our findings in column 3 using the state-level business-cycle indices.

Overall, our analyses provide evidence that banks’ equity ratio, profitability, and loan loss provisions are directly and significantly related to individual bank risk. The composition of banks’ loan portfolio yields valuable insights for identifying institutions with significant idiosyncratic risk exposures. In addition, we document that individual bank risk has a strong state-level business cycle component with higher levels of idiosyncratic risk in the context of deteriorating state-level economic conditions.

< Please insert Table 4 about here >

5.4. Robustness Checks

We perform various robustness checks for our empirical results by first focusing on methodological issues and then on the economic variables and factor structure. We begin with a discussion and detailed analysis of the democratic and sequential orthogonalization approaches to ensure that the selected decomposition technique does not bias our results (5.4.1). Then, we estimate variance decompositions with an augmented factor structure (5.4.2). These factors, including the Fama and French (1993) factors, and two additional economic variables, were already used as risk factors for banks in other studies. This analysis is designed to control for potentially omitted risk factors for explaining bank stock returns. In section 5.4.3, we investigate the determinants of banks’ market risk exposure, thereby taking into account that market risk itself represents a mixture of other common risk factors.

5.4.1. Orthogonalization Technique

Our empirical analysis builds on the democratic factor orthogonalization technique of Klein and Chow (2013) that is relatively new in the literature and has not been widely applied for analyzing bank risk so far. In section 3.1, we have discussed this approach in response to the shortcomings of the sequential procedure and emphasized that the democratic approach can best resemble the original factor series. Interestingly, this suggests that the individual explanatory power of democratically orthogonalized factors should be comparable to the individual variance shares of their original counterparts, i.e. when the factors are leading the sequential procedure. Therefore, democratically orthogonalized factors should provide information that is similar to the information provided by the original factor series, but without any cross-correlations. We further analyze this aspect to ensure that our conclusions are not biased
by the selected orthogonalization technique. For this purpose, we report descriptive statistics of each individual factor’s variance share with both, the democratic technique and the sequential procedure. While the former corresponds to the variance shares discussed in section 5.2, the latter is applied using each individual factor either (i) as the leading factor or (ii) as the last factor in the orthogonalization sequence. When the factor leads the sequence, its explanatory power is expected to be larger than when it enters the sequence last. Consistent with the analysis in section 5.2, we use a rolling window of 36 months for decomposing systematic bank risk.

We focus on the four factors \( LTB \), \( CORP \), \( HY \), and \( SOV \) because \( REIT \) and \( MKT \) are sequentially orthogonalized before entering the variance decomposition. Table 5 reports statistics on each factor’s variance share over rolling three-year estimates corresponding to the democratic technique (“Democratic”) in column 1 as well as the sequential approach (“Sequential First”, “Sequential Last”) in columns 2 and 3, respectively. The columns 4 and 5 report differences between “Sequential First” and “Democratic” (“First – Dem”) as well as between “Sequential First” and “Sequential Last” (“First” – “Last”). Inferences are based on the average and median variance shares, their 25th and 75th percentiles as well as their minimum and maximum values.

\[\text{Please insert Table 5 about here}\]

The results suggest that average differences based on the democratic technique (column 4) are relatively small over all factors and range between 1.4 percent (\( SOV \)) to 3.8 percent (\( CORP \)). Inferences using median differences are identical while the absolute magnitudes are smaller for \( LTB \), \( CORP \), and \( SOV \), with the latter being close to zero. When analyzed in relative terms, i.e. dividing mean or median values of column 1 (3) by the respective values in column 2, the results do not change our conclusions. Except for \( CORP \), the relative numbers are close to or well above 80 percent. \( HY \) is most closely related to the original factor’s explanatory power with a ratio of 91 percent. The relatively small ratio for \( CORP \) is consistent with our results in section 5.2 underlining that \( CORP \) is of lower importance for bank stock returns. In general, these findings support the perspective that, on average, the democratic technique well resembles the information embedded in the original factor series. In contrast, the respective figures in column 5 are much larger, suggesting that positioning each factor at the end of the sequence generates orthogonalized factor series that reflect much less economic information compared to the original factors. Again, this interpretation is supported by relative figures.
To augment the preceding analysis we also present differences between “Democratic” and “Sequential Last” with respect to “Sequential First” over time. For this purpose, we utilize information from the entire time series of each factor’s rolling variance shares depending on the three orthogonalization approaches. To allow for a comparison of estimation methods we proceed as follows. For each month and each factor, we calculate the difference between (i) “Sequential First” and “Democratic” as well as between (ii) “Sequential First” and “Sequential Last”. This estimation leads to eight time series (four per orthogonalization technique) of differences in variance shares with respect to “Sequential First”. Then we calculate the mean of these four time-series per month which gives us an average deviation for “Democratic” and an average deviation for “Sequential Last” from “Sequential First”. These time series are presented in Figure 4.

