Bank business models, managerial discretion and risk efficiency*

Lieven Baele[†] Valerie De Bruyckere[‡] Olivier De Jonghe [§]

Rudi Vander Vennet[¶]

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Abstract

This paper develops a stochastic-frontier based methodology to jointly test for market monitoring and influencing in a sample of US Bank Holding Companies (BHC) over the period 1991-2008. First, we confirm the existence of market monitoring by linking stock market-based risk measures to business model indicators and fundamental bank characteristics (in particular, constituents of the acronym CAMEL). Second, we interpret distance from the efficient frontier as a measure of inefficiency relative to its best performing peers, and show that the variance of this component is predominantly related to management discretion and opaqueness, and less so to business complexity. Finally, we find much stronger evidence for the influencing channel of market discipline compared to most of the existing literature. Banks tend to improve their operating performance and contain their risk in response to a deteriorating risk-inefficiency score.

Keywords: banking, risk, market discipline, opaqueness, management discretion, stochastic frontier

JEL: G21, G28, L25

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[†]CentER, Netspar, Tilburg University, Warandelaan 2, Tilburg, The Netherlands.

[‡]Department of Financial Economics, Ghent University, W. Wilsonplein 5D, 9000 Ghent, Belgium.

[§]Corresponding author, olivier.dejonghe@ugent.be, Ghent University, Kuiperskaai 55E, 9000 Ghent, Belgium.

[¶]Department of Financial Economics, Ghent University, W. Wilsonplein 5D, 9000 Ghent, Belgium.

1 Introduction

Is market discipline the Holy Grail that curbs bank risk-taking? Or does it increase financial instability? Can the stock market assess bank risk and influence bank behavior? Clearly, by putting market discipline as one of the cornerstones of the third pillar of the Basel II accord, bank regulators put high hope on market discipline being (or becoming) a powerful complement to regulatory oversight. However, both empirical research and factual evidence predominantly support the view that market discipline is, at best, a weak disciplining mechanism.

According to Bliss and Flannery (2002) market discipline has two components: market monitoring and market influencing. They define market monitoring as the ability of security holders to accurately assess the condition of the firm, and influencing as the ability of those assessments to cause subsequent managerial actions[1]. While there is considerable evidence of market monitoring (see e.g. Flannery and Sorescu (1996) and Morgan and Stiroh (2001)), research examining the market influencing channel is more scarce and generally inconclusive. Bliss and Flannery (2002) fail to find evidence that bank stock or bond holders effectively influence bank indicators controlled by bank managers, such as the leverage position of the BHC, factors affecting bank asset risk, changes in the number of employees and the amount of uninsured liabilities. Gendreau and Humphrey (1980) find that banks are penalized for higher leverage by a higher cost of debt and equity, but find no evidence that these relative cost changes induce bank managers to alter their leverage position relative to other banks. Ashcraft (2008) shows that the proportion of subordinated debt in total regulatory capital has a positive effect on the probability that a bank recovers from financial distress, suggesting that bank debtholders are able to significantly influence the behavior of distressed banks. Cihak, Maechler, Schaeck, and Stolz (2009) find evidence for debtholder discipline in a sample of small and medium-sized commercial banks in the US over the period 1990-2007: Bank managers are more likely to be removed if the bank is financially weak, and this effect is stronger for banks subject to discipline exerted by large debtholders. The authors find no conclusive evidence of discipline exerted by shareholders or depositors, nor that forced turnovers consistently improve bank performance (even at windows of three years after the turnover).

[1] The Federal-Reserve-System (1999) distinguishes direct and indirect influencing. Indirect influencing refers to supervisory responses to specific market signals, whereas direct market influencing refers to the ability of the market's assessment of the bank's risk profile and whether this can induce the bank to avoid risky situations.

In this paper, we add to this literature by developing an innovative empirical setup to examine the ability of stock market investors to monitor and influence bank risk for a sample of US BHCs over the period 1991-2008. Our starting point is that different strategic choices by bank managers lead to different business models with different risk profiles. However, we recognize that investors do not evaluate the risk of each bank in isolation. Rather, they assess the riskiness of a particular bank relative to its peers. We capture this feature by estimating a stochastic risk frontier, similar to the well known cost efficiency frontier, capturing the minimum risk that the most risk efficient banks with a certain business model can achieve. Banks with a higher than optimal risk will be located above the efficient frontier. We define risk inefficiency as the deviations from this optimal frontier. According to the monitoring dimension of the market discipline hypothesis, we expect that stock market investors are able to discriminate between banks with different asset, funding and revenue characteristics. Hence, our hypothesis is that the risk frontier can be explained by these observable bank characteristics. This would be evidence that the stock market can and does discriminate between banks with different risk profiles linked to different business models. In a next step we investigate the determinants of the deviations from the efficient risk frontier in each of the three dimensions: total bank risk, market risk and bank-specific risk. We hypothesize that risk inefficiency; put differently, discretion in bank shareholders' assessment of a bank's risk profile; may be caused by three potential determinants: business model complexity, managerial discretion and opaqueness. Finally, we investigate the influencing part of the market discipline hypothesis. When a bank's risk profile deviates from the efficient frontier, the higher than optimal risk will be translated in a higher capital or funding cost. This should induce banks to alter their risk profile by altering the underlying business model characteristics. Consequently, we investigate whether or not deviations from the efficient risk frontier cause banks to improve their risk profile by changing the quality of their balance sheets and operational performance, e.g. by increasing their operating performance or improving the credit quality of their loan portfolio.

Our empirical results confirm that stock market investors are able to monitor bank risk: stock market investors identify differences in bank risk based on observable characteristics and associate variation in these variables with different levels of systematic or bank-specific risk. We document substantial heterogeneity in the risk inefficiency scores of banks with different business model characteristics. Since the risk inefficiency measures exhibit considerable variation across banks, it is important to investigate the potential sources of the variation. We consider three potential determinants. First, business model complexity is proxied by the relative concentration in the loan portfolio, the deposit mix and the revenue structure, measured with a Hirschmann-Herfindahl index. Overall, we find that from a risk monitoring perspective, stock market investors value the portfolio effect of diversification more than the increased complexity that diversification may entail. Second, the degree of managerial discretion is measured as the potential for bank managers to smooth reported income by using loan loss provisioning and the realization of security gains or losses in a discretionary way. We find that stock market investors punish discretionary behavior, especially in the case of security gains and losses. More unpredictable banks will exhibit larger deviations from the efficient risk frontier in all risk dimensions. This further corroborates the ability of the stock market to identify and punish discretionary bank behavior. Third, the relative opaqueness of banks is captured by the dispersion of earnings forecasts using IBES data. We find strong evidence that the degree of opaqueness is positively related to the variance of the risk inefficiency scores.

Finally, we investigate the influencing hypothesis by analyzing if and to what extent bank managers react to high risk inefficiency scores over a medium to long-run horizon. The hypothesis is that banks exhibiting a relatively high degree of risk inefficiency will respond by taking remedial action in order to adjust their risk profile in line with their peers. This can e.g. be achieved by increasing capital, by lowering the asset risk or by improving operational performance. In contrast to most of the extant literature, we find evidence of market influencing. However, this observation only holds for some dimensions of the banks' risk profile and only for those banks that are punished most by the stock market, i.e. banks with the largest deviations from the efficient risk frontier. Our evidence lends at least partial support to a benign influence of stock market discipline on banks.

We obtain these empirical results based on a sample of listed US bank holding companies for the period 1991-2008. This sample has a number of characteristics that make it well suited for the research question we address. First, the sample size is quite large. Over the full sample period, we observe 655 different cross-sectional units. Moreover, although we only look at one type of financial institution, i.e. BHCs, we still observe banks with various types of business models. As such, we can identify heterogeneity in risk across and within business models. Second, the US equity market is the most liquid and developed in the world and hence it offers more scope to examine effective market discipline by shareholders. Third, our study requires the mapping between two different data types; accounting information and market information. This mapping is provided by the research department of the NY Fed and controls for mergers and acquisitions and delistings. Fourth, the reporting of the accounting variables occurs in mandatory and pre-specified reports. This harmonization allows for a better test of the impact of disclosure and transparency on bank risk. Finally, this paper investigates market discipline in the stock market. Whether market discipline should be analyzed in the stock market, the bond market or the market of deposits, is an ongoing debate. Morgan and Stiroh (2001) state that bondholders focus only on downside risks and as a result are more closely aligned with the interests of bank supervisors. However, as shown by Ashcraft (2008), the effect of shareholders on managerial decisions is potentially stronger than the influence of bondholders, especially when shareholders have a large stake in the bank. According to Sundaresan (2001) and Kwan (2002b), stock market data have an advantage over bond market data in terms of higher quality. Stock market data are more likely to incorporate up-to-the-minute information than bond prices, because stocks are traded more frequently, are easier to short, and because they are followed by more professional analysts than bonds.

The remainder of this paper is structured as follows. Section 2 introduces a new setup to assess the different components of market discipline, i.e. market monitoring and influencing, in a unified framework. We first explain the features and advantages of modelling bank risk along an efficient frontier in Section 2.1 . In Section 2.2, we describe how we construct market-based measures of risk and return. Section 3 contains an empirical assessment of the presence of market discipline of US BHCs. This section consists of three subsections, each related to one of the crucial ingredients of market discipline. In Section 3.1.1, we estimate a stochastic frontier model that relates the different risk measures to bank characteristics (market monitoring). In Section 3.2, we consider business model complexity as a potential source of opaqueness. Moreover, we relate the volatility of the inefficiency term to measures of managerial discretion and opaqueness, where opaqueness is proxied by dispersion in analysts' forecasts. Section 3.3 presents the evidence of market influencing. Section 4 concludes this paper.

2 A new test for Market Discipline

2.1 A stochastic frontier model with scale heterogeneity

Past literature has tested the market monitoring hypothesis by relating risk exposures to bank-specific characteristics in a linear regression framework (see e.g. Flannery and Sorescu (1996)**, Saunders, Strock, and Travlos (1990),** Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007)). We extend this model in two important ways. First, we estimate a stochastic frontier instead of a linear regression model. This allows us to distinguish between banks that are on the frontier (given the characteristics associated with their business model), and less efficient banks. Second, we add scale heterogeneity to the otherwise constant volatility stochastic frontier model. Apart from some econometric advantages, this permits us to gain insight in which bank characteristics make it more likely that a bank will be situated far from the optimal frontier, i.e. that it is risk inefficient. The most general version of our model is:

$$Risk_{i,t} = \beta_0 + \beta X_{i,t-1} + u_{i,t} + v_{i,t} \tag{1}$$

$$\nu_{i,t} \sim iid\ N(0, \sigma_v^2) \tag{2}$$

$$u_{i,t} \sim iid\ \left| N(0, \sigma_{u_{i,t}}^2) \right| \tag{3}$$

Equation (1) relates bank-specific stock market based risk measures $Risk_{i,t}$ to various lagged[2] bank-specific characteristics $X_{i,t}$. Contrary to the linear model, we assume that the part of $Risk_{i,t}$ not explained by bank characteristics can be further decomposed in a pure noise component, $\nu_{i,t} \sim iid\ N(0, \sigma_v^2)$ and in one-sided departures (risk inefficiencies), $u_{i,t}$, from the stochastic frontier, which is determined by the equation $\hat{\beta}_0 + \hat{\beta} X_{i,t-1}$. We model these risk inefficiencies by means of a half-normal distribution truncated at zero (to capture non-negativity), $u_{i,t} \sim iid\ |N(.)|$. Banks on or close to the frontier are considered to be most efficient, *given* their characteristics $X_{i,t}$. Notice that this model collapses to a standard linear model when the variances of the inefficiency terms $\sigma_{u_{i,t}}^2$ are small relative to the variance of the purely random component σ_v^2. In case of a constant variance of the inefficiency terms, this can be easily verified by testing whether or not $\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right) = 0$. As we will show later, this hypothesis is strongly

[2] We use one-year lagged values rather than contemporaneous measures to alleviate potential endogeneity problems and to account for the lag with which accounting information is disclosed.

rejected, favoring the stochastic frontier analysis over the linear model.

Standard applications of stochastic frontier models typically assume that the variance of the half-normal distribution is constant, both across banks and time, i.e. $u_{i,t} \sim iid \left|N(0, \sigma_u^2)\right|$. This assumption may be problematic for a number of reasons. First, the distribution of inefficiencies is likely to be different across banks, and correlated with bank characteristics. Second, the variance of the bank-specific inefficiency scores is likely to vary through time, e.g. because banks take actions to reduce inefficiencies over time. We incorporate scale heterogeneity by making the variances of the bank-specific inefficiency scores a linear function of a number of bank-time specific characteristics $Z_{i,t}$:

$$\sigma_{u_{i,t}}^2 = \exp\left(\delta_0 + \delta Z_{i,t}\right) \tag{4}$$

We use the exponential function to guarantee that the variance is positive at all times and across all banks. This model reduces to a standard stochastic frontier without scale heterogeneity when $\delta = 0$. As we will show later, also this hypothesis is soundly rejected.

2.2 Measuring Bank Risk

As argued in the introduction, our bank risk measures are stock market based. As a first measure of risk, we use the total volatility $\sigma_{i,t}$ in the weekly excess returns of bank i. In addition, we use the single index model to decompose total volatility into a systematic and a bank-specific component. Let $R_{i,t}$ and $R_{m,t}$ represent the excess weekly returns for bank i and the market, respectively. We estimate systematic risk, our second risk measure, as the bank-specific β_i in the regression $R_{i,t} = \alpha_i + \beta_{i,t} R_{m,t} + e_{i,t}$. Because $R_{m,t}$ and $e_{i,t}$, the bank-specific shock, are orthogonal by construction, we can calculate bank-specific risk $h_{i,t}$ easily as the square root of the difference between total and systematic variance: $h_{i,t} = \sqrt{\sigma_{i,t}^2 - \beta_i^2 \sigma_{m,t}^2}$. Our fourth stock market-based measure acknowledges that higher risk may be compensated by a higher return, and is computed as the ratio of the bank stock's weekly return and total volatility. While well diversified investors are mainly interested in the systematic risk incorporated in the bank equity returns as well as the risk-return trade-off, regulators, bank managers, large stakeholders, and bank customers will mostly care about idiosyncratic and and total volatility. As the market portfolio, we use NYSE/AMEX/NASDAQ value-weighted returns including dividends and stock splits from the CRSP Stock File Indices. All returns are in excess of the 3-Month US Treasury bill rate.

We allow the different risk measures to vary at the quarterly frequency, which is also the highest frequency at which the bank-specific data is available. We estimate the four stock market based indicators at the end of each quarter using a moving window of weekly returns over the four last quarters. We deliberately choose for this one-year rolling window estimation procedure for two main reasons. First, the focus of our analysis is more on understanding the dynamics and drivers of longer-term risk measures, rather than on the statistical description of high-frequency (transitory) changes in banking risk, i.e. we focus on medium-term shareholder discipline. Second, by using an annual instead of a quarterly window, we better capture the typical persistence in beta estimates (Ghysels and Jacquier (2006) and Ang and Kristensen (2010)) while at the same time reducing estimation noise. Apart from using annual windows, we further reduce estimation noise by only including those banks that are frequently traded. As a threshold, we impose that the bank stock's traded volume should be non-zero in at least 80 percent of trading days. Moreover, as a robustness check, we perform our analysis on a subset of banks whose market betas have a *tstat* of at least one in absolute value[3].

