Systemic Risk and Bank Business Models*

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– PRELIMINARY DRAFT, COMMENTS ARE WELCOME –

Abstract In this study we disentangle two dimensions of bank's systemic risk: The level of bank tail risk and the linkage between the tail risk of a bank and severe shocks in the financial system. We employ a measure on the systemic risk of financial institutions that can be decomposed into two subcomponents reflecting these dimensions. Empirically, we show quantitatively how bank characteristics are related to bank tail risk and systemic linkage. The relations between bank characteristics and these dimensions determine the relation between bank characteristics and systemic risk. Certain characteristics that are irrelevant to the soundness of a financial institution taken in isolation turn out to be important for the level of systemic risk, and vice versa. Our analytical framework helps to evaluate differences in scope and directions of policy under the micro- and macroprudential objectives of regulation.

Keywords: Financial institutions, financial stability, tail risk, macroprudential regulation, non-interest income.

JEL Classification Numbers: G10, G21, G28

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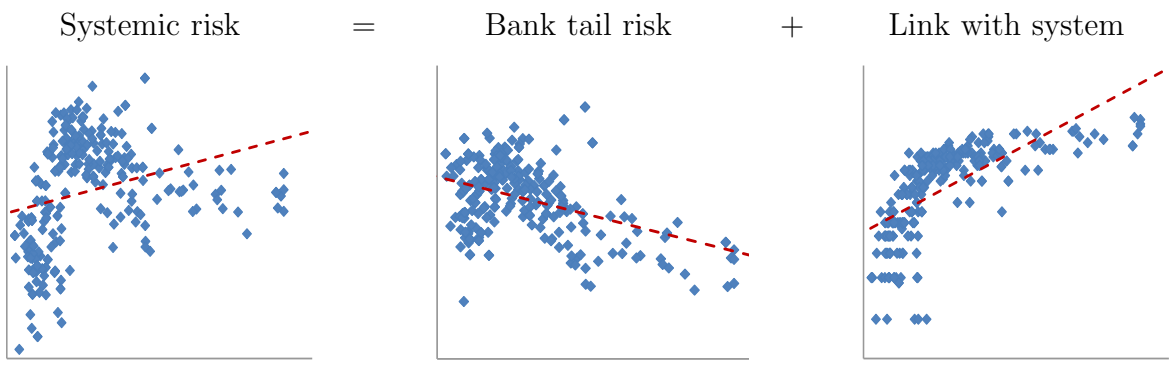
1 Introduction

The performance of financial institutions during the global financial crisis raised the interest for understanding systemic risk in the financial industry. Regulators have realized that not only the probability of individual bank failures is relevant for financial stability, but also whether those failures occur simultaneously. With the second concern in mind, the debate on banking regulation has been broadened towards a macroprudential approach. The focus on limiting banks' systemic risk differs from the regulatory regime before the global financial crisis, which focused predominantly on the soundness of financial institutions taken in isolation. In this paper, we decompose bank's systemic risk into two dimensions: The level of bank's tail risk and the linkage between bank's tail risk and severe shocks in the financial system. We show quantitatively how the characteristics of bank business models are related to systemic risk via these two dimensions. This is achieved by employing a measure on systemic risk that can also be decomposed into measures on these two dimensions. Empirically, some characteristics that are irrelevant to bank's tail risk turn out to be important for bank's systemic risk, and vice versa.

In our study the systemic risk of a financial institution is conceptualized as its sensitivity to severe shocks in the financial system. A financial system consisting of banks that are more sensitive to systemic shocks is also more likely to exhibit simultaneous bank failures, or, a systemic banking crisis. Bank's total tail risk can be attributed to both shocks in the financial system and other shocks. For banks with the same level of tail risk, a bank whose tail risk is more related to shocks in the financial system should be considered as more systemically risky, because, compared to its peers, such a bank is expected to suffer larger losses in case of a systemic crisis. Hence, whether banks are sensitive to systemic shocks depends on whether systemic shocks accounts for a relatively large fraction of their tail risk. We call this systemic linkage. Conversely, for banks with the same level of systemic linkage, the one with a higher level of tail risk should be considered as more systemically risky. To conclude, from our discussion two dimensions of bank's systemic risk arise: The level of bank's tail risk and the bank's systemic linkage.