< Please insert Figure 4 about here >

The results indicate that the level of “FirstDem” (bold line) is consistently smaller than the level of “FirstLast” (dashed line). This finding is supported by the grey shaded area which represents the difference between both lines. Before the onset of the recent crisis, the difference “FirstDem” is almost entirely below five percent while “FirstLast” exceeds this level by far. At the beginning of the 1990s as well as in the mid of 1997, “FirstLast” reaches its maximum at roughly 20 percent, suggesting that the explanatory power attributed to each factor strongly diverges from the original factor series. The corresponding level of “FirstDem” is significantly smaller so that the democratic technique better resembles the information associated with the original factor series. During the onset of the financial crisis in 2007-2008, both differences become more volatile. However, “FirstDem” is still consistently closer to the original factors’ variance shares. To the end of the sample period, the divergence between the original factors’ individual explanatory power and both orthogonalization approaches increases. This finding indicates that individually, i.e. when each factor enters the sequence in first position, the factors capture a dominant share of systematic bank return variance. However, the democratic technique still performs remarkably better than “FirstLast” as shown by the strong increase of the grey shaded area from 2012 onwards.

Overall, the democratic approach generates variance shares that are close to the variance shares when each factor is analyzed individually without orthogonalization. This finding supports our conclusions from the main analyses by underlining that the democratic orthogonalization is better suited than the sequential approach for decomposing bank stock return variance.
5.4.2. Additional Risk Factors

To verify the robustness of our empirical results with respect to alternative risk factors and to make our findings comparable to other empirical studies, we separately control for the Fama and French (1993) factors $SMB$ and $HML$ as well as an additional term spread factor ($TERM$) and the $TED$ spread.²² $TERM$ is defined as the yield difference between 10-year constant-maturity US government bonds and 3-months US treasury bills while $TED$ is the yield difference between the 3-months London Interbank Offered Rate (LIBOR) and 3-months US treasury bills. The Fama and French stock market factors have been extensively used in empirical studies, however, with a focus on non-financial firms.²³ While Viale et al. (2009) apply the three-factor model on a sample of US banks they do not document compelling evidence for the importance of $SMB$ and $HML$. An explicit term spread factor has been studied by Demsetz and Strahan (1997) and Viale et al. (2009), while $TED$ is commonly perceived as a measure for the financial sector’s credit risk and as an indicator for funding illiquidity in the banking sector (Baele et al. 2013).²⁴

In Figures 5, 6 and 7, we document that our main findings are robust with respect to separately including the Fama and French factors, $TERM$, and $TED$. The factors $SMB$ and $HML$ are negligible for most of the sample period. Only during the period between 1999 and 2003 $SMB$ improves the overall explanatory power of our general model while $HML$ contributes to the R-squared in the recent crisis period. Changes in the steepness of the yield curve temporarily capture some portion of banks’ return variance, i.e. when the difference between long-term and short-term yields increases as during the early 1990s and the recent crisis. This result indicates the banks’ risk exposure to maturity transformation. For $TED$, we also document some explanatory power at the beginning of the sample period as well as during the recent financial crisis. The exposures are consistent with $TED$ providing information that is relevant in periods of financial market stress and may point to risk aversion effects or funding liquidity constraints.

Overall, these robustness checks support our main conclusions. They offer further evidence that banks’ exposure to the six risk factors reflecting interest rate risk, credit risk, sovereign risk, real estate risk, and market risk account for the dominant share of banks’ system-

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²² For brevity, we do not report the results of our panel regressions that use either one of these three alternative model frameworks. However, the empirical findings are strongly robust and do not change our conclusions regarding individual bank risk. All results are available from the authors upon request.