As in Demsetz and Strahan (1997), Schuermann and Stiroh (2006), and Viale, James, and Fraser (2009), we experiment with adding additional risk factors (such as inflation, the short-term interest rate, or the term and default spread) next to of the market factor. However, we find the explanatory power and more importantly the significance of these factors to be low relative to the market factor. Moreover, whether or not additional factors are included does hardly have an effect on the estimated market betas and idiosyncratic risk. Consequently, we do not include exposures to factors other than the market as additional risk factors.

Table 1 shows some summary statistics on the market-based risk and return measures. The total sample consists of $16,134$ bank-quarter observations. The average market beta equals 0.63. There is substantial variation[4] in the sample, with betas ranging from -0.58 to 2.01. Total *annualized* volatility ranges from about 10 percent to more than 78 percent, and has an average of 27.5 percent. Average

[3] This heuristical measure is often used in the forecasting literature, and was recently using in a factor model setting in Baele, Bekaert, and Inghelbrecht (2010).

[4] Compared to Stiroh (2006a), our average beta is higher (0.63 versus 0.45) and has lower extremes (-0.58 versus -1.55 for minimum and 2.01 versus 3.41 for maximum beta). These differences are mainly due to our exclusion of infrequently traded stocks, whose betas are notoriously difficult to estimate accurately, and winsorizing all variables at 1%.

total idiosyncratic volatility (25.27) is less than 10% below the average total volatility estimate, indicating that the market component of risk only explains a small proportion of total risk. The mean average weekly return across banks is 0.33 percent, with a range from −2.83 percent to 4.83 percent. The weekly risk-adjusted return amounts to 8.14 percent, or about 0.59 annually, which is only slightly above the long-term average for the S&P500 and the estimates of Stiroh (2006a).

2.3 A new setup to test the faces of market discipline

Flannery (2001) dissects market discipline and identifies a number of components: (i) monitoring, (ii) information revelation and opacity, (iii) (in)direct influencing. The main goal and contribution of this paper is to analyze the faces of market discipline (Flannery (2001)) in one set-up . First, the estimated stochastic frontier should provide evidence of monitoring. This frontier could be labeled as a 'rule equation' that equity market participants use to translate a certain business model into various risk metrics. Random noise makes the 'rule' stochastic. Second, the analysis of scale heterogeneity, i.e. modeling the variance of the deviations from the stochastic frontier as in Eq.(4), provides new evidence on the opaqueness of bank activities and managerial actions. The volatility of the inefficiency scores is the discretion that equity market participants employ in their assessment, which leads to random mark-ups to the 'rule'[5]. Finally, in our integrated methodology, we investigate the influencing hypothesis by analyzing if and to what extent bank managers react to high risk inefficiency scores over a medium to long-run horizon. The hypothesis is that banks exhibiting a relatively high degree of risk inefficiency will respond by taking remedial action in order to adjust their risk profile in line with their peers.

The next Section 3 consists of three subsections that provide empirical evidence for each of the components. Subsection 3.1 reports estimation results from the stochastic frontier model developed in Section 2.1. Subsection 3.2 develops the new concept of risk inefficiency scores, and analyzes the determinants of their variance. In the final section, we document the presence of market influencing.

[5] As such, our model is related to a regression model with multiplicative heteroscedasticity as proposed by Harvey (1976). Cerquiero, Degryse, and Ongena (2007) employ such a model to determine the factors that drive the extent to which loan officers stick to rules or employ discretion in loan rate setting. Our model differs in assuming that the rules set the minimum risk level that can always be achieved. Deviations from the rule may be due to noise (not determined by discretion) and a one-sided discretionary component.

3 Bank business models and risk exposures: monitoring and influencing

3.1 Monitoring bank risk

3.1.1 The Stochastic Frontier: Determinants

To assess how potential differences in the composition of assets, liabilities and operational characteristics of the banks are reflected in various measures of bank risk, we relate each of our four measures to four sets of bank characteristics, reflecting respectively: (i) overall bank strategy, (ii) the bank's funding structure, (iii) asset mix and (iv) revenue diversity. We motivate inclusion of each of these groups below. This paper is the first to combine a detailed funding, asset mix and revenue breakdown for a large period of time in one setup. Hence, we shed light on market monitoring of a wide range of business models. Moreover, controlling for as many as possible business model characteristics is important from an econometric point of view. By including as many as possible determinants in the stochastic frontier analysis, we avoid that the inefficiency term is capturing a 'third variable' not included in the model. Our vector $X_{i,t}$ of bank-specific characteristics is hence given by:

$$X_{i,t} = [Constituents\ of\ CAMEL,\ Funding\ Structure,\ Asset\ Mix,\ Revenue\ Streams]_{i,t} \qquad (5)$$

The definition and construction of each variable is described in the Appendix, summary statistics in Table 2. All data are collected from the publicly available FR Y-9C reports. Information of the FR Y-9C report is linked to banks' stock prices using the match provided on the website of the Federal Reserve Bank of New York[6]. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters in the period 1991-2008. As argued before, we exclude banks that have non-zero volume in less than 80 percent of trading days. The total sample consists of 16,134 observations on 655 bank holding companies.

We now motivate the bank-specific variables group by group, and discuss parameter estimates linking those variables to the different risk measures in parallel. The discussion is based on the estimation results reported in Table 3.

[6] http://www.ny.frb.org/research/banking_research/datasets.html

Bank Strategy Variables The bank-specific proxies for overall bank strategy are similar in spirit to the constituent parts of the CAMELs ratings used by US supervisory authorities. These variables capture strategic choices made by bank managers that may affect a bank's risk profile. We include the regulatory Tier 1 capital ratio and the liquid-to-total assets ratio to incorporate the possibility that better capitalized and more liquid institutions may be less vulnerable to market-wide shocks. Asset quality is measured by the ratio of loans past due 90 days or more and non-accrual loans to total loans. We also take into account differences in bank efficiency by including the cost-to-income ratio. This ratio measures the overheads or costs of running the bank as a percentage of total operating income before provisions. Finally, we include (the log of) bank size[7] to allow for the possibility that larger banks may be more exposed to market-wide events, and bank profitability to control for a risk-return trade-off.

The top panel of Table 3 indicates that stock market participants accurately track the effect of the different bank strategy variables on the systematic, idiosyncratic and total risk of banks. First, larger banks are more exposed to market-wide shocks than smaller banks, but have lower total and idiosyncratic risk[8]. This is in line with other research on US BHC's (see e.g. Stiroh (2004)). Second, we find that better capitalized banks have a lower systematic, total and idiosyncratic risk. This result is not only statistically but also economically significant: A one standard deviation increase in the Tier 1 capital ratio leads to a decrease in market risk with 0.057 (about 9 percent of the average beta). In addition, prudent banks with a large regulatory capital buffer have lower risk-adjusted returns. Banks with a higher non-performing loans ratio (a measure of asset quality) have a significantly higher total and idiosyncratic volatility and lower risk-adjusted returns. For most BHCs the core business is still gathering deposits and granting loans. Therefore, it is not surprising that credit risk is a major component of their overall risk. More prudent lending (less NPL) will thus result in lower idiosyncratic and total volatility. Banks facing a higher

[7]Bank size is, to a large extent, the outcome of strategy choice made by banks and is hence highly correlated with the other control variables, and, more importantly, with the measures that capture the various business models we consider. Therefore, we orthogonalize size with respect to all other variables. The natural logarithm of total assets is regressed on all independent variables. The idea is to decompose bank size in an organic growth component and a historical size component, the residual.

[8]Because idiosyncratic risk constitutes the largest fraction of total risk, it is not surprising that that their results exhibit similar patterns. All things equal, one expects that this similarity will be reduced for these bank characteristics that have an opposite effect on systematic risk and idiosyncratic risk, in particular for high beta banks.

cost-to-income ratio tend to have lower betas but higher idiosyncratic volatility. The positive impact on total volatility suggests that the latter effect is dominating. The positive and significant coefficient for ROE on RAR implies that stock market investors perceive past accounting returns as a signal of future performance. Moreover, it has a risk-reducing effect on both total and idiosyncratic volatility. As expected, the liquid-to-total asset ratio has a significantly negative effect mainly on the market beta (-0.037, or nearly 6 percent of the average market beta).

Funding Structure Banks can fund their activities with different types of deposits. We decompose total deposits in three types: Interest-bearing core deposits, noninterest-bearing deposits and large time deposits. The first is the share of deposits held by retail depositors. Although consumers and small businesses also hold non-interest-bearing demand deposits and large time deposits (those exceeding $100,000), we follow Hirtle and Stiroh (2007) and exclude these balances from our retail deposit measure. A significant portion of the latter two types of deposits are held by wholesale customers, such as mid-sized and larger businesses, especially at larger banks. Wholesale funding providers are generally sensitive to changes in the credit risk profile of the institutions to which they provide these funds and to the interest rate environment. Such fund providers should closely track the institution's financial condition and may be likely to curtail such funding if other investment opportunities offer more attractive interest rates. Moreover, retail depositors are protected by deposit insurance schemes. Hence, as retail and wholesale depositors have different incentives to monitor bank risk, their relative share in total deposits may have an impact on the various bank risk exposures.

The empirical results are different regarding the structure versus the level of the deposit base. With respect to the funding composition, we find that a large fraction of time deposits increases banks' idiosyncratic and total volatility. Note that the share of non-interest-bearing deposits (i.e. demand deposits) is the omitted benchmark share, which means that the coefficients have to be interpreted as the differential effect they have on bank risk, relative to the omitted share. A larger share of interest bearing core deposits reduces total (-0.0231) and systematic or market risk (-0.229), but also affects risk-adjusted returns negatively. These findings are in line with Hirtle and Stiroh (2007), who conclude that retail banking may be a relatively stable activity, but it also yields a low return. These results are also in line with the observations in the 2007-9 financial crisis. Banks relying heavily on wholesale funding suffered the most from the dry-up of liquidity in the interbank market. We find evidence that the stock market acknowledges the riskiness of this business model, as we find that the stock market participants assign higher risk to banks relying more on wholesale funding and less on retail funding. This is evidence of monitoring of the funding composition of the bank. With respect to the level of deposits (the ratio of deposits to assets), conclusions are mixed. We find that overall market risk decreases with the fraction of deposits in total assets. However, the effect on idiosyncratic risk is opposite and larger in absolute magnitude, implying a higher total risk for banks with a larger deposit base. Banks with a larger deposit-to-asset ratio produce higher risk-adjusted returns.

Asset Mix Next to including the loan-to-asset ratio, we classify loans according to borrower types. The loan portfolio composition may have an impact on stock market participants' perceptions of banks' risk exposures. We categorize loans as commercial and industrial loans, real-estate related loans, consumer loans, agricultural loans and a catch-all share that includes all other loans. We leave the real estate loan share out of the equation to avoid perfect collinearity. The sign and coefficients of the other loan shares can thus be interpreted as the differential impact they have on bank risk, compared to real estate loans. Banks' loan portfolio composition varies substantially in the sample. The average bank's loan portfolio consists of 62% real estate loans, 20% C&I loans and 12% consumer loans. The remainder are agricultural and other loans. Some banks focus on only one type of loans; others hold a well diversified portfolio (in terms of types of loans).

Agricultural loans have a significant risk-reducing effect, both in terms of systematic, total, and idiosyncratic risk. However, since the share of agricultural loans is small and the dispersion is low, the economic impact is also negligible. Banks with a higher proportion of consumer loans tend to be more exposed to overall market shocks, but face a lower idiosyncratic and total volatility. The elasticity of the market beta with respect to the consumer loan share is 17 percent. The commercial and industrial loan share has a small negative impact on market betas, but no effect on total and idiosyncratic risk. Consequently, we do not confirm the evidence by Morgan and Stiroh (2001) who found that bond spreads are increasing in credit card and commercial and industrial lending[9]. Overall, banks with a focus on real

[9]This divergence may be due to the sample period (they only cover the '93-'98 period) as well as sample composition

estate loans (the core business of most banks) will have lower systematic risk and higher risk-adjusted returns.

Revenue Streams The aforementioned bank activities of deposit-taking and lending predominantly generate interest margin. However, some banks also generate a substantial amount of non-interest income (Stiroh (2006a)). Historically, service charges on deposit accounts accounted for the vast majority of non-interest income (due to restrictions on the type of financial activities that bank holding companies were allowed to undertake). However, this has altered substantially due to consecutive steps of deregulation. Therefore, we also include variables capturing the importance of income generated by fiduciary activities and trading-related income. All other activities that generate non-interest income are captured in the other non-interest income share. Since the Gramm-Leach-Bliley act of 1999 allows banks to expand their scope of activities, the latter category (capturing income from (re)insurance underwriting, investment banking, venture capital,...) has become the largest of the non-interest income shares.

Previous studies have documented that non-interest income is in general more risky than interest income (e.g. Stiroh, 2006b). Our breakdown of non-interest income in four subcomponents yields new insights. First, relative to the omitted interest income share, all non-interest income subcomponents lead to higher market betas. This is consistent with the argument that insurance underwriting, investment banking and venture capital activities may increase the banks' exposure to market-wide shocks. The effect is not surprisingly highest for the trading revenue share, arguably the most cyclical component of non-interest income. Second, the income share from fiduciary activities has a negative effect on the level of total and idiosyncratic volatility, most likely because of its earnings smoothing effect. The effect of the other non-interest rate components on volatility is mixed and mostly insignificant. Looking at the breakdown of non-interest income, we observe that it is predominantly the other non-interest income share that is affecting total risk.

Finally, we include three indicators to measure the potential diversification effects of liquidity risk on the asset and liability side of the balance sheet. Gatev, Schuermann, and Strahan (2009) find that transaction deposits reduce liquidity risk stemming from bank lending. Banks exposed to loan-liquidity risk without high levels of transaction deposits have higher risk. On the contrary, banks exposed to

(only larger banks have publicly traded bonds).

loan-liquidity risk with high levels of transaction deposits have lower total risk. The effect of this deposit-lending hedge is stronger in periods of tight markets. Hence, we include the ratio of unused commitments to total commitments plus loans to measure the liquidity risk at the asset side. The ratio of transaction deposits to total deposits is included to capture liquidity risk on the liability side. Bank risk[10] is expected to rise with unused commitments (reflecting asset-side liquidity risk exposure) and the use of transaction deposits (reflecting liability-side liquidity risk exposure). The synergy effect is measured by the interaction term of the ratio of unused loan commitments with transaction deposits. All three effects are confirmed in our sample. Both unused loan commitments and transaction deposits increase total bank risk, but the combination of both (the coefficient of the interaction term is -0.12) provides a statistically and economically significant hedge against liquidity risk and reduces the risk of the bank. Similar effects are obtained with respect to idiosyncratic volatility, but the synergy effects are not marginally significant. In addition, deposit-loan synergies also lead to higher risk-adjusted returns.