These conceptualizations of systemic risk and systemic linkage do not have a direc-

Figure 1: Systemic risk and bank size



The figures show the relation between different dimensions of systemic risk (vertical axes) and bank size (on the horizontal axis) in 2007Q4. The dashed lines show fitted linear trend lines. Bank size is measured by log(Total Assets). The first panel shows the relation between bank size and the sensitivity of banks to large shocks in the financial system, i.e., $\log(\hat{\beta}^T)$. The second panel shows relation between bank size and the tail risk of the bank, IR. The third panel shows the relation between bank size and the intensity of the link between the extreme events in the financial system and the tail risk of a bank, SL.

tional flavor: We simply measure the sensitivity regardless the direction of shock propagation. From a regulator's point of view, even if a bank only passively suffers from large systemic shocks, it should be regulated more tightly since the bank often fails with a large number of other banks, which imposes a larger cost on the economy due to financial instability; see e.g. Acharya and Yorulmazer (2007), Acharya (2009) and Wagner (2010).

To illustrate the decomposition of systemic risk, we demonstrate an example in Figure 1. Figure 1 plots banks' size against our systemic risk measure and the two subcomponents measuring bank's tail risk and systemic linkage. The systemic risk measure equals to the sum of its two subcomponents. We observe downwards and upwards trends in the size-tail risk and size-systemic linkage relations respectively. Since the latter dominates the former, on the aggregated level, larger banks exhibits higher systemic risk. From such a decomposition analysis, one may not only conclude that size relates to systemic risk, but also that the relation is mainly through a relation with the systemic linkage dimension. On the tail risk dimension, large banks taken in isolation seem to be less risky. This decompositino might partly explain why microprudential regulation has hardly been concerned with bank size before the global financial crisis, while bank size arises as an indicator in the macroprudential debate; see e.g. FSB (2011). We will explore similar de-

compositions for other characteristics of bank business models, which gives more insight on how those characteristics are related to systemic risk.

Empirically, we measure the systemic risk of financial institutions by estimating the sensitivity of bank's equity returns to severe shocks in the financial system. More precisely, conditional upon extremely adverse shocks in the financial system, we estimate the coefficient in a linear relation between the bank's returns and shocks in the financial system. There is a strong analogy between this coefficient and other systemic risk measures. Theoretically, we show how the estimated coefficient quantifies all cross-sectional variation in the Marginal Expected Shortfall (MES), which is the systemic risk measure proposed by Acharya et al. (2009, 2012). An advantage of the estimated coefficient is that it can be decomposed into two subcomponents that reflect the bank's tail risk and the linkage between the bank's tail risk and severe shocks in the financial system. This serves our purpose to examine the relations between bank characteristics and the two dimensions of systemic risk.

Since the coefficient describes the relation between the bank and shocks in the financial system conditional upon large adverse shocks in the financial system, the systemic risk measure has to be estimated from relatively few observations. The problem of estimating such a relation among financial returns has been studied by Van Oordt and Zhou (2011). They propose a method to estimate the relation based on Extreme Value Theory (EVT). Van Oordt and Zhou (2013) apply this methodology in an asset pricing framework and show that estimates are relatively persistent over time and that historical estimates help to predict which stocks suffer relatively large losses in market crashes. By applying the same model in a banking context, it can be interpreted as a systemic risk measure. We further run panel regressions on our systemic risk measure and its subcomponents with respect to characteristics of bank business models to identify through which dimension bank characteristics are related to systemic risk. Quantitatively, we show how these two effects balance each other in determining the level of systemic risk.

Our study contributes to two strands of literature. First, we contribute to the literature on measuring systemic risk. To name a few examples; see the CoVaR measure

of Adrian and Brunnermeier (2011), the volatility contribution of Lehar (2005), the distress insurance premium of Huang et al. (2009, 2012), the CoRisk measure of Chan-Lau (2010), the measure based on principal component analysis of Billio et al. (2012) and the Shapley value developed by Drehmann and Tarashev (2013).[1] Compared to the existing measures, our measure has the aforementioned decomposition into the bank's tail risk and the linkage between the bank's tail risk and severe shocks in the financial system. Further, it is estimated exclusively from so-called tail events in financial markets. This approach reduces the potential consequences of mixing the empirical structure observed in relatively calm periods with the structure observed during extreme events.