²³ We thank Kenneth R. French for providing the data on $SMB$ and $HML$ on his website.

²⁴ Although $TED$ incorporates the London Interbank Offered Rate (LIBOR) which was manipulated by several large banks, we do not assume these practices to affect our empirical findings because these manipulations were only small in the order of a few basis points and they were not systematic in one direction (Boudt et al. 2013).
atic return variance. Hence, we are confident that we have not omitted any relevant systematic risk factors in our model.

5.4.3. Residual Market Risk Exposures

The overall exposure to systematic market risk averages 23 percent over the three-year rolling window estimations (Figure 3). To further analyze this exposure with respect to the influence of other types of risk factors, we decompose the market factor residuals from rolling 36-months regressions using the democratic technique of Klein and Chow (2013) with respect to three factors besides $SMB$ and $HML$: (i) the Federal Reserve’s broad trade-weighted US foreign exchange basket in percentage changes ($FX$), (ii) a market-wide illiquidity factor in first differences ($ILLIQ$), and (iii) the Chicago Board Options Exchange volatility index in first differences ($VIX$). From this analysis, we can draw further inferences on the effective risk composition of banks’ market risk exposure documented in Figure 3.

While $SMB$ and $HML$, by construction, represent equity market risks, $FX$, $ILLIQ$, and $VIX$ also have been analyzed for other asset classes. Therefore, we view foreign exchange risk, illiquidity risk, and volatility risk as not being unique to stock returns, but instead, command a relevant role for explaining a wide range of asset returns including hedge fund and mutual fund returns, fixed income instruments and currencies. Consequently, we interpret these variables as representing risk perceptions that are common across asset classes, but nevertheless contribute to disentangling the mixture of factors influencing banks’ market risk exposure.

The motivation for $FX$ representing market-wide rather than a bank specific risk has already been discussed in section 2.2. From this discussion we would expect that it contributes to the explanation of banks’ residual market risk exposure. Illiquidity risk has been widely analyzed for equity, mutual fund and hedge fund returns as well as for corporate bonds (Acharya et al. 2013) and currencies (Mancini et al. 2013). Independent of the asset class, the authors agree that illiquidity risk represents a common risk factor in returns, especially in stress periods. Building on these findings, Hu et al. (2013) propose a market-wide rather than an asset class specific illiquidity risk factor designed to reflect arbitrage conditions in the financial markets.

25 Alternatively, we also have applied robustness checks with sequentially orthogonalizing the Fama and French (1993) factors and the three additional risk factors. Not surprisingly, the explanatory power of factors that enter the sequence first is larger in this context. Therefore, we decide to use the democratic technique that is not subject to the discretionary choice of a starting vector and orthogonalization sequence but treats all variables on an equal footing. However, the robustness checks are available from the authors upon request.
capital market.\textsuperscript{26} The \textit{VIX} is a measure of market expectations of short-term volatility based on S&P 500 stock index option prices. It does not represent a systematic bank risk factor which is supported by the large number of studies that have used the \textit{VIX} in different research contexts. For instance, its interpretation as a fear gauge, an indicator for panic effects, and a general measure of investors’ risk aversion have contributed to its use in empirical studies.

< Please insert Figure 8 about here >

Figure 8 shows that the five factors capture an average of 40 percent of banks’ market risk exposure. \textit{FX}, \textit{ILLIQ}, and \textit{VIX} explain, on average, 22 percent, and a maximum of about 52 percent of the residual market returns. \textit{SMB} and \textit{HML} account for an average variance share of 18 percent with a maximum of 41 percent. Among the first three variables, the dominant variable is \textit{VIX} followed by \textit{FX}, while \textit{ILLIQ} is less relevant. \textit{HML} is particularly relevant during the first half of the sample period while \textit{SMB} is widely negligible except for the years 2005-2007. During the stock market’s growth period subsequent to the dot.com bubble, volatility risk becomes the major determinant of market risk exposure. Foreign exchange risk commands an increasing variance share exactly when both, volatility risk and the explanatory power of the market factor, decline. The period starts in mid 2005 and ends in early 2009 when the variance share of the market factor rebounds. For this period, one can conclude that although \textit{FX} commands an increasing fraction of residual market return variance, its relevance with respect to bank stock returns should be negligible due to the rapidly declining explanatory power of \textit{MKT}. Illiquidity risk is widely negligible except for the time periods around the recession of the early 1990s, the Russian default in 1998, and the beginning of the Greek sovereign debt crisis in 2009. This finding supports the importance of liquidity in the context of financial crises and periods of financial market turmoil. In general, these findings are supported by Table 3 (Panel B) in terms of the coefficients’ statistical significance over the full period and the three sub-periods.