Overall, we find substantial evidence that the riskiness of banks can be successfully modeled along an efficient frontier. We can conclude that the stock market accurately tracks the different risks associated with the balance sheet and income statement characteristics. This is evidence of the first step in market discipline, market monitoring. The source and nature of the cross sectional and time variation of the business model inefficiencies is the subject of the next section.

3.1.2 Inefficiency scores

The stochastic frontier model we employ in this paper decomposes bank risk in three components: the frontier, random noise and deviations from the frontier. The frontier is the fitted value of the relationship between a bank risk measure and bank characteristics. An error term makes the frontier stochastic. We interpret deviations from the frontier as the amount of discretion that bank shareholders use in assigning a risk metric to a bank, conditional on the set of bank characteristics. Technically, we could establish the relationship between the different risk variables and bank characteristics using a standard linear regression model. Table 3 reports a number of indicators that clearly point to the superiority of the stochastic frontier. First, the variance of the random noise component (last line in panel B of Table 3)

[10] Gatev, Schuermann, and Strahan (2009) construct a measure of bank stock return volatility based on a GARCH(1,1) model on daily returns. Their measure is most similar to our measure of total volatility.

is significantly different from zero, indicating that Stochastic Frontier Analysis is preferred over a non-parametric Data Envelopment Analysis approach. Second, the variance of the random noise is almost always smaller than the variance of the inefficiency score. In a set-up with a constant variance of the inefficiency term, one typically tests whether $\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$ is different from zero. In a model with scale heterogeneity, σ_u^2 may vary by bank and over time which makes γ bank and time-varying. The first line of panel B of Table 3 shows that the variance of the one-sided error term is significantly different from zero (as the constant in the scale equation is significant). When we compute γ for the average bank in our sample, we obtain a value of 0.78, 0.94, 0.93, and 0.60 in columns 1 to 4. Hence, the variance of the inefficiency term is large compared to the random noise for each of the risk metrics.

Table 4 and Figure 1 provide more information on what is captured by these risk inefficiency scores. In Table 4, we report the overall mean and standard deviation as well as two other sources of variation in the obtained efficiency scores. They are the within variation, due to changes in efficiency for a given bank over time, as well as the between variation, which captures differences in the average risk efficiency across banks. Column 5 contains information on the relative importance of each source of variance. For each of the four efficiency scores, the overall variation is due to both within and between variation. However the relative importance of each component varies. The between variation is larger than the within variation for idiosyncratic and total risk inefficiency. The relative importance of each component is almost exactly the opposite for market risk inefficiency. With respect to risk-adjusted return inefficiency, the within variation is more than twice as large as the between variation.

Additional insight in the properties of these four risk inefficiency metrics can be obtained from Figure 1[11]. The graphs are constructed in the following fashion. Figure 1 consists of four subplots, one for each risk metric. Each subplot presents the average inefficiency score (the deviation from the stochastic frontier) of four portfolios in "event time". Each quarter, we sort BHCs into quartiles (i.e. four portfolios) according to the level of the risk inefficiency score. We denote the four quartiles as: Very High (most risk inefficient), High, Medium, and Low (closest to the frontier). The portfolio formation quarter is denoted as time period 1. We then compute the average efficiency score for each portfolio in each of the subsequent

[11] The figure is inspired by Lemmon, Roberts, and Zender (2008), who investigate the persistent nature of firm capital ratios. This methodology is ideally suited for investigating the cross-sectional dispersion and time evolution of bank characteristics over longer periods.

12 quarters, holding the portfolio composition constant (except for BHCs that exit the sample). We repeat these two steps of sorting and averaging for every quarter in the sample period (1993-2007). This process generates 60 sets of event-time averages, one for each quarter in our sample. We then compute the average risk inefficiency of each portfolio across the 60 sets within each event quarter. This portfolio sorting is done for market, idiosyncratic and total risk inefficiency as well as risk-adjusted return inefficiency. The dashed lines surrounding the portfolio averages represent 90% confidence intervals. They are computed as the average standard error across the 60 sets of averages (Lemmon, Roberts, and Zender (2008)).

The graphs confirm and extend the information depicted in Table 4 on the within and between variation in risk inefficiency scores. At portfolio formation time (event time 1), there are large and significant differences between the four quartiles. However, these differences remain significant only for about 4 to 5 quarters. For each risk metric, the least efficient banks' risk inefficiency score improves substantially in the first four quarters after which portfolios are created. Similarly, the most efficient banks exhibit a gradual deterioration of their efficiency score towards the sample mean. By and large, after approximately one year, the mean risk efficiency scores of two adjacent groups are no longer statistically different from each other. Hence, banks converge relatively fast to the average inefficiency score. Differences between the Low and Very High group, the two extremes, are somewhat more persistent. Except for risk-adjusted return inefficiency, the confidence intervals of the highest and lowest quarterly are still not overlapping three years after portfolio formation time.

Overall, the results in Table 4 and Figure 1 demonstrate that the inefficiency scores are not a fixed effect[12], i.e. risk inefficiency is not time invariant, nor completely random at each point in time. In the next section, we analyze which factors affect dispersion in the inefficiency scores. Finally, Section 3.3 investigates if and how much the (level of the) inefficiency scores induces bank managers to respond to negative market signals.

[12] In fact, we also estimate the baseline equation without the one-sided error term but with bank fixed effects. The correlation between the fixed effects and the efficiency scores is around 0.50 when we inspect systematic, idiosyncratic and total risk. The correlation is only -0.17 for risk-adjusted returns, which is in line with the observation that the within variation dominates the between variation in the risk-adjusted inefficiency scores.

3.2 Scale heterogeneity: Determinants

One of the contributions of this paper is that we provide insights into the determinants of bank risk inefficiencies by making the bank-specific variance of the inefficiency term $\sigma^2_{u_{i,t}}$ a function of observable bank characteristics. We interpret this dispersion in inefficiency as the degree of discretion exercised by bank shareholders in their assessment of bank risk profiles. We hypothesize that this discretionary behavior of shareholders is related to respectively (1) business model complexity, (2) cosmetic accounting, and (3) opaqueness, proxied by the disagreement among forecasters about future earings-per-share. We now motivate each of these variables individually, and discuss the estimation results in parallel.

3.2.1 Business Model Complexity[13]

An important business model decision for banks is the scope of their franchise. In complex, diversified firms such as large BHCs, assessing the financial condition of a conglomerate might be harder compared to assessing the financial strength of a specialized firm. To test whether the complexity of bank business models makes BHCs harder to monitor, we include Hirschman Herfindahl indices (HHI) of specialization in each of the core business activities of banks: a HHI for diversification in funding (deposit diversification), a HHI for loan diversification, a HHI for revenue diversity in general (the mix between interest and non-interest income) and a HHI capturing diversity of the four non-interest income components. A higher value of the HHI indicates that a bank has a focused orientation in that type of activity. Lower values point to more diversification. Diversification of activities might, however, also yield more risk efficient banks if the shocks to the different types of activities are imperfectly correlated (Laeven and Levine (2007)). Hence, one view is that the true performance and riskiness of specialized banks is easier to assess (or that shareholders use less discretion as they expect that shocks to different business lines will cancel out). The other is that more diversified banks may also be harder to monitor as they leave more scope for managerial discretion.

As the two effects of business model complexity work in opposite directions, we try to disentangle them by controlling for earnings volatility. If the portfolio risk-reduction view holds, we should also find

[13] Although the stochastic frontier model with scale heterogeneity is modeled in one step, the results are discussed in two steps. The results of a stochastic frontier model without scale heterogeneity are similar and are available upon request.

that banks with more stable profits (potentially caused by combining imperfectly correlated activities) are more risk efficient. In addition, BHCs may alter their scope either by restructuring their activities or by expanding their size. The latter strategy induces another source of potential opacity as assessing expanding firms is more difficult. We include loan growth to control for banks' overall expansion strategy. A high growth rate might indicate that banks expanded via mergers and acquisitions or attracted a new pool (of probably more risky) borrowers (e.g. an expansion into subprime loans), see e.g. Knaup and Wagner (2009).

The empirical results can be found in Table 5. Recall that a higher HHI indicates more specialization. We find that many of the estimated relationships are significant and have a positive sign. Hence, this indicates that from a monitoring perspective bank shareholders value the portfolio effects of diversification more than the increased complexity that diversification may entail (the estimated coefficients represent the net effect of the two opposing forces). The HHI of the loan portfolio is always significant, with a positive sign. The more specialized the loan portfolio, the more discretion bank shareholders use in their assessment of banks' risk profile. This suggests that the portfolio effect dominates the bank complexity effect. Note that this effect is not only statistically, but also economically significant. A one standard deviation increase in the loan specialization increases the dispersion in market beta inefficiencies with 35% and that of total volatility with 15%. The balance between interest income and non-interest income has an opposite effect on systematic risk compared to idiosyncratic and total risk. A more balanced mix reduces the total and idiosyncratic risk, but increases the variance of market beta inefficiency. This is consistent with Wagner (2009) who documents that diversification at financial institutions entails a trade-off. Functional diversification may reduce idiosyncratic risk, but it also makes systemic crises more likely[14]. However, specialization in only one of the four non-interest rate income categories univocally increases all risk components. Finally, less diversification in the funding structure leads to higher stock market discretion with respect to market risk, but has no effect on both idiosyncratic and total risk.

Contrary to our expectations, a higher loan growth does not lead to more dispersion in the different

[14] For a sample of listed European banks, Baele, De Jonghe, and Vander Vennet (2007) also find that the diversification of revenue streams increases the systematic risk of banks while the effect on bank-specific risk component is predominantly downward sloping in their sample. Moreover, De Jonghe (2009) documents that the shift towards non-traditional banking activities increased systemic instability in European banking.

risk inefficiencies. In fact, the effect is even negative for market risk. This suggests that loan growth results in less discretionary behavior by bank equity holders. More stable earnings, reflected by a lower ROE volatility, lead to a lower dispersion in idiosyncratic, total and RAR inefficiency scores. For instance, a one standard deviation increase in ROE volatility leads to an increase in the variance of (total volatility) inefficiency of 11%.This suggests that the preference that shareholders have for stable revenue streams dominates the potential negative effects of earnings smoothing and managerial discretion on their ability to assess the situation of the bank. This issue is investigated in more detail in the next section.

3.2.2 Managerial Discretion and Earnings forecast dispersion

As emphasized in Hirtle (2007), disclosure plays an important role in market discipline since market participants need to have meaningful information on which to base their judgments of risk and performance. We measure disclosure in a qualitative sense and focus on the extent to which bank managers have discretion in reporting certain accounting items with a potential impact on their perceived risk profile. We hypothesize that the variance of the inefficiency term will be larger for banks with more discretion in earnings.

To empirically investigate this hypothesis, we test whether bank-specific volatility of the inefficiency term $\sigma^2_{u_{i,t}}$ is increasing in measures of managerial discretion. Managers can both over- and underprovision for expected loan losses and both postpone or prepone the realization of securities gains and losses. As in Beatty, Ke, and Petroni (2002) and Cornett, McNutt, and Tehranian (2009), we measure discretionary loan loss provisioning and discretionary realized securities gains and losses by running a fixed-effects regressions[15] of loan loss provisioning on total assets, non performing loans, loan loss allowances and all different loan classes. The discretionary component of loan loss provisioning is the absolute value of the error term of this regression. Similarly, the discretionary component of realized security gains and losses is the absolute value of the error term of the regression of realized security gains and losses on total assets and unrealized security gains and losses. If managers use more discretion in loan loss provisioning and realizing trading gains, the residuals of these models will be larger. Both point to discretion in earnings management and obscuring true performance. While unexpected loan loss provisions and security gains and losses may make bank performance more difficult to assess, it is often used to smooth earnings over

[15] Results from these regressions are not reported here, but are available upon request.

time (Laeven and Majnoni (2003)). Recall however, that a measure of volatility of accounting profits is already incorporated.

Secondly, we relate the volatility of the inefficiency term to opaqueness, measured by the dispersion in analysts' earnings per share (EPS) forecasts. This measure is widely used in the accounting literature to measure firm transparency (see e.g. Lang, Lins, and Maffett (2009)), and by Flannery, Kwan, and Nimalendran (2004) to compare the opaqueness of US bank holding companies with similar-sized non-banking firms. We obtain the earnings forecast data from the Institutional Brokers Estimate System (IBES). Data from IBES are used since they cover the broadest number of analysts and provide the most comprehensive database with the longest history of years available. We calculate the dispersion measure on a quarterly basis as the cross-sectional dispersion in the most recent forecast of all analysts that made their prediction within the last year. We include only the analysts' last forecasts, and require this forecast to be made in the 4 quarters prior to the end of the quarter to avoid that stale forecasts would bias our dispersion measure. To avoid the documented downward bias in forecasted EPS induced by the way IBES adjusts for stock splits, we closely follow the adjustment method described in Diether, Malloy, and Scherbina (2002) and Glushkov and Robinson (2006). Finally, we only include the quarterly dispersion measure if at least two separate analyst forecasts are available. After applying the different filters, we end up with a dataset consisting of 412 banks[16] and 8448 bank-quarter observations. The average number of analyst forecasts per bank per quarter is a satisfying 8.25.

The estimation results are presented in the right-hand side panel of Table 5. We do not only include the managerial discretion and disagreement measures, but also loan growth, ROE volatility and the different business model complexity indicators. It is comforting that the results for those variables are very similar in the reduced sample compared to the full sample. With respect to management discretion,

[16]We loose a significant number of bank-quarter observations when matching the existing dataset with IBES data. Both datasets are merged as follows. The main identifier in IBES is the IBES ticker, whereas the main identifier in CRSP is the permno of the bank. Hence, in order to merge the information of both files, the best approach is to use common secondary identifiers to construct a linking table that relates the permno of the bank to the IBES ticker. We follow the procedure proposed by WRDS (Moussawi (2006)), which assigns a score to each match, according to the quality of the link. For our sample of 794 bank holding companies (i.e. the number of BHCs in the database before imosing our liquidity criterium and matching with the FRY-9C reports), 688 banks have a corresponding IBES ticker. 632 of the banks have a score of 0, indicating the best match (the CUSIP code and date is the same, and the company name matches).

we find that bank shareholders exercise more discretion in their assessment of all risk measures for banks exhibiting a high discretionary behavior in the realization of their securities gains/losses. A one standard deviation increase in this discretion measure leads to a 13% (10%) increase in the dispersion of market beta inefficiencies (total risk). Discretionary behavior in the amount of loan loss provisioning matters less. However, the main goal of active discretion in loan loss provisioning is earnings smoothing, which is considered favourably (i.e. stable profit streams lead to a lower variance of the inefficiency scores). In fact, the leeway managers permit themselves in dealing with problem loans seems to help in reducing the discretionary behavior of bank equity holders with respect to market risk. Dispersion in IBES analyst forecasts unambiguously increases the variance of the inefficiency scores in all risk metrics. This does not only suggest that banks differ substantially in their degrees of opaqueness, but also that bank equity holders take these differences into account. The dispersion in market beta (total risk) inefficiencies increases with 12% (20%) in response to a one standard deviation increase in analysts' forecast dispersion.