Second, we contribute to the literature on identifying which bank characteristics are related to systemic risk. For macroprudential policy it is useful to measure systemic risk and identify indicators of systemic risk at the bank level. Academic literature has provided several measures on systemic risk and there is a growing literature on identifying bank characteristics that are related to systemic risk; see e.g. Brunnermeier et al. (2012), Vallascas and Keasey (2012), López-Espinosa et al. (2012, 2013), Girardi and Ergün (2013) and Anginer et al. (2014). Comparing with these examples, besides identifying bank characteristics related to systemic risk, we also identify whether the relation is through the bank's tail risk or through the linkage between the bank's tail risk and severe shocks in the financial system. This insight is important to understand the impact of microprudential regulation on the level of bank's systemic risk. It also helps to identify where micro- and macroprudential objectives may potentially lead to differences in the scope and direction of regulation.

The paper is organized as follows. Section 2 discusses the methodology. Section 3 gives a description of the data. We discuss our empirical results in Section 4. Robustness checks are in Section 5. Section 6 provides some concluding remarks.

[1] A broader survey on 31 systemic risk analytics can be found in Bisias et al. (2012).

2 Methodology

In this section we discuss our framework on how to decompose systemic risk into the bank's tail risk and the linkage between the bank's tail risk and severe shocks in the financial system. The subsections discuss successively the systemic risk measure, the estimation methodology, the decomposition of systemic risk into bank tail risk and systemic linkage, and the estimated regression models.

2.1 Systemic risk measure

We measure banks' systemic risk by evaluating the sensitivity of banks to shocks in the financial system. A natural measure on that would be the coefficient from a linear relation between indicators on the status of one bank and the system; see e.g. Nijskens and Wagner (2011). However, the relation between financial institutions and financial system may be quite differently for small shocks and severe shocks; see e.g. Knaup and Wagner (2012). To avoid mixing the sensitivity to severe shocks and the co-movement with small shocks, we consider a linear relation between the equity returns of a financial institution and the financial system conditional on extremely adverse shocks in the financial system.

Let R_i and R_s denote the return on the equity of bank i and the return on an equity investment in the financial system. Then we measure systemic risk by the coefficient β_i^T in the following linear tail model

$$R_i = \beta_i^T R_s + \varepsilon_i \text{ for } R_s < -VaR_s(\bar{p}), \tag{2.1}$$

where $VaR_s(\bar{p})$ is the Value-at-Risk of an equity investment in the financial system, which is exceeded with some small probability $\bar{p}$, and where ε_i represents the shocks from other sources which are assumed to be independent of the shocks in the financial system represented by R_s. The linear tail model is only assumed in case of extremely adverse shocks in the financial system, i.e., only if $R_s < -VaR_s(\bar{p})$. Hence, we do not make any assumption on the relation between the bank and the financial system during tranquil

periods.

The coefficient β_i^T could be regarded as a systemic risk measure by construction: banks with a higher β_i^T are expected to suffer from a larger capital losses in case of an extremely adverse shock in the financial system. There is a strong analogy between the coefficient β_i^T and the MES measure discussed by Acharya et al. (2009, 2012). From the definition of MES and the linear tail model in Eq. (2.1), it is straightforward to get that, for $p < \bar{p}$,

$$MES_i(p) := -\mathbb{E}[R_i | R_s \leq -VaR_s(p)] = -\beta_i^T \mathbb{E}[R_s | R_s \leq -VaR_s(p)] = \beta_i^T ES_s(p), \quad (2.2)$$

where $ES_s(p)$ denotes the expected shortfall of R_s defined as $ES_s(p) = -\mathbb{E}[R_s | R_s \leq -VaR_s(p)]$. Since the expected shortfall of the return on the financial system, $ES_s(p)$, is invariant across different banks, the dispersion in the MES measure across institutions is solely attributed to the cross-sectional differences in β_i^T. Hence, the coefficient β_i^T can be interpreted as a description of the cross-sectional variation in the MES, but it abstracts from potential time variation in the level of tail risk in the financial system as measured by the expected shortfall, $ES_s(p)$.

2.2 Estimation

The main difficulty in estimating coefficient β_i^T is the low number of observations corresponding to extremely adverse shocks in the financial system. Given the small probability $\bar{p}$, there are only a few observations corresponding to the tail scenario $R_s \leq -VaR_s(\bar{p})$. Therefore, one runs the risk of large estimation uncertainty when estimating β_i^T with conventional methods such as using an OLS regression. To deal with the low number of tail observations, we estimate β_i^T by an EVT approach. Van Oordt and Zhou (2011), propose an estimator of β_i^T based on EVT in a heavy-tailed environment. This estimator of β_i^T has a smaller mean squared error than an OLS regression if the estimation is based on a few tail observations only.