Although the market residuals are corrected for the effects of banking-industry risk factors, overall our findings are consistent with the perspective that market risk exposures reflect information associated with systematic variation in other factors. This result is consistent with Fama and French (1993) interpreting the market factor as a “hodgepodge” of common risk factors. Our analyses support the view of market risk representing a non-transparent, opaque aggregate of other, market-wide risk exposures rather than a clear-cut

\textsuperscript{26} The data is available on the website of Jun Pan (http://www.mit.edu/~junpan/).
bank risk factor. Among them, $FX$, $ILLIQ$, and $VIX$ are not unique to the stock market but also have been documented to explain movements in the market values of other asset classes.

5.5. Contagion Effects and Systemic Risk

In light of our empirical findings for the systematic and unsystematic bank risks, we briefly discuss the economically and politically important issues of contagion effects and systemic risk. The fundamental idea of portfolio theory is that a firm’s total risk can be divided into two components, systematic risk and unsystematic risk (Markowitz 1952). Systematic risk is non-diversifiable and consequently investors demand a risk premium for holding it, whereas unsystematic or idiosyncratic risk is the company-specific component of a firm’s total risk. It is usually diversifiable and therefore negligible in large portfolios unless stock returns are highly positively correlated. Thus, for a portfolio consisting of a sufficiently large number of national and international industrial firms, unsystematic risk is diversified and only the systematic risk exposure is relevant for valuation.

In contrast, for banks it is important to recognize that these diversification benefits supposedly hold primarily in non-crisis periods when idiosyncratic risk is rather uncorrelated and diversifiable. However, this relationship may rapidly change in crisis periods when correlations between individual banks’ stock returns increase. In fact, for investors holding a diversified portfolio of bank stocks, distress at one particular institution may directly affect other banks through spillover or contagion effects and therefore the correlation structure of returns. To analyze the impact of these spillover effects they are usually separated into “informational contagion” and “non-informational contagion” (Kaufman 1994; Bessler and Nohel 2000). Helwege (2010) adds the idea of “counterparty contagion” that emanates from the strong interconnectedness of financial institutions. Informational contagion affects banks that have one or more common characteristics such as loan and bond holdings with the distressed institution. Thus, common asset holdings such as subprime mortgages lead market participants to simultaneously re-assess individual banks in response to changes in the quality of these assets. In contrast, non-informational contagion occurs when negative news about an individual bank also adversely affects other banks, even including healthy institutions that have few if any common characteristics with the distressed institution. In this case, market participants cannot discriminate between solvent and troubled banks, but instead assume that all banks are

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27 This type of contagion may emerge when market participants cannot easily infer whether banks (i) have exposures to similar types of assets (Bessler and Nohel 2000) or (ii) may be subject to negative valuation signals such as a dividend omission that has initially been released by one bank (Bessler and Nohel 1996).
exposed to similar risks. Thus, non-informational contagion effects are also called sun-spot events (Diamond and Dybvig 1983). Counterparty contagion describes the failure of several banks in response to a bank failure, however, without having common asset exposures. For instance, in the absence of creditor protection, the failure of the Continental Illinois Bank would have affected nearly 2,300 individual banks that held deposits at or loaned funds to the bank but did not necessarily have similar types of assets (Kaufman and Scott 2003).

While Kaufman (1994) notes that spillover effects may also exist in the context of distress at nonbanks, bank contagion is considered to appear faster, spread to a larger proportion in the industry, lead to a larger percentage of failures, and spill over to other industries as well. In this context, the concept of systemic risk has recently received particular attention from both, regulators and academics. Systemic risk is considered to affect not only the initial industry but have more widespread effects on other industries as well as the (macro-) economy and is often ascribed to institutions in the banking sector. While it is theoretically defined either from a macro-level or micro-level perspective, there exists no generally agreed upon empirical measure. For instance, Bisias et al. (2012) review a total of 31 potential indicators for systemic risk. These include theoretically promising network measures that capture the interconnectedness among institutions, which represents an important condition for risk to disseminate throughout a system.