The policy implication is that transparency is essential for market discipline to be effective. Regulation should be designed to lower the degree of discretion that bank managers can exercise, e.g. by imposing transparent and binding anti-cyclical loan loss provisioning rules. A reduction in the opacity of banks can be achieved by fostering information disclosure, e.g. through a timely and accurate publication of relevant on and off balance sheet risk exposures.

3.3 Influencing: Banks respond to increasing risk inefficiency

In the previous sections, we discussed how risk inefficiency scores can be interpreted as the discretionary component of the risk assessment by bank shareholders. We showed that this discretionary component is related to managerial discretion, business model complexity and the disagreement on the bank's actual performance by other bank monitors (analysts' earnings forecast dispersion). We now take our analysis one step further. The influencing channel of market discipline implies that bankers should take off-setting actions to align their risk profile with the interest of shareholders. To assess whether the influencing channel of market discipline is supported in our sample, we analyze if and to what extent bank managers respond to a high risk inefficiency score. As bank strategies are sticky in the short term and restructuring typically occurs as as series of incremental adjustments, we are predominantly interested in medium to long run changes in the constituents of the CAMEL acronym (Tier 1 Risk-Based Capital Ratio, Non Performing Loans ratio, Cost to Income, Return on Equity and Liquid Assets), which can be considered as outcomes of the multitude of possible, small adjustments.

Our graphical analysis of influencing behavior is presented in five panels in Figure 2. Each panel corresponds to one of the five components of the acronym CAMEL and contains subplots graphing the effect of, respectively, market risk inefficiency (upper left plot), idiosyncratic volatility inefficiency (upper right plot), total volatility inefficiency (lower left plot) and risk-adjusted return inefficiency (lower right plot) on the specific CAMEL rating component. We now describe the construction of the different graphs for the first element of the CAMEL rating, the Tier 1 Risk-Based Capital Ratio. The construction of the graphs for the other indicators is identical. Each subplot presents the average capital ratio of four quartile portfolios in event time, where period 1 is the portfolio formation period. For each quarter, we form four portfolios by ranking banks based on their actual inefficiency score. Holding the portfolios fixed for the next 20 quarters, we compute the average capital ratio for each portfolio. For example, in 1993:Q1, we sort banks into four groups based on their market risk inefficiency scores. For each quarter from 1993:Q1 to 1997:Q4, we compute the average capital ratio for each of these four portfolios. Note that the set-up of this graph differs from Figure 1 and the concept of Lemmon, Roberts, and Zender (2008) in that the sorting variable (inefficiency) differs from the plotted response variable (bank characteristic). We repeat this process of sorting and averaging for every quarter from 1993:Q1 to 2007:Q4. Subsequently, we average the average capital ratios across "event time". The dotted lines on the graph depict a 90% confidence interval around the mean evolution of the response variable. To make magnitudes comparable across subplots and the different constituents of CAMEL, we rescale each portfolio with the average evolution (in the event time framework) of the response variable of interest. An additional benefit from rescaling by the mean is that the numbers on the Y-axis can easily be interpreted as a proportional deviation from the mean response. Rescaling also allows us to control for a potential survivorship bias: Recall that after sorting, the set of banks is held constant except for exit. If the reason of exit is unrelated to the sort variable, then the scaling neutralizes the effect of exits, as they will affect the conditional response (of each quartile) in a similar way as the unconditional mean evolution. The legend on the graphs correspond to the four quartiles: Very High (most risk inefficient), High, Medium, and Low (closest to the frontier).

The graphs can be interpreted as impulse-response functions. The impulses are given by assigning a bank to a certain risk inefficiency quartile (hence, different subplots correspond to different types of impulses). The responses are the observed medium to long term reaction in bank strategic variables to a certain impulse (hence, different panels correspond to different response variables).

Before we discuss each graph in detail, two more general conclusions emerge. First, in 16 of the 20 plots, if a portfolio lies outside of the 90% confidence interval, it is typically the line associated with the most risk inefficient group. Hence the stock market disciplines the least risk efficient banks most, which is reassuring from a financial stability point of view. Second, the least informative impulse is the sort based on market risk inefficiency. Bank managers tend to react less to the discretionary component in systematic risk.

The strongest evidence in favor of market influencing can be inferred from the proxy for asset quality (non performing loans ratio) and bank profitability (return on equity). For all four inefficiency scores, we observe that at portfolio formation time, the average non-performing loans ratio of the most risk inefficient group is significantly larger than the mean (around 20% higher), reflecting the higher credit risk of risk-inefficient banks. We observe that these banks seem to adjust their credit portfolio such that ex-post credit risk decreases. However, the adjustment takes place at a snail's pace. Only after 8 to 10 quarters, the non-performing loan ratio of the high risk inefficient group is sufficiently reduced to make it is no longer significantly different from the mean. This result might be caused by a number of strategies. Bank managers may increase monitoring and screening efforts (better trained personnel, adopting a more advanced credit scoring method). At the same time, they may slightly alter their loan portfolio composition (mix of type of loans or type of borrowers). We defer disentangling the different channels to future research, and focus instead on the overall outcome of this multitude of possible actions.

We also find strong evidence that banks belonging to the least inefficient group take actions that result in increases in the return on equity ratio. At event time 1, risk inefficient banks have on average an ROE ratio that is 10 percent lower than that of the mean bank. Banks that are punished the most (i.e. have a high risk inefficiency score) gradually improve their performance. The line corresponding to the most inefficient group enters the significance bounds around the mean after 7 to 10 quarters, depending on the risk metric.

Bank managers of the least risk efficient banks do not only take actions to improve their credit quality and profitability, they also tend to reduce costs and strengthen their regulatory capital base. Risk inefficient banks are the least efficient ones in terms of cost management, i.e. they have the highest cost-to-income ratios. There is some evidence that they reduce their cost-income ratio, but even three years after they are labeled as risk inefficient their cost-income ratio is still statistically different from the mean. Our failure to find signs of convergence may be the result of two counteracting effects. First, the cost-income ratio may not be a 'strategic action variable' for bank management, but rather the result of different, potentially opposite reactions (e.g. an increase in cost due to better credit risk monitoring, combined with more profits, may leave the cost-income ratio unaltered). The most idiosyncratic and total risk inefficient banks are better capitalized at portfolio formation time (though not statistically different). Moreover, they take actions to strengthen their regulatory capital base compared to the average bank in response to being penalized by shareholders' assessment of a bank's risk profile. The limited impact on bank capital may be the result of persistence in bank capital ratios. There exists ample evidence that banks only gradually adjust their capital ratios towards the optimal target capital ratio (see Flannery and Rangan (2006) for evidence on non-financial firms). The ratio of liquid assets to total assets does not seem to be influenced by shareholder discretion.

Figure 1 in Section 3.1.2 has shown that efficiency scores converge rather fast to their unconditional mean. On average, after less than four quarters, the efficiency score of the least inefficient group is no longer statistically different from the slightly more risk efficient group. The low persistence in efficiency scores makes our findings on market influencing actually stronger. Banks respond by taking actions when they are classified as being the least risk efficient ones, even though this may be a temporary but strong signal.

In sum, in contrast to most of the literature, we do find evidence of market influencing. However, this evidence is limited to the banks that are punished the most by bank shareholders. Bank managers tend to take actions to improve their credit risk and operating performance if they are assessed to be substantially more risk inefficient than their peers. This is reassuring for the Third Pillar of Basel II which relies on a type of market discipline that is more benign and commonplace than market participants forcing bank runs, executive turnovers or outright defaults. However, we want to stress that our approach only identifies that bank managers take certain actions that result in an overall effect. Our aim was not to identify a precise channel, as we believe the actual outcome is a result of a multitude of changes. In addition, although we show that some constituents of the acronym CAMEL move in the desired direction after a negative market assessment, our approach does not allow us to assess whether this is due to direct versus indirect influencing. That is, we are not identifying whether the supervisory authorities are taking actions at times of adverse shareholders assessments. Hence, as in most other studies addressing this issue, the evidence has to be interpreted with caution since it is impossible to disentangle the market discipline effect from other sources of discipline, such as actions taken by the supervisory authorities.

4 Conclusions

The financial crisis of 2007-9 has illustrated that the choice of business models and transparency in banking may have profound consequences for the risk profile of the banks. For example, banks with excessive reliance on wholesale funding have been exposed as vulnerable to liquidity shocks (e.g. Northern Rock). The US investment banks suffered severe losses in their trading and derivative activities, leading to the failure of one of the big houses (Lehman), the forced takeover of others (e.g. Merrill Lynch), and the conversion to bank holding companies of the largest institutions. Retail banks appear to have been able to weather the storm relatively unscathed, although some retail franchises turned out to be vulnerable to problems in other parts of diversified banks (e.g. Washington Mutual). Hence, even within certain bank business models, we noticed a large discrepancy of banks' vulnerability to adverse shocks. The question is whether information about BHC risk can be extracted from stock market information and whether market signals are sufficiently strong to force banks to alter their risk profile. These are the two faces of market discipline: monitoring and influencing. If the stock market is able to monitor bank risk, this information is useful for supervisors and they should include market-based risk indicators in their information set. If the stock market would also be able to influence bank risk behavior, this can be complementary to supervisory actions and even reinforce them.

In this paper, we develop an empirical setup to examine the ability of stock market investors to monitor and influence bank risk in a sample of US BHCs over the period 1991-2008. The first component of market discipline, market monitoring, requires market participants to identify relevant bank risks and discriminate between banks with different risk exposures. We are particularly interested in differences in risk exposures that result from differences in business models. We consider not only a set of control variables related to the CAMEL ratings to capture the strategic business model choices by banks. We also included proxies capturing the funding and asset structure of the banks and the composition of their revenues. Our empirical results confirm that stock market investors are able to monitor bank risk.

Since we want to analyze the riskiness of a particular bank relative to its peers, we estimate a stochastic risk frontier, similar to the well known cost efficiency frontier, capturing the minimum risk that the most risk efficient banks with a certain business model can achieve. We find evidence that the differences in risk exposures of observationally equivalent banks are more than just random noise. Hence, measured deviations from the frontier capture discretion in shareholders' assessment of bank risk. We define risk inefficiency as the deviations from this optimal frontier. We also hypothesize that risk inefficiency may be caused by three potential determinants: business model complexity, managerial discretion and opaqueness. Therefore, we use the stochastic frontier setup to analyze whether or not there is scale heterogeneity in the inefficiency scores. We find that stock market investors punish discretionary behavior, especially in the case of security gains and losses. More unpredictable banks will exhibit larger deviations from the efficient risk frontier in all risk dimensions. This further corroborates the ability of the stock market to identify and punish discretionary bank behavior. We also find strong evidence that the degree of opaqueness is positively related to the variance of the risk inefficiency scores. The policy implication is that transparency is essential for market discipline to be effective. Regulation should be designed to lower the degree of discretion that bank managers can exercise, e.g. by imposing transparent and binding anti-cyclical loan loss provisioning rules. A reduction in the opacity of banks can be achieved by fostering information disclosure, e.g. through a timely and accurate publication of relevant on and off balance sheet risk exposures.

Finally, we investigate the influencing hypothesis by analyzing if and to what extent bank managers react to high risk inefficiency scores over a medium to long-run horizon. The hypothesis is that banks exhibiting a relatively high degree of risk inefficiency will respond by taking remedial action in order to adjust their risk profile. This can e.g. be achieved by increasing capital, by lowering the asset risk or by improving operational performance. In contrast to most of the extant literature, we find evidence of market influencing. However, this observation only holds for some dimensions of the banks' risk profile, especially the quality of the loan portfolio and return on equity. Yet the reactions are found to be most substantial for those banks that are punished most by the stock market, i.e. banks with the largest deviations from the efficient risk frontier. This is where action is most wanted and as such the market plays a useful role. Hence, our evidence lends at least partial support to a benign influence of stock market discipline on banks. However, as in most other studies addressing this issue, the evidence has to be interpreted with caution since it is impossible to disentangle the market discipline effect from other sources of discipline, such as actions taken by the supervisory authorities.

References

Ang, A., and D. Kristensen, 2010, "Testing Conditional Factor Models," *Columbia University Working Paper.*

Ashcraft, A., 2008, "Does the market discipline banks? New evidence from regulatory capital mix," *Journal of Financial Intermediation*, 17(4), 543–561.

Baele, L., G. Bekaert, and K. Inghelbrecht, 2010, "The Determinants of Stock and Bond Return Comovements," *Review of Financial Studies, Article in Press.*

Baele, L., O. De Jonghe, and R. Vander Vennet, 2007, "Does the stock market value bank diversification?," *Journal of Banking and finance*, 31(7), 1999–2023.

Beatty, A., B. Ke, and K. Petroni, 2002, "Earnings management to avoid earnings declines across publicly and privately held banks," *The Accounting Review*, 77(3), 547–570.

Bliss, R., and M. Flannery, 2002, "Market discipline and the governance of U.S. bank holding companies: monitoring versus influencing," *European Finance Review*, 6(3), 361–395.

Cerquiero, G., H. Degryse, and S. Ongena, 2007, "Rules versus discretion in loan rate setting," *CEPR Discussion Paper NÂř 6450.*

Cihak, M., A. Maechler, K. Schaeck, and S. Stolz, 2009, "Who disciplines bank managers?," *International Monetary Fund, Working Paper 09/272.*

Cornett, M., J. McNutt, and H. Tehranian, 2009, "Corporate governance and earnings management at large U.S. bank holding companies," *Journal of Corporate Finance*, 15(4), 412–430.

De Jonghe, O., 2009, "Back to the basics in banking? A Micro-Analysis of Banking System Stability," *Journal of Financial Intermediation*, forthcoming.

Demsetz, R., and P. Strahan, 1997, "Diversification, Size and Risk at Bank Holding Companies," *Journal of Money, Credit and Banking*, 29(3), 300–313.

Diether, K. B., C. J. Malloy, and A. Scherbina, 2002, "Differences of opinion and the cross section of stock returns," *Journal of Finance*, 57(5), 2113–2141.

Federal-Reserve-System, 1999, "Using subordinated debt as an instrument of market discipline, Report of a study group on subordinated notes and debentures," *Board of Governors Staff Study NÂř 172*.

Flannery, M., 2001, "The faces of market disciplie," *Journal of Financial Services Research*, 20(2-3), 107–119.

Flannery, M., S. Kwan, and M. Nimalendran, 2004, "Market evidence on the opaqueness of banking firm's assets," *Journal of Financial Economics*, 71(3), 419–460.