Suppose R_i and R_s follow heavy-tailed distributions with tail indices ζ_i and ζ_s, re-

spectively.[2] Under the weak conditions $\zeta_s < 2\zeta_i$ and $\beta_i^T \geq 0$, Van Oordt and Zhou (2011) obtain that

$$\beta_i^T = \lim_{p \to 0} \tau_i(p)^{1/\zeta_s} \frac{VaR_i(p)}{VaR_s(p)}, \tag{2.3}$$

where $VaR_i(p)$ and $VaR_s(p)$ are the Value-at-Risks (VaRs) of R_i and R_s with probability level p and $\tau_i(p)$ is the level of tail dependence between R_i and R_s defined as

$$\tau_i(p) := \Pr(R_i < -VaR_i(p) | R_s < -VaR_s(p)). \tag{2.4}$$

Empirically, all components in Eq. (2.3) can be estimated by existing estimators in EVT. The estimator of β^T is thus given by combining the estimators of its components as follows. With n observations on the pair (R_i, R_s), we consider the tail region as the k worst observations.[3] The coefficient β_i^T is then estimated by

$$\hat{\beta}_i^T := \widehat{\tau_i(k/n)}^{1/\hat{\zeta}_s} \frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_s(k/n)}, \tag{2.5}$$

where the tail index ζ_s is estimated by the estimator proposed in Hill (1975); $\widehat{VaR}_i(k/n)$ and $\widehat{VaR}_s(k/n)$ are estimated by the $k-th$ worst return on the bank's stock and the financial index; and $\widehat{\tau_i(k/n)}$ is the non-parametric estimator of $\tau_i =: \lim_{p \to 0} \tau_i(p)$ established in multivariate EVT; see Embrechts et al. (2000). The estimator $\hat{\beta}_i^T$ is consistent, even under temporal dependence such as volatility clustering; see Van Oordt and Zhou (2011).

2.3 Decomposition

The β_i^T and its estimator can be decomposed into two components that represents measures on systemic linkage and individual risk respectively. From Eq. (2.3), we observe that the sensitivity to extreme shocks is driven by two components, $\frac{VaR_i(p)}{VaR_s(p)}$ and $\tau_i(p)^{1/\zeta_s}$.

[2] A distribution is called heavy-tailed if it decays at a power law speed in the tail. Formally, for R_i it means $\Pr(R_i < -u) = u^{-\zeta_i} l_i(u)$ with $\lim_{u \to \infty} \frac{l_i(tu)}{l_i(u)} = 1$ for all $t > 1$.

[3] To guarantee the consistency of $\hat{\beta}_i^T$, theoretically, k is a sequence depending on n such that $k := k(n) \to \infty$ and $k(n)/n \to 0$ as $n \to +\infty$. In practice, samples are finite and k is fixed at a certain level. For all our estimations, we fix $k = 40$ in case of four years of daily returns, which corresponds to $k/n \approx 4\%$.

The first component, $\frac{VaR_i(p)}{VaR_s(p)}$, is the quotient between the VaR of bank i and that of the financial index. For example, if this component bears the value 2, then a 1\$ investment in the stock of an individual institution bears twice the tail risk of a 1\$ investment of the financial index. This component measures the amount of bank's tail risk without revealing whether the tail risk of a particular bank is related to severe shocks in the financial system. Since the denominator $VaR_s(p)$ is homogeneous across all financial institutions, the cross-sectional variation in the first component is solely due to the variation in the tail risks of individual banks, the $VaR_i(p)$s.

The second component, $\tau_i(p)^{1/\zeta_s}$, measures the relation between the the tail risk of an individual bank and severe shocks in the financial system. Cross-sectional differences in this component are solely due to the variation in the measure of tail dependence across different banks, the $\tau_i(p)$s. Similar to the correlation coefficient, the level of the $\tau_i(p)$ is independent of the distribution of the tail risk of the bank, i.e., the distribution of R_i.[4] Therefore, it contains information only on the dependence between extreme shocks in the financial system and severe losses suffered by a particular bank, without revealing the level of risk for an individual bank. Hence, it reveals information on systemic linkage only. Further, it is notable that the component $\tau_i(p)^{1/\zeta_s}$ can be interpreted as the fraction of banks' tail risk that is associated with severe shocks in the financial system.[5]

We intend to assess how bank characteristics are related to the sensitivity of banks to severe shocks in the financial system, in particular, by being related to either the bank's individual tail risk and/or to the dependence between the bank's tail risk to severe shocks in the financial system. We address such a distinction by applying the aforementioned decomposition of $\hat{\beta}_i^T$. Consider the logarithm transformation of the estimator of β_i^T as

$$\log \hat{\beta}_i^T = \frac{1}{\hat{\zeta}_s} \log \widehat{\tau_i(k/n)} + \log \frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_s(k/n)} =: SL_i + IR_i. \tag{2.6}$$

[4]This can easily be verified with Eq. (2.4).