Without a proper assessment of the inherent risks undertaken by banks, any regulation is likely to be ineffective for preventing bank failures and stabilizing the banking system in the long-run. Our study adds to this perspective in that we provide new empirical evidence for the capital market's assessment of banks' riskiness and its strong-time variation in periods of financial distress. In short, understanding the dynamics of banks’ systematic and unsystematic risks are important from an investor's perspective and for providing an adequate framework for discriminating between various types of bank risks, whereas contagion effects and systemic risk are more of a bank management’s and bank regulator’s concern. Differentiating between these risks, their interactions and time variability is a prerequisite for analyzing how systematic and unsystematic bank risk contribute or lead to financial contagion effects and systemic risk are more of a bank management’s and bank regulator’s concern. Differentiating between these risks, their interactions and time variability is a prerequisite for analyzing how systematic and unsystematic bank risk contribute or lead to financial contagion effects and systemic risk are more of a bank management’s and bank regulator’s concern. Differentiating between these risks, their interactions and time variability is a prerequisite for analyzing how systematic and unsystematic bank risk contribute or lead to financial contagion effects and

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28 Helwege (2010) also considers the (theoretical) failure of American International Group (AIG) as a typical example for counterparty contagion. According to her reasoning, it would have led to widespread failures in the financial system due to the strong interconnectedness resulting from financial contracts such as CDS. However, she also notes that counterparty contagion is rather unlikely to emerge in financial systems because it assumes that institutions along the “failure chain” hold quite undiversified asset portfolios.

29 In this context, Lang and Stulz (1992) document that the existence of contagion crucially depends on industry characteristics, with industries having rather high leverage ratios such as the banking sector experiencing stronger contagion effects.
systemic risk. Most importantly, the objective of our study is to encourage discussions among academics, regulators, and politicians of the following question: Which risk concept provides an adequate and best measure for banks’ riskiness and should be the focus of bank regulatory reforms. Answering this question is an interesting but challenging task and left for future research.

6. Conclusions

Over the last three decades, the US banking industry has experienced significant regulatory and structural changes as well as several crisis periods. The scope of the recent financial crisis has highlighted the imminent riskiness of banks and the importance to ensure a well functioning and solvent banking system. In this context, identifying and measuring the contemporaneous risk exposures of banks has received renewed academic research interest. In this study we analyze the systematic and unsystematic bank risk exposures for a sample of US bank holding companies for the period from 1986 to 2012. Using stock market data, we decompose banks’ return variance with respect to systematic banking-industry and systematic market-wide risk factors by applying the democratic orthogonalization technique of Klein and Chow (2013). The banking-industry risk factors are derived from the banks’ risk transformation function, while market-wide risk factors denote relevant risk factors for all firms, i.e. banks and industrials alike. In contrast, the unsystematic or idiosyncratic risk measures individual bank risk that remains unexplained by the systematic risk factors.

Our empirical findings indicate that (1) credit risk is an important factor in crisis periods that (2) banks’ real estate exposure is significant in periods of adverse real estate market conditions and that (3) sovereign risk becomes important in recent years, while (4) banks’ interest rate risk exposure has changed over time. In the latest periods, interest rate risk sensitivity has become positive, most likely due to the growth in asset securitization and secondary loan markets, but also due to lower interest rate levels which have favored mortgage prepayments and a decline in banks’ assets duration. An analysis of individual bank risk indicates that banks with significantly higher levels of idiosyncratic risk have lower equity capital, higher loan loss provisions, and more exposure to real estate loans. Moreover, individual bank risk exhibits a strong business cycle component. Our results are robust to alternative risk factor specifications including the Fama and French (1993) factors, the term spread, and the TED spread. We also provide evidence that banks’ market risk exposure represents a combination of other commonly applied risk factors. Besides Fama and French’s size and value factors, these include foreign exchange risk, illiquidity risk, and volatility risk. Importantly, the last
three variables can be interpreted as asset-wide risk factors as they also explain risk exposures of other asset classes including bonds, mutual funds, hedge funds, and currencies.