Flannery, M., and S. Sorescu, 1996, "Evidence of bank market discipline in subordinated debenture yields: 1983-1991," *The Journal of Finance*, 51(4), 1347–1377.

Flannery, M. J., and K. P. Rangan, 2006, "Partial adjustment toward target capital structures," *Journal of Financial Economics*, 79(3), 469–506.

Gatev, E., T. Schuermann, and P. E. Strahan, 2009, "Managing Bank Liquidity Risk: How Deposit-Loan Synergies Vary with Market Conditions," *Review of Financial Studies*, 22(3), 995–1020.

Gendreau, B., and D. Humphrey, 1980, "Feedback effects in the market regulation of bank leverage: time-series and cross-section analysis," *The Review of Economics and Statistics*, 62(2), 277–280.

Ghysels, E., and E. Jacquier, 2006, "Market Beta Dynamics and Portfolio Efficiency," *Working Paper*.

Glushkov, D., and D. Robinson, 2006, "Note on IBES Unadjusted Data," *WRDS Documentation on IBES*.

Harvey, A., 1976, "Estimating regression models with multiplicative heteroscedasticity," *Econometrica*, 44(3), 461–466.

Hirtle, B., 2007, "Public disclosure, Risk and Performance at Bank Holding Companies," *Federal Reserve bank of New York Staff Report NÂř 293.*

Hirtle, B., and K. Stiroh, 2007, "The return to retail and the performance of U.S. banks," *Journal of Banking and finance*, 31(4), 1101–1133.

Knaup, M., and W. Wagner, 2009, "A Market-Based Measure of Credit Quality and Banks' Performance During the Subprime Crisis," *Tilburg University (CentER) Discussion Paper 2009-35S.*

Kwan, S., 2002b, "Bank security prices and market discipline," *FRBSF Economic Letter NÂř 37.*

Laeven, L., and R. Levine, 2007, "Is there a diversification discount in financial conglomerates?," *Journal of Financial Economics*, 85(2), 331–367.

Laeven, L., and G. Majnoni, 2003, "Loan loss provisioning and economic slowdowns: too much, too late?," *Journal of Financial Intermediation*, 12(2), 178–197.

Lang, M., K. Lins, and M. Maffett, 2009, "Transparency, liquidity and valuation: International Evidence," *Weiss Center Working Paper*, Wharton School (University of Pennsylvania).

Lemmon, M. L., M. R. Roberts, and J. F. Zender, 2008, "Back to the beginning: Persistence and the cross-section of corporate capital structure," *Journal of Finance*, 63(4), 1575–1608.

Morgan, D., and K. Stiroh, 2001, "Market disciplie of banks: the asset test," *Journal of Financial Services Research*, 20(2), 195–208.

Moussawi, R., 2006, "Linking CRSP and IBES data," *WRDS Documentation on IBES.*

Saunders, A., E. Strock, and N. G. Travlos, 1990, "Ownership Structure, Deregulation, and Bank Risk Taking," *Journal of Finance*, 45(2), 643–654.

Schuermann, T., and K. Stiroh, 2006, "Visible and hidden risk factors for banks," *FRB of New York Staff Report NÂř 252.*

Stiroh, K., 2004, "Diversification in banking: is noninterest income the answer?," *Journal of Money, Credit and Banking*, 36(5), 853–882.

——— , 2006a, "A portfolio view of banking with interest and noninterest activities," *Journal of Money, Credit and Banking*, 38(5), 1351–1361.

——— , 2006b, "New evidence on the determinants of bank risk," *Journal of Financial Services Research*, 30(3), 237–263.

Sundaresan, S., 2001, "Supervisor and market analysts: what should research be seeking?," *Journal of Financial Services Research*, 20(2-3), 275–280.

Viale, A., W. James, and D. Fraser, 2009, "Common risk factors in bank stocks," *Journal of Banking and finance*, 33(3), 464–472.

Wagner, W., 2009, "Diversification at Financial Institutions and Systemic Crsises," *Journal of Financial Intermediation, Forthcoming.*

Table 1: Summary statistics of the market-based risk and return measures

	N	Mean	Std.Dev.	Minimum	Maximum
Market risk	16134	0.6335	0.5047	-0.5846	2.0051
Idiosyncratic volatility	16134	0.2527	0.1062	0.1001	0.7818
Total volatility	16134	0.2752	0.1085	0.1082	0.8077
Return	16134	0.0033	0.0053	-0.0283	0.0483
Risk Adjusted Return	16134	0.0814	0.1338	-0.2479	0.3863

This table contains information on the equity market-based risk and return measures. Market exposures are a measure of the firm's systematic risk and is obtained from a single index model. The idiosyncratic risk is the volatility of the residuals of the model, computed as the standard deviation of the (weekly) residuals on a yearly basis, rolling over each quarter. For the calculation of total volatility, we take the standard deviation of the bank stock returns within a year, rolling over the quarters. We then annualize total and idiosyncratic volatility by multiplying with $\sqrt{52}$. We also compute a market-based risk-adjusted return measure, which is obtained by dividing average weekly returns by total volatility. The variables are measured over the period 1991-2008 on a quarterly basis. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume for at least 20% of the observations. The total sample consists of 16134 observations on 655 bank holding companies.

Table 2 panel A: Summary statistics of the Independent Variables in the mean equation of the Stochastic Frontier Model

	N	Mean	Std.Dev.	Minimum	Maximum
	Bank Strategy Variables				
Bank Size	16134	15.0622	1.5826	12.1940	19.7128
Tier 1 Risk Based Capital Ratio	16134	11.7927	3.2186	6.2257	26.6625
Non Performing Loans Ratio	16134	0.0117	0.0133	0.0000	0.0860
Cost to Income	16134	0.6375	0.1177	0.3771	1.1957
Return on Equity	16134	0.0329	0.0175	-0.0862	0.0693
Liquid Assets	16134	0.0487	0.0917	-0.1694	0.3737
	Funding Structure				
Non-Interest Bearing Deposits Share	16134	0.1441	0.0736	0.0174	0.4040
Interest Bearing Core Deposits Share	16134	0.6950	0.1297	0.2137	0.9000
Large Time Deposits Share	16134	0.1383	0.0888	0.0193	0.4556
Deposits to Total Assets Share	16134	0.7619	0.1077	0.3446	0.9236
	Asset Mix				
Real Estate Loan Share	16134	0.6273	0.1882	0.0615	0.9789
Commercial and Industrial Loan Share	16134	0.1943	0.1195	0.0038	0.6405
Agricultural Loan Share	16134	0.0101	0.0208	0.0000	0.1244
Consumer Loan Share	16134	0.1205	0.1005	0.0010	0.4989
Other Loan Share	16134	0.0417	0.0598	0.0000	0.3550
Loans to Total Assets	16134	0.6402	0.1217	0.2057	0.8714
	Revenue Streams				
Interest Income Share	16134	0.7366	0.1398	0.2456	0.9597
Non-Interest Income Share	16134	0.2634	0.1398	0.0403	0.7544
Fiduciary Activities Income Share	16134	0.0383	0.0615	0.0000	0.4002
Service Charges on Deposit Accounts Share	16134	0.0740	0.0368	0.0002	0.1808
Trading Revenue Share	16134	0.0063	0.0192	-0.0079	0.1138
Other Non-Interest Income Share	16134	0.1413	0.1166	0.0086	0.6652
	Deposit Loan Synergies				
Deposit Loan Synergies	16134	0.0456	0.0368	0.0007	0.3167
Unused Loan Commitments Share	16134	0.2002	0.1183	0.0241	0.6577
Transaction Deposits Share	16134	0.2264	0.1067	0.0298	0.5070

This table contains information on the independent variables used in the mean equation of the stochastic frontier model. The variables are measured over the period 1991-2008 on a quarterly basis. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume more than 20% of the observations. The total sample consists of 16134 observations on 655 bank holding companies. Bank size is measured as the natural logarithm of total assets expressed in US$ thousands and deflated to 2007:Q4 values. All other variables are measured as ratios. For detailed information on the exact computation of the ratios, we refer to Appendix A. Income statement data are reported on a calendar year-to-date basis in the FRY9C reports and are therefore converted to quarter-to-quarter changes before computing ratios. The reported values are winsorized at the 1% level.

Table 2 panel B: Summary statistics of the Independent Variables in the scale heterogeneity of the Stochastic Frontier Model

	Full Sample					Reduced Sample				
	N	**mean**	**sd**	**min**	**max**	**N**	**mean**	**sd**	**min**	**max**
Volatility of ROE	16134	0.0123	0.0092	0.0010	0.0622	8448	0.0118	0.0080	0.0010	0.0482
Loan Growth	16134	0.1323	0.1542	-0.2505	0.6686	8448	0.1423	0.1481	-0.2505	0.6686
Funding Specialization	16134	0.5555	0.1263	0.1024	0.8167	8448	0.5432	0.1337	0.1024	0.8167
Loan Portfolio Specialization	16134	0.5200	0.1603	0.2712	0.9657	8448	0.5159	0.1615	0.2712	0.9657
Income Specialization	16134	0.6521	0.0973	0.5006	0.9288	8448	0.6326	0.0937	0.5006	0.9288
Specialization in non-traditional, non-interest income generating activities	16134	0.4912	0.1414	0.3021	0.9654	8448	0.4957	0.1412	0.3021	0.9654
Dispersion in IBES analyst forecasts						8448	0.0692	0.1230	0.0000	1.0250
Discretion in loan loss provisioning						8448	0.0129	0.0243	0.0000	0.1311
Discretion in realizing securities gains and losses						8448	0.0366	0.0620	0.0000	0.8299

This table contains information on the independent variables used in the scale heterogeneity of the stochastic frontier model. The sample selection criteria for the Full Sample and the Reduced Sample are the same as in Table 2, panel A. However, the Reduced sample contains only 8448 observations on 412 bank holding companies, due to the limited availability of IBES forecasts. Although the sample size is reduced by almost half, the summary statistics are comparable across the Full and Reduced sample.

Table 3 panel A: Bank business models and risk exposures: the monitoring role

	Market Risk	Idiosyncratic Volatility	Total Volatility	Risk Adjusted Return
	Bank Strategy Variables			
Bank Size	0.154***	-0.0101***	-0.00277***	-0.00393***
	(0.00343)	(0.000554)	(0.000600)	(0.000633)
Tier 1 Risk Based Capital Ratio	-0.0176***	-0.000614***	-0.00160***	-0.00101***
	(0.00128)	(0.000206)	(0.000226)	(0.000231)
Non Performing Loans Ratio	-0.292	0.861***	0.842***	-0.142**
	(0.316)	(0.0484)	(0.0530)	(0.0566)
Cost to Income	-0.637***	0.0502***	0.0210***	0.0175**
	(0.0412)	(0.00696)	(0.00757)	(0.00747)
Return on Equity	0.0492	-0.226***	-0.239***	0.257***
	(0.280)	(0.0489)	(0.0536)	(0.0492)
Liquid Assets	-0.403***	0.0196**	0.0133	0.0112
	(0.0493)	(0.00787)	(0.00855)	(0.00872)
	Funding Structure			
Interest Bearing Core Deposits Share	-0.229***	-0.0133	-0.0231**	-0.0628***
	(0.0530)	(0.00852)	(0.00930)	(0.0105)
Large Time Deposits Share	-0.0972	0.0336***	0.0126	-0.0377***
	(0.0595)	(0.00996)	(0.0109)	(0.0113)
Deposits to Total Assets Share	-0.432***	0.0462***	0.0181**	0.0507***
	(0.0474)	(0.00770)	(0.00837)	(0.00841)
	Asset Mix			
Commercial and Industrial Loan Share	0.136***	-0.00195	0.00715	-0.0449***
	(0.0344)	(0.00544)	(0.00590)	(0.00659)
Agricultural Loan Share	-0.679***	-0.176***	-0.209***	-0.0415
	(0.147)	(0.0239)	(0.0257)	(0.0278)
Consumer Loan Share	0.327***	-0.0579***	-0.0431***	-0.0651***
	(0.0405)	(0.00613)	(0.00672)	(0.00762)
Other Loan Share	1.197***	-0.0602***	-0.00399	-0.0427***
	(0.0819)	(0.0136)	(0.0149)	(0.0149)
Loans to Total Assets	-0.114***	-0.00793	-0.0130**	-0.0229***
	(0.0348)	(0.00560)	(0.00608)	(0.00637)
	Revenue Streams			
Fiduciary Activities Income Share	0.583***	-0.0837***	-0.0515***	-0.0533***
	(0.0686)	(0.0104)	(0.0115)	(0.0130)
Service Charges on Deposit Accounts Share	1.158***	-0.0272*	0.0213	-0.0184
	(0.106)	(0.0165)	(0.0179)	(0.0199)
Trading Revenue Share	1.658***	-0.0869**	-0.0477	-0.0362
	(0.215)	(0.0339)	(0.0371)	(0.0407)
Other Non-Interest Income Share	0.268***	0.0114*	0.0280***	0.0130
	(0.0427)	(0.00648)	(0.00713)	(0.00830)
	Deposit Loan Synergies			
Deposit Loan Synergies	0.664***	-0.0637	-0.120***	0.103**
	(0.240)	(0.0389)	(0.0429)	(0.0435)
Unused Loan Commitments Share	-0.00131	0.0349***	0.0501***	0.0327***
	(0.0681)	(0.0108)	(0.0119)	(0.0118)
Transaction Deposits Share	-0.0404	0.0209*	0.0332***	-0.0458***
	(0.0702)	(0.0112)	(0.0123)	(0.0124)
Constant	1.165***	0.130***	0.189***	0.421***
	(0.0830)	(0.0133)	(0.0145)	(0.0153)
Observations	16134	16134	16134	16134

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the mean equation of the stochastic frontier model. Stochastic frontier analysis allows decomposing the error term in random noise and a measure of risk inefficiency. We estimate a ‘cost’ function for systematic, idiosyncratic and total risk and a ‘profit’ function for risk-adjusted returns. That is, in the latter the inefficiency score captures a shortfall from the frontier, whereas in the former the inefficiency score measures excess risk above the frontier. We relate bank characteristics that capture banks’ business models to four different risk measures. They are respectively systematic risk, idiosyncratic risk, total volatility and risk-adjusted returns. The variables are measured over the period 1991-2008 at a quarterly basis. To be more specific, bank balance sheets are observed and measured as stock values at a quarterly basis. Data from the income statement is reported on a cumulative basis over the accounting year and are therefore first transformed to quarterly increments. The risk exposures are estimated using 52 weekly observations over rolling quarters. The independent variables are lagged four quarters. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume more than 20% of the observations. The total sample consists of 16134 observations on 655 bank holding companies. Time dummies are included in each column (but not reported).

Table 3 panel B: An analysis of scale heterogeneity in the Stochastic Frontier Model

	Full Sample				Reduced Sample			
	Market Risk	**Idiosyncratic Volatility**	**Total Volatility**	**Risk Adjusted Return**	**Market Risk**	**Idiosyncratic Volatility**	**Total Volatility**	**Risk Adjusted Return**
ln(variance of inefficiency)=Scale heterogeneity								
Constant	-2.319***	-6.759***	-6.553***	-5.577***	-2.666***	-7.006***	-6.771***	-5.833***
	(0.168)	(0.120)	(0.123)	(0.211)	(0.296)	(0.177)	(0.186)	(0.283)
Volatility of ROE	22.60***	40.06***	40.22***	18.11***	-4.255	25.90***	24.97***	31.01***
	(1.725)	(1.337)	(1.365)	(2.178)	(3.817)	(2.753)	(2.835)	(4.069)
Loan Growth	-0.634***	-0.0302	-0.106	0.119	0.350**	0.762***	0.719***	-0.482***
	(0.0987)	(0.0785)	(0.0790)	(0.122)	(0.162)	(0.118)	(0.120)	(0.182)
Funding Specialization	0.832***	0.108	0.00383	-1.752***	0.252	0.377**	0.175	-1.836***
	(0.173)	(0.120)	(0.123)	(0.232)	(0.307)	(0.167)	(0.175)	(0.302)
Loan Portfolio Specialization	1.403***	0.561***	0.714***	0.955***	2.324***	0.599***	0.846***	1.298***
	(0.133)	(0.100)	(0.103)	(0.172)	(0.230)	(0.147)	(0.156)	(0.237)
Income Specialization	-1.334***	1.294***	1.017***	0.684***	-1.917***	0.710***	0.257	0.525
	(0.196)	(0.148)	(0.151)	(0.260)	(0.357)	(0.227)	(0.237)	(0.364)
Specialization in non-traditional, non-interest income generating activities	0.839***	1.438***	1.548***	0.122	0.985***	1.548***	1.736***	0.0978
	(0.125)	(0.0992)	(0.100)	(0.156)	(0.204)	(0.140)	(0.146)	(0.220)
Dispersion in IBES analyst forecasts					0.954***	1.316***	1.454***	0.397**
					(0.185)	(0.147)	(0.151)	(0.192)
Discretion in loan loss provisioning					-3.534***	0.425	-0.155	1.982*
					(1.065)	(0.716)	(0.746)	(1.030)
Discretion in realizing securities gains and losses					1.935***	1.227***	1.573***	-0.173
					(0.363)	(0.307)	(0.309)	(0.411)
ln(variance of random noise)								
	-2.635***	-7.085***	-6.836***	-5.702***	-2.608***	-7.064***	-6.705***	-5.789***
	(0.0361)	(0.0434)	(0.0431)	(0.0348)	(0.0506)	(0.0545)	(0.0525)	(0.0444)
Observations	16134	16134	16134	16134	8448	8448	8448	8448

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

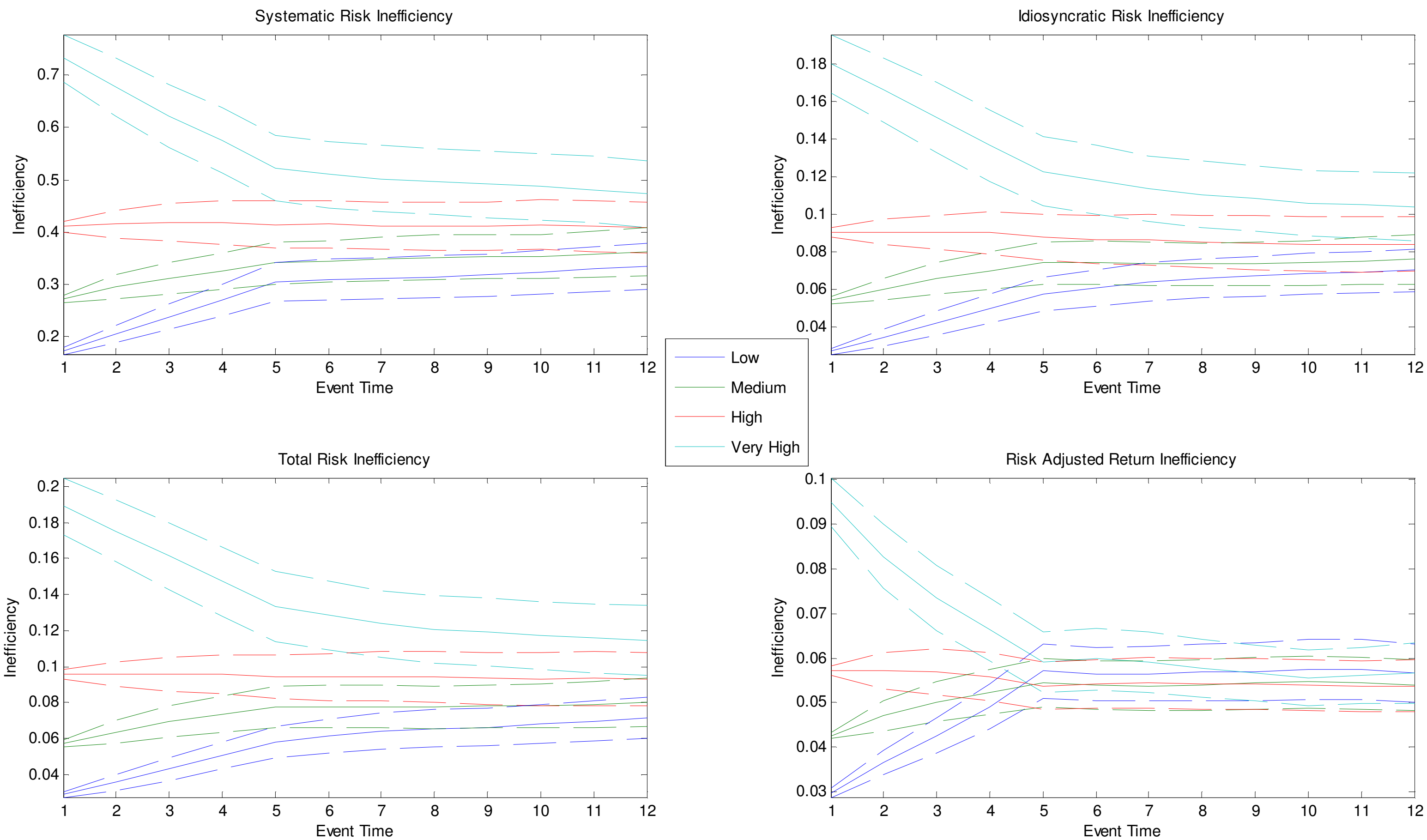
In this table we provide the results for the scale heterogeneity in the stochastic frontier model, where the volatility of the inefficiency term is related to two sets of variables. In the Full Sample, the bank-specific volatility of the inefficiency term is related to the complexity or specialization of the banking firm. We use Hirschmann-Herfindahl indices of specialization or diversification across the various business model characteristics. The higher the value of the index, the more the bank is specialized in that area. We also include the past loan growth and the volatility of the ROE as independent variables. In the Reduced Sample, we introduce the dispersion in IBES analyst forecast as a measure of bank opaqueness and proxies for various aspects of (discretion in) (earnings) management, such as discretion in loan loss provisioning and the realization of securities gains and losses, earnings volatility.

Table 4: Variance decomposition of the risk inefficiency scores

		Mean	Std.Dev.	Share of between/within variation in total variation	Minimum	Maximum	Observations	
Market risk inefficiency	overall	0.4002	0.2595		0.0621	2.0884	N	16134
	between		0.1681	38.55%	0.1192	1.2427	n	655
	within		0.2122	61.45%	-0.6194	1.8699	T	25
Idiosyncratic volatility inefficiency	overall	0.0888	0.0752		0.0061	0.6608	N	16134
	between		0.0670	57.04%	0.0164	0.5242	n	655
	within		0.0582	42.96%	-0.2411	0.5251	T	25
Total volatility inefficiency	overall	0.0940	0.0779		0.0075	0.6712	N	16134
	between		0.0695	57.93%	0.0183	0.5573	n	655
	within		0.0592	42.07%	-0.2176	0.5314	T	25
RAR Inefficiency	overall	0.0564	0.0293		0.0127	0.2783	N	16134
	between		0.0179	31.98%	0.0182	0.2416	n	655
	within		0.0261	68.02%	-0.0341	0.2417	T	25

This table provides information on the risk efficiency scores of the stochastic frontier model with scale heterogeneity. We estimate a 'cost' function for systematic, idiosyncratic and total risk and a 'profit' function for risk-adjusted returns. That is, in the latter the inefficiency score captures a shortfall from the frontier, whereas in the former the inefficiency score measures excess risk above the frontier (lower bound of one). The risk efficiency scores may vary by bank and quarter and are obtained for US BHCs over the period 1991-2008. We decompose the variation of each risk inefficiency score in the between variation (variation in bank means) and within variation (variation in deviations from a bank-specific mean).

Figure 1: Cross-sectional and temporal variation in risk inefficiency scores

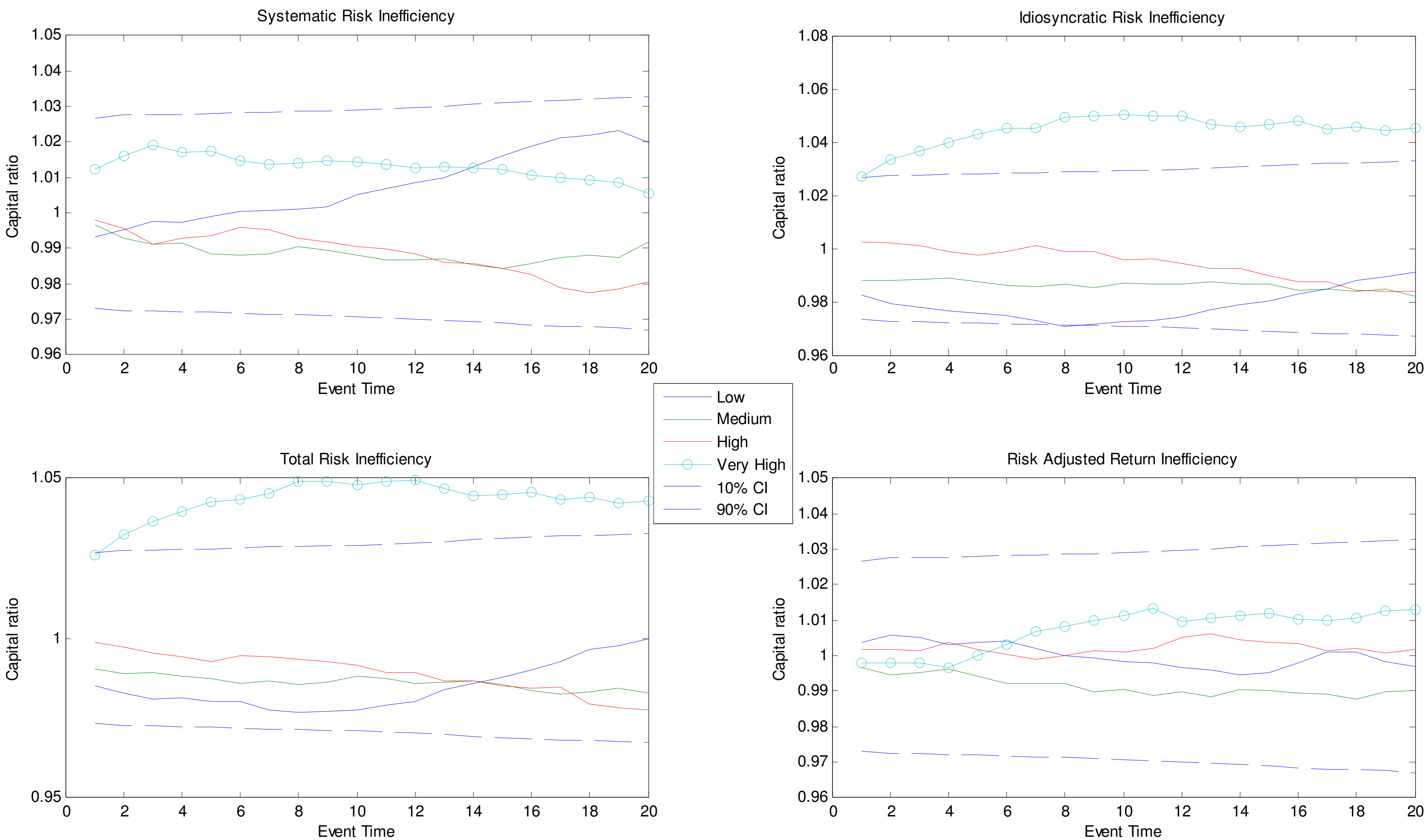


Note: Figure 1 consists of four subplots, one for each risk metric. Each subplot presents the average inefficiency score (the deviation from the stochastic frontier) of four portfolios in “event time”. Each quarter, we sort BHCs into quartiles (i.e., four portfolios) according to the risk inefficiency score. We denote the four quartiles as: Very High (most risk inefficient), High, Medium, and Low (closest to the frontier). The portfolio formation quarter is denoted time period 1. We then compute the average efficiency score for each portfolio in each of the subsequent 12 quarters, holding the portfolio composition constant (except for BHCs that exit the sample). We repeat these two steps of sorting and averaging for every quarter in the sample period (1993-2007). This process generates 60 sets of event-time averages, one for each quarter in our sample. We then compute the average risk inefficiency of each portfolio across the 60 sets within each event quarter. This portfolio sorting is done for market, idiosyncratic and total risk inefficiency as well as risk-adjusted return inefficiency. The dashed lines surrounding the portfolio averages represent 90% confidence intervals. They are computed as the average standard error across the 60 sets of averages (Lemmon et al., 2008).