Overall, our findings provide new insights into banks’ exposure to banking-industry, market-wide and asset-wide systematic risk factors as well as individual bank risk determinants. Understanding these risk factors, their interactions and time variability is a prerequisite for analyzing how they may contribute or lead to financial contagion effects and systemic risk, which is of particular macro-prudential interest. Hence, our results provide an alternative framework for discussing the effectiveness of regulatory statutes and reforms for the financial system as well as for the supervision and monitoring of individual banks.
References


This figure presents the time series of the systematic risk factors. *LTB, CORP, HY, SOV, REIT,* and *MKT* represent the interest rate of US long-term government bonds, the spread between BAA and AAA corporate bonds, the spread between high-yield bonds and the aforementioned corporate spread, the sovereign spread between peripheral European countries and the German government bond, the real estate index, and the CRSP value-weighted market portfolio, respectively.
Figure 2: Performance of the value-weighted bank portfolio and the market portfolio

This figure presents the performance of the value-weighted bank portfolio and the value-weighted market portfolio over the sample period. The individual sub-periods are separated by vertical lines.
Figure 3: Rolling Variance Decomposition for Bank Holding Companies

This figure presents the rolling variance decomposition for the value-weighted bank portfolio with an estimation window of 36 months. The sum of the banking-industry risk factors’ explanatory power is denoted by the bold line. The performance of the value-weighted bank portfolio is shown by the dotted line.
Figure 4: Time-Variation of Differences in Orthogonalization Techniques

This figure presents the differences between orthogonalization techniques based on a rolling estimation window of 36 months. “FirstDem” (bold line) denotes the difference in factors’ variance shares between “SequentialFirst” and “Democratic” while “FirstLast” (dashed lined) represents the difference between “SequentialFirst” and “SequentialLast”. The shaded area reflects the difference between both lines.
Figure 5: Rolling Variance Decomposition for Bank-Holding Companies with SMB and HML

This figure presents the rolling variance decomposition for the value-weighted bank portfolio with an estimation window of 36 months. Besides the systematic risk factors of Figure 3, the model also incorporates the Fama and French (1993) factors $SMB$ and $HML$. The sum of the banking-industry risk factors’ explanatory power is denoted by the bold line. The performance of the value-weighted bank portfolio is shown by the dotted line.
Figure 6: Rolling Variance Decomposition for Bank Holding Companies with TERM

This figure presents the rolling variance decomposition for the value-weighted bank portfolio with an estimation window of 36 months. Besides the systematic risk factors of Figure 3, the model also incorporates a separate term spread factor (TERM). The sum of the banking-industry risk factors’ explanatory power is denoted by the bold line. The performance of the value-weighted bank portfolio is shown by the dotted line.
This figure presents the rolling variance decomposition for the value-weighted bank portfolio with an estimation window of 36 months. Besides the systematic risk factors of Figure 3, the model also incorporates the TED spread (TED). The sum of the banking-industry risk factors’ explanatory power is denoted by the bold line. The performance of the value-weighted bank portfolio is shown by the dotted line.
Figure 8: Rolling Variance Decomposition for the Residual Market Factor

This figure presents the rolling variance decomposition for banks’ residual market risk exposure as shown in Figure 3 (dotted line). The residual market risk exposure is decomposed using the Fama and French (1993) factors $SMB$ and $HML$, a trade-weighted foreign exchange risk factor ($FX$), a market-wide illiquidity measure ($ILLIQ$), and a volatility index ($VIX$).
Table 1: Multiple Structural Break Test

<table>
<thead>
<tr>
<th>No. of Breaks</th>
<th>F-statistic</th>
<th>Scaled F-Statistic</th>
<th>Critical Value</th>
</tr>
</thead>
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<tr>
<td>0 vs. 1 ***</td>
<td>6.51</td>
<td>45.55</td>
<td>26.16</td>
</tr>
<tr>
<td>1 vs. 2 ***</td>
<td>6.01</td>
<td>42.09</td>
<td>27.74</td>
</tr>
<tr>
<td>2 vs. 3</td>
<td>2.75</td>
<td>19.27</td>
<td>28.5</td>
</tr>
</tbody>
</table>

Break dates: November 1999 October 2007

This table presents the results of Bai and Perron’s (1998, 2003) multiple structural break test. The method is applied with sequential tests for the hypothesis of L versus L+1 breaks where L is the number of breaks. The test uses a trimming value of 0.20 and allows for a maximum of three structural breaks. The error distributions are allowed to differ between the individual sub-periods and the estimations are robust to heteroscedastic as well as serially correlated residuals. *** denotes statistical significance at the 1%-level.