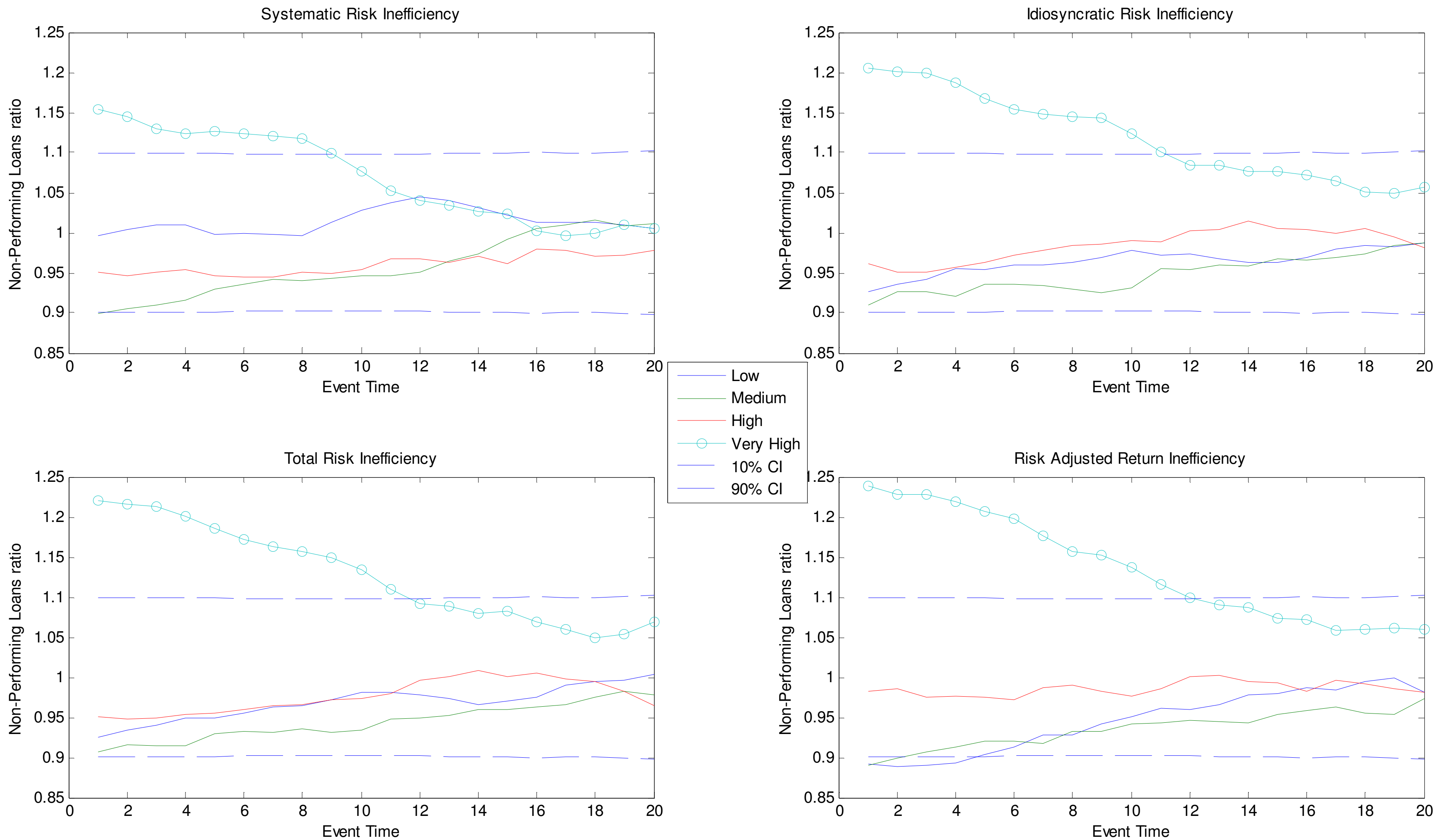
Figure 2: Impulse (inefficiency scores) - response (CAMEL constituents) evidence on market influencing

Note: Figure 2 consists of five panels, which correspond to the five components of the acronym CAMEL. The description of the construction of the graphs is based on the first panel (panel A: Tier 1 Risk-Based Capital Ratio). Each panel can be read accordingly (panel B, C, D and E contain respectively Non Performing Loans ratio, Cost to Income, Return on Equity and Liquid Assets). The four subplots of each panel correspond to how bank capital responds respectively to market inefficiency (upper left plot), idiosyncratic volatility inefficiency (upper right plot), total volatility inefficiency (lower left plot) and risk-adjusted return inefficiency (lower right plot). Each subplot presents the average capital ratio of four portfolios in event time, where period 1 is the portfolio formation period. For each quarter, we form four portfolios by ranking banks based on their actual inefficiency score. Holding the portfolios fixed for the next 20 quarters, we compute the average capital ratio for each portfolio. For example, in 1993:Q1, we sort banks into four groups based on their market inefficiency scores. For each quarter from 1993:Q1 to 1997:Q4, we compute the average capital ratio for each of these four portfolios. Note that the set-up of this graph differs from Figure 1 and the concept of Lemmon, Roberts and Zender (2008) in that the sorting variable (inefficiency) differs from the plotted response variable (bank characteristic). We repeat this process of sorting and averaging for every quarter in our sample horizon. After performing this sorting and averaging for every quarter from 1993:Q1 to 2007:Q4, we average the average capital ratios across "event time". The dotted lines on the graph depict a 90% confidence interval around the mean evolution of the response variable. To make magnitudes comparable across subplots and the different constituents of CAMEL, we rescale each portfolio with the average evolution (in the event time framework) of the response variable of interest to arrive at the four lines in each subplot figure. As we rescale all lines by this mean evolution, the confidence interval is constructed around 1. The numbers of the Y-axis can hence be interpreted as a proportional deviation from the mean response. The legend on the graphs correspond to the four quartiles: Very High (most risk inefficient), High, Medium, and Low (closest to the frontier). The graphs can be interpreted as impulse-response functions. The impulses are given by assigning a bank to a certain risk inefficiency quartile (hence, different subplots correspond to different types of impulses). The responses are the observed medium to long term reaction in bank strategic variables to a certain impulse (hence, different panels correspond to different response variables).

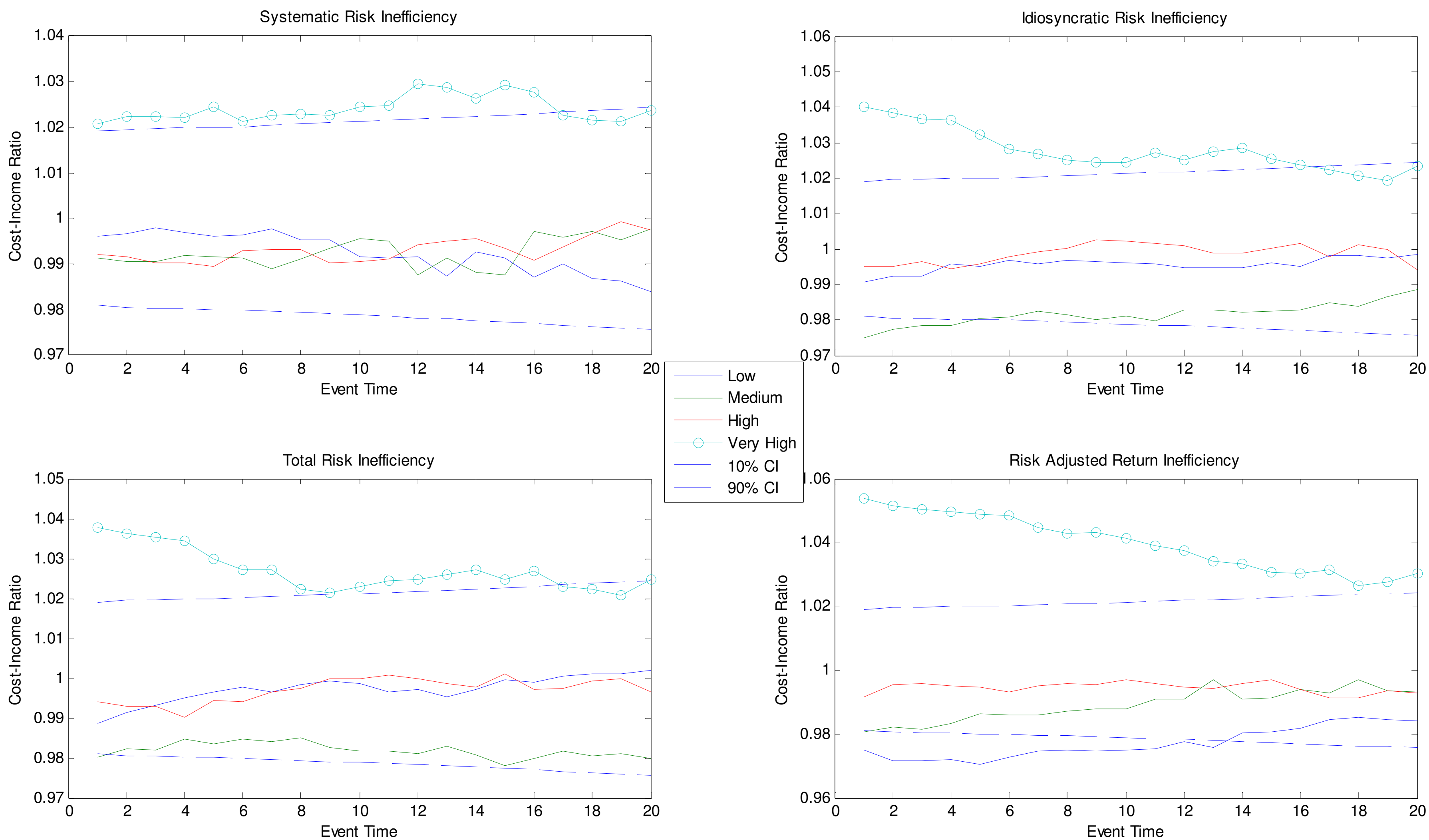
Panel A: Tier 1 Risk-Based Capital Ratio