Table 2: Descriptive Statistics

Panel A: Descriptive Statistics for Bank Portfolio Returns

<table>
<thead>
<tr>
<th></th>
<th>Full Period</th>
<th>1st Sub-Period 01/87 - 10/99</th>
<th>2nd Sub-Period 11/99 - 09/07</th>
<th>3rd Sub-Period 10/07 - 12/12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.006</td>
<td><strong>0.011</strong></td>
<td>0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td>SD</td>
<td>0.066</td>
<td>0.059</td>
<td>0.047</td>
<td>0.098</td>
</tr>
<tr>
<td>Sharpe</td>
<td>0.094</td>
<td>0.192</td>
<td>0.087</td>
<td>-0.033</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.640</td>
<td>-1.080</td>
<td>0.263</td>
<td>-0.267</td>
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<tr>
<td>Kurtosis</td>
<td>5.598</td>
<td>6.174</td>
<td>3.599</td>
<td>3.429</td>
</tr>
<tr>
<td>Min</td>
<td>-0.288</td>
<td>-0.255</td>
<td>-0.104</td>
<td>-0.288</td>
</tr>
<tr>
<td>Max</td>
<td>0.244</td>
<td>0.149</td>
<td>0.156</td>
<td>0.244</td>
</tr>
<tr>
<td>Normal</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Panel B: Descriptive Statistics for Bank Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Full Period</th>
<th>1st Sub-Period 01/87 - 10/99</th>
<th>2nd Sub-Period 11/99 - 09/07</th>
<th>3rd Sub-Period 10/07 - 12/12</th>
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<tr>
<td>assets</td>
<td>15.854</td>
<td>15.561</td>
<td>15.907</td>
<td>16.346</td>
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<tr>
<td>equity</td>
<td>0.087</td>
<td>0.083</td>
<td>0.089</td>
<td>0.095</td>
</tr>
<tr>
<td>rel</td>
<td>0.644</td>
<td>0.563</td>
<td>0.711</td>
<td>0.751</td>
</tr>
<tr>
<td>cil</td>
<td>0.186</td>
<td>0.211</td>
<td>0.168</td>
<td>0.151</td>
</tr>
<tr>
<td>cl</td>
<td>0.118</td>
<td>0.166</td>
<td>0.080</td>
<td>0.052</td>
</tr>
<tr>
<td>nii</td>
<td>0.224</td>
<td>0.208</td>
<td>0.239</td>
<td>0.238</td>
</tr>
<tr>
<td>roa</td>
<td>0.008</td>
<td>0.009</td>
<td>0.010</td>
<td>0.003</td>
</tr>
<tr>
<td>pll</td>
<td>0.006</td>
<td>0.006</td>
<td>0.004</td>
<td>0.011</td>
</tr>
</tbody>
</table>

This table presents the descriptive statistics of our bank sample. Panel A reports the average monthly return ("Mean"), the monthly standard deviation ("SD"), the sharpe ratio ("Sharpe"), skewness and kurtosis, the minimum ("Min") and maximum ("Max") monthly return, and the results of Jarque-Bera test statistics. Panel B reports the averages of individual bank characteristics. These include the log of total assets, the equity-to-assets ratio, the relative share of real estate loans, commercial and industrial loans, and consumer loans, the ratio of non-interest income to total income, the return on assets, and the ratio of provisions to loan losses to total loans. ** denote statistical significance at the 5% level.
Table 3: Beta Exposures and Changes of Beta Exposures

Panel A: Bank Portfolio

<table>
<thead>
<tr>
<th></th>
<th>Full Period</th>
<th>1st Sub-Period 01/87 - 10/99</th>
<th>2nd Sub-Period 11/99 - 09/07</th>
<th>3rd Sub-Period 10/07 - 12/12</th>
<th>Change (2nd - 1st)</th>
<th>Change (3rd - 2nd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha</td>
<td>0.006***</td>
<td>0.012***</td>
<td>0.003</td>
<td>0.000</td>
<td>-0.009***</td>
<td>-0.003</td>
</tr>
<tr>
<td>LTB</td>
<td>-0.011</td>
<td>-0.284***</td>
<td>0.224***</td>
<td>0.377**</td>
<td>0.508***</td>
<td>0.102</td>
</tr>
<tr>
<td>CORP</td>
<td>-0.150**</td>
<td>-0.108</td>
<td>0.068</td>
<td>-0.258***</td>
<td>0.176</td>
<td>-0.323***</td>
</tr>
<tr>
<td>HY</td>
<td>-0.514***</td>
<td>-0.588***</td>
<td>-0.372***</td>
<td>-0.436***</td>
<td>0.216***</td>
<td>-0.048</td>
</tr>
<tr>
<td>SOV</td>
<td>-0.291***</td>
<td>-0.160***</td>
<td>-0.456</td>
<td>-0.311***</td>
<td>-0.296</td>
<td>0.116</td>
</tr>
<tr>
<td>REIT</td>
<td>0.534***</td>
<td>0.392***</td>
<td>0.350***</td>
<td>0.828***</td>
<td>-0.042</td>
<td>0.474***</td>
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<tr>
<td>MKT</td>
<td>0.906***</td>
<td>0.971***</td>
<td>0.656***</td>
<td>1.036***</td>
<td>-0.315**</td>
<td>0.385</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>66%</td>
<td>75%</td>
<td>47%</td>
<td>73%</td>
<td>-28%</td>
<td>26%</td>
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Panel B: Residual Market Factor

<table>
<thead>
<tr>
<th></th>
<th>Full Period</th>
<th>1st Sub-Period 01/87 - 10/99</th>
<th>2nd Sub-Period 11/99 - 09/07</th>
<th>3rd Sub-Period 10/07 - 12/12</th>
<th>Change (2nd - 1st)</th>
<th>Change (3rd - 2nd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha</td>
<td>0.001</td>
<td>0.000</td>
<td>0.003</td>
<td>0.001</td>
<td>0.003</td>
<td>-0.002</td>
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<tr>
<td>FX</td>
<td>-0.103</td>
<td>0.046</td>
<td>-0.226***</td>
<td>-0.196**</td>
<td>-0.273***</td>
<td>0.031</td>
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<td>ILLIQ</td>
<td>-0.183</td>
<td>-0.180***</td>
<td>-0.041</td>
<td>-0.083**</td>
<td>0.139</td>
<td>-0.042</td>
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<tr>
<td>VIX</td>
<td>-0.366***</td>
<td>-0.381***</td>
<td>-0.496***</td>
<td>-0.214**</td>
<td>-0.114</td>
<td>0.281**</td>
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<td>SMB</td>
<td>-0.022</td>
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<td>-0.007</td>
<td>-0.083</td>
<td>0.078</td>
<td>-0.076</td>
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<tr>
<td>HML</td>
<td>-0.483***</td>
<td>-0.775***</td>
<td>-0.405***</td>
<td>0.187</td>
<td>0.371***</td>
<td>0.592***</td>
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<tr>
<td>Adj. R²</td>
<td>33%</td>
<td>49%</td>
<td>44%</td>
<td>14%</td>
<td>-5%</td>
<td>-30%</td>
</tr>
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</table>

This table presents beta coefficients from time series regressions for the bank portfolio (Panel A) and the residual market factor (Panel B). The regression results are reported for the full period as well as the three individual sub-periods. Standard errors are robust to heteroskedasticity and autocorrelation following Newey and West (1987) with 12 lags. *** and ** denote statistical significance at the 1% and the 5% levels, respectively.
Table 4: Determinants of Individual Bank Risk

<table>
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<td><strong>76.19</strong>*</td>
<td><strong>79.98</strong>*</td>
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This table presents the results from fixed-effects panel regressions analyzing the determinants of individual bank risk. The variables are detailed in section 3.3. All regressions include year dummies and the standard errors are clustered at the individual bank level. *** and ** denote statistical significance at the 1% and the 5% levels, respectively.
Table 5: Descriptive Statistics for Orthogonalization Techniques

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This table presents descriptive statistics for the robustness checks using alternative orthogonalization methodologies. Based on rolling 36-months variance decompositions, the separate panels report each factor’s average variance share (“Mean”), median variance share (“Median”), the lower 25th and upper 75th percentiles, and the minimum and maximum, respectively.