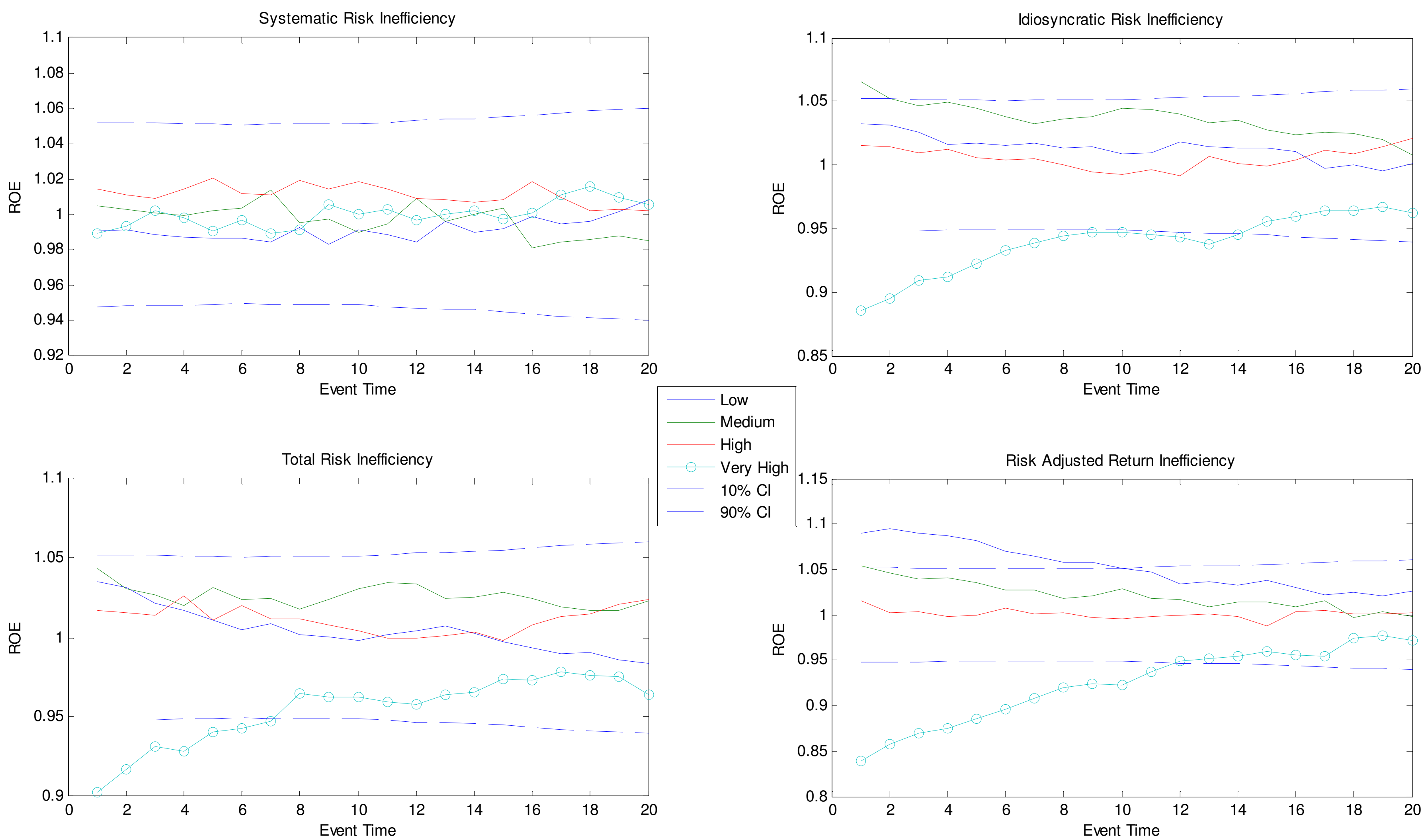
Panel B: Non Performing Loans Ratio



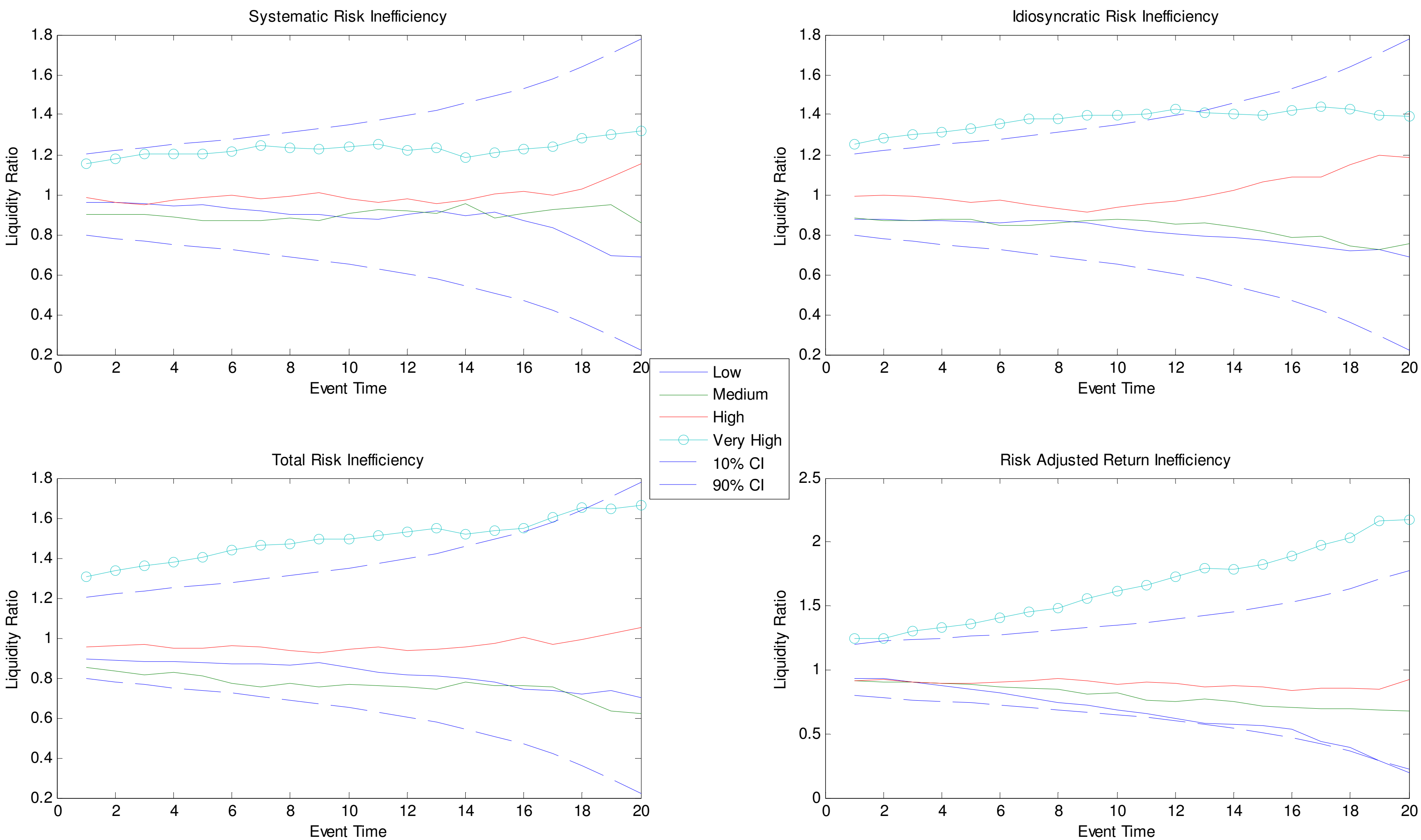
Panel C: Cost to Income Ratio



Panel D: Return on Equity



Panel E: Liquid Assets Ratio



Appendix: Definition of bank ratios

Bank Size	**ln(bhck2170) , deflated to 2007:Q4 dollars**	
	bhck2170	TOTAL ASSETS
Tier 1 Risk Based Capital Ratio	**(before 1996): own computations based on 'Optional Worksheet to Compute Risk-Based Capital Ratios for Consolidated Bank Holding Company' in the instructions to the FRY9C reporting form**	
	(from 1996): bhck8274/ bhcka223	
	bhck8274	TIER 1 CAPITAL ALLOWABLE UNDER THE RISK-BASED CAPITAL GUIDELINES
	bhcka223	RISK-WEIGHTED ASSETS (NET OF ALLOWANCES AND OTHER DEDUCTIONS)
Non Performing Loans ratio	**(bhck5525 - bhck3506 + bhck5526 - bhck3507 + bhck1616) / bhck2122**	
	bhck5525	TOTAL LOANS, LEASING FINANCING RECEIVABLES AND DEBT SECURITIES AND OTHER ASSETS - PAST DUE 90 DAYS OR MORE AND STILL ACCRUING
	bhck3506	DEBT SECURITIES AND OTHER ASSETS - PAST DUE 90 DAYS OR MORE AND STILL ACCRUING
	bhck5526	TOTAL LOANS, LEASING FINANCING RECEIVABLES AND DEBT SECURITIES AND OTHER ASSETS – NONACCRUAL
	bhck3507	DEBT SECURITIES AND OTHER ASSETS – NONACCRUAL
	bhck1616	TOTAL LOANS AND LEASES – RESTRUCTURED
	bhck2122	TOTAL LOANS AND LEASES, NET OF UNEARNED INCOME
Cost to Income	**bhck4093 / (bhck4074 + bhck4079)**	
	bhck4093	TOTAL NONINTEREST EXPENSE
	bhck4074	NET INTEREST INCOME
	bhck4079	TOTAL NONINTEREST INCOME
Return on Equity	**bhck4340 / bhck3210**	
	bhck4340	NET INCOME (LOSS)
	bhck3210	TOTAL EQUITY CAPITAL
Liquid Assets to Total Assets	**(until 1994): bhck0081 + bhck0395 + bhck0397 + bhck0276 + bhck0277 - bhck0278 - bhck0279 + bhck0400) / Total Assets Total Assets**	
	(from 1997 until 2002): bhck0081 + bhck0395 + bhck0397 + bhck1350 - bhck2800 + bhck0213 + bhck1287) / Total Assets Total Assets	
	bhck0081	NONINTEREST-BEARING BALANCES AND CURRENCY AND COIN
	bhck0395	INTEREST-BEARING BALANCES IN U.S. OFFICES
	bhck0397	INTEREST-BEARING BALANCES IN FOREIGN OFFICES, EDGE AND AGREEMENT SUBSIDIARIES AND IBFS
	bhck0276	FEDERAL FUNDS SOLD

	bhck0277	SECURITIES PURCHASED UNDER AGREEMENTS TO RESELL
	bhck0278	FEDERAL FUNDS PURCHASED
	bhck0279	SECURITIES SOLD UNDER AGREEMENTS TO REPURCHASE
	bhck0400	U.S. TREASURY SECURITIES - BOOK VALUE (EXCLUDING TRADING ACCOUNTS)
	bhck0213	FAIR VALUE OF HELD-TO-MATURITY U.S. TREASURY SECURITIES
	bhck1287	FAIR VALUE OF AVAILABLE-FOR-SALE U.S. TREASURY SECURITIES
	bhck1350	FEDERAL FUNDS SOLD AND SECURITIES PURCHASED UNDER AGREEMENTS TO RESELL IN DOMESTIC OFFICES OF THE BANK AND OF ITS EDGE AND AGREEMENT SUBSIDIARIES, AND IN IBFS
	bhck2800	FEDERAL FUNDS PURCHASED AND SECURITIES SOLD UNDER AGREEMENTS TO REPURCHASE
	bhdmb987	FEDERAL FUNDS SOLD IN DOMESTIC OFFICES
	bhckb989	SECURITIES PURCHASED UNDER AGREEMENTS TO RESELL
	bhdmb993	FEDERAL FUNDS PURCHASED IN DOMESTIC OFFICES
	bhckb995	SECURITIES SOLD UNDER AGREEMENTS TO REPURCHASE
Deposits to Total Assets Share	**(bhdm6631 + bhdm6636 + bhfn6631 + bhfn6636)/ Total assets**	
	bhdm6631	DEPOSITS: NONINTEREST-BEARING (DOMESTIC OFFICES)
	bhdm6636	TOTAL INTEREST-BEARING DEPOSITS DOMESTIC OFFICES
	bhfn6631	DEPOSITS: NONINTEREST-BEARING (FOREIGN OFFICES)
	bhfn6636	TOTAL INTEREST-BEARING DEPOSITS IN FOREIGN OFFICES
Non-Interest Bearing Deposits Share	**(bhcb2210 + bhod3189 + bhfn6631) / Total Deposits**	
	bhcb2210	TOTAL DEMAND DEPOSITS
	bhod3189	NONINTEREST-BEARING BALANCES IN DOMESTIC OFFICES OF OTHER DEPOSITORY INSTITUTIONS
	bhfn6631	DEPOSITS: NONINTEREST-BEARING (FOREIGN OFFICES)
Interest Bearing Core Deposits Share	**(bhcb3187 + bhod3187 + bhcb2389 + bhod2389 + bhcb6648 + bhod6648) / Total Deposits**	
	bhcb3187	NOW, ATS AND OTHER TRANSACTION ACCOUNTS (IN DOMESTIC OFFICES OF COMMERCIAL BANKS)
	bhod3187	NOW, ATS AND OTHER TRANSACTION ACCOUNTS
	bhcb2389	TRANSACTION SAVINGS DEPOSITS (IN DOMESTIC OFFICES OF COMMERCIAL BANKS)
	bhod2389	TRANSACTION SAVINGS DEPOSITS (IN DOMESTIC OFFICES OF OTHER DEPOSITORY INSTITUTIONS)
	bhcb6648	TOTAL TIME DEPOSITS OF LESS THAN $100,000 (IN DOMESTIC OFFICES OF COMMERCIAL BANKS)
	bhod6648	TOTAL TIME DEPOSITS OF LESS THAN $100,000 (IN DOMESTIC OFFICES OF OTHER DEPOSITORY INSTITUTIONS)
Large Time Deposits Share	**(bhcb2604 + bhod2604) / Total Deposits**	
	bhcb2604	TOTAL TIME DEPOSITS OF $100,000 OR MORE (IN DOMESTIC OFFICES OF COMMERCIAL BANKS)
	bhod2604	TOTAL TIME DEPOSITS OF $100,000 OR MORE (IN DOMESTIC OFFICES OF OTHER DEPOSITORY INSTITUTIONS)

Transaction Deposits Share	**(bhcb2210 + bhod3189 + bhfn6631+ bhcb3187 + bhod3187)/Total Deposits**	
Loans to Total Assets	**bhck2122 / Total Assets**	
	bhck2122:	TOTAL LOANS AND LEASES, NET OF UNEARNED INCOME
Commercial and Industrial Loan Share	**(bhck1763 + bhck1764) / Total Loans**	
	bhck1763	COMMERCIAL AND INDUSTRIAL LOANS TO U.S. ADDRESSEES
	bhck1764	COMMERCIAL AND INDUSTRIAL LOANS TO NON-U.S. ADDRESSEES
Real Estate Loan Share	**bhck1410 / Total Loans**	
	bhck1410	LOANS SECURED BY REAL ESTATE
Agricultural Loan Share	**bhck1590 / Total Loans**	
	bhck1590	LOANS TO FINANCE AGRICULTURAL PRODUCTION AND OTHER LOANS TO FARMERS
Consumer Loan Share	**(before 2001): (bhck2008 + bhck2011) / Total Loans**	
	(from 2001): (bhckb538 + bhckb539 + bhck2011) / Total Loans	
	bhck2008	CREDIT CARDS AND RELATED PLANS
	bhck2011	OTHER LOANS
	bhckb538	LOANS TO INDIVIDUALS FOR HOUSEHOLD, FAMILY, AND OTHER PERSONAL EXPENDITURES (I.E., CONSUMER LOANS)(INCLUDES PURCHASED PAPER): CREDIT CARDS
	bhckb539	LOANS TO INDIVIDUALS FOR HOUSEHOLD, FAMILY, AND OTHER PERSONAL EXPENDITURES (I.E., CONSUMER LOANS)(INCLUDES PURCHASED PAPER): OTHER REVOLVING CREDIT PLANS
Other Loan Share	**1 - (C&I Loans + Real Estate Loans + Agriculture Loans + Consumer Loans) / Total Loans**	
Unused (non retail) Loan Commitments Ratio	**(bhck3816 + bhck3817 + bhck3818 + bhck6550) / (bhck3816 + bhck3817 + bhck3818 + bhck6550 + Total Loans)**	
	bhck3816	COMMERCIAL REAL ESTATE, CONSTRUCTION, AND LAND DEVELOPMENT: COMMITMENTS TO FUND LOANS SECURED BY REAL ESTATE
	bhck3817	UNUSED COMMITMENTS - SECURITIES UNDERWRITING
	bhck3818	UNUSED COMMITMENTS - OTHER
	bhck6550	COMMERCIAL REAL ESTATE, CONSTRUCTION, AND LAND DEVELOPMENT: COMMITMENTS TO FUND LOANS NOT SECURED BY REAL ESTATE
Interest Income Share	**bhck4074 / (bhck4074 + bhck4079)**	
	bhck4074	NET INTEREST INCOME
	bhck4079	TOTAL NONINTEREST INCOME

Non-Interest Income Share	**bhck4079 / (bhck4074 + bhck4079)**
Fiduciary Activities Income Share	**bhck4070/ (bhck4074 + bhck4079)**
Service Charges on Deposit Accounts Share	**bhck4483 / (bhck4074 + bhck4079)**
Trading Revenue Share	**(before 1996): bhck1655 + bhck4077** **(from 1996 until 1997): bhcka220 + bhck4076** **(from 1997): bhcka220**

bhck1655	TRADING GAINS (LOSSES) AND FEES FROM FOREIGN EXCHANGE TRANSACTIONS ON OTHER GAINS (LOSSES) FROM FOREIGN TRANSACTIONS
bhck4077	NONINTEREST INCOME ON OTHER GAINS (LOSSES) AND FEES FROM TRADING ASSETS AND LIABILITIES
bhcka220	TRADING REVENUE
bhck4076	NONINTEREST INCOME ON OTHER FOREIGN TRANSACTION GAINS (LOSSES)

Other Non-Interest Income Share	**(before 2001): bhck4078 + bhck4399** **bhckb497** **bhckb496 + bhckb497** **bhckc387 + bhckb496 + bhckb497**

bhck4078	OTHER NONINTEREST INCOME
bhck4399	OTHER SERVICE CHARGES, COMMISSIONS, AND FEES
bhck8560	NET GAINS ON SALES OF LOANS
bhck8561	NET GAINS ON OTHER REAL ESTATE OWNED
bhckb490	INVESTMENT BANKING, ADVISORY, BROKERAGE, AND UNDERWRITING FEES AND COMMISSIONS
bhckb491	VENTURE CAPITAL REVENUE
bhckb492	NET SERVICING FEES
bhckb493	NET SECURITIZATION INCOME
bhckb494	INSURANCE COMMISSIONS AND FEES
bhckb496	NET GAINS (LOSSES) ON SALES OF OTHER ASSETS (EXCLUDING SECURITIES)
bhckb497	OTHER NONINTEREST INCOME
bhckc386	INSURANCE AND REINSURANCE UNDERWRITING INCOME
bhckc387	INCOME FROM OTHER INSURANCE AND REINSURANCE ACTIVITIES
bhckb496	NET GAINS (LOSSES) ON SALES OF OTHER ASSETS (EXCLUDING SECURITIES)
bhckb497	OTHER NONINTEREST INCOME
bhckc886	FEES AND COMMISSIONS FROM SECURITIES BROKERAGE
bhckc888	INVESTMENT BANKING, ADVISORY, AND UNDERWRITING FEES AND COMMISSIONS

	bhckc887	FEES AND COMMISSIONS FROM ANNUITY SALES

The following variables enter the equation to estimate the discretionary behaviour of bank manager as in Beatty et al. (2002). (bank size, loan loss provisions and the five different loan shares are defined above)

Loan Loss Provisions	**bhck4230**	*PROVISION FOR LOAN AND LEASE LOSSES*
Loan Loss Allowance	**bhck3123**	*ALLOWANCE FOR LOAN AND LEASE LOSSES*
Realized Security Gains and Losses	**(bhck3521 + bhck 3196)**	
	bhck3521	*REALIZED GAINS (LOSSES) ON HELD-TO-MATURITY SECURITIES (from 1994 onwards)*
	bhck3196	*REALIZED GAINS (LOSSES) ON AVAILABLE-FOR-SALE SECURITIES (from 1994 onwards)*
Unrealized Security Gains and Losses	**bhck8434**	*NET UNREALIZED HOLDING GAINS (LOSSES) ON AVAILABLE-FOR-SALE SECURITIES (from 1994 onwards)*

Note: detailed info on the selected series can be obtained from http://www.federalreserve.gov/reportforms/mdrm/DataDictionary/search.cfm.
That website provides information on the definition, the start and end date of each series as well as info regarding the comparability over time.