[5]Suppose the tail risk of bank 1 is completely associated with severe shocks in the financial system (no other sources of risk). Then $VaR_1(p) = \beta_1^T VaR_s(p)$. Hence, in general, $\beta_i^T VaR_s(p)$ could be interpreted as the "amount of bank's tail risk that is associated with severe shocks in the financial system". From Eq. (2.5) we have $\widehat{\tau_i(k/n)}^{1/\hat{\zeta}_s} \widehat{VaR}_i(k/n) = \hat{\beta}_i^T \widehat{VaR}_s(k/n)$. Hence, the 'fraction' $\widehat{\tau_i(k/n)}^{1/\hat{\zeta}_s}$ of bank's tail risk $\widehat{VaR}_i(k/n)$ can be interpreted as "the amount of bank's tail risk that is associated with severe shocks in the financial system".

From the discussion above, the subcomponent SL_i measures the systemic linkage of bank i to the system while the other subcomponent IR_i measures the individual risk of bank i. In total, the log of the estimated systemic risk measure, $\hat{\beta}_i^T$, equals to the sum of the systemic linkage measure and the bank's tail risk measure.

2.4 Regression models

Our empirical analysis is based on estimating three different regression models. Suppose the bank characteristics of bank i in period t are denoted by X_{it}. Then we estimate the coefficients in the following three models from panel data on bank holding companies

$$\log \hat{\beta}_{it}^T = \alpha_{1t} + X_{it}\theta + \upsilon_{it}, \tag{2.7}$$

$$SL_{it} = \alpha_{2t} + X_{it}\delta + \xi_{it}, \tag{2.8}$$

$$IR_{it} = \alpha_{3t} + X_{it}\gamma + \nu_{it}, \tag{2.9}$$

where α_{1t}, α_{2t} and α_{3t} are time fixed effects and where υ_{it}, ξ_{it} and ν_{it} are the error terms. To take full advantage of the cross-sectional dispersion among the financial institutions in our panel, we do not include bank fixed effects.[6] To deal with the serial correlation among observations of the error terms over time and the cross-sectional correlation across banks at the same point in time we estimate standard errors that are clustered on both the bank and time level.

Note from Eq. (2.6) that the dependent variable in the model in Eq. (2.7) is the sum of those in Eqs. (2.8) and (2.9). Hence, theoretically it holds that the relation between a certain bank characteristic and the log of β_{it}^T, as presented by θ equals to the sum of the relation between that bank characteristic and the bank's tail risk, represented by γ, and its relation with its systemic linkage, represented by δ.[7] With the estimated coefficients $\hat{\gamma}$ and $\hat{\delta}$ it is possible to assess via which dimensions bank characteristics are related to the sensitivity of an individual institution to extreme shocks in the financial system. In

[6] In the robustness checks we do consider bank fixed effects.

[7] This relation holds also empirically, i.e., $\hat{\theta} = \hat{\gamma} + \hat{\delta}$, because we will estimate the regression models in Eqs. (2.7)–(2.9) with separated least squares (panel) regressions.

addition, we can asses how these these two relations balance each other in the relation between bank characteristics and the level of systemic risk.

3 Data

We use equity returns to calculate the systemic risk measure and its subcomponents. For that purpose, we collect stock market data from CRSP on US Bank Holding Companies from 1991 to 2011. At end of each quarter, we use four year daily equity returns preceding to that day to estimate the three dependent variables, the $\hat{\beta}_{it}^{T}$ and its two sub-components. To guarantee that selected banks are liquidly traded on the equity market, each selected bank must has at least 60% non-zero daily returns in all estimation windows. The financial index used for the estimation is the Fama-French industrial portfolio 'Bank' collected from the website of Kenneth French.[8]

We construct the characteristics of bank business models based on data collected from the publicly available FR Y-9C reports. With obtaining quarterly observations in the same sample period, we calculate the following indicators at end of each quarter. The calculated indicators be categorized into four groups. (i) Main characteristics of bank business models: the size of banks measured by the logarithm of total assets, the CAMEL ratios and the growth rate of total assets. Here the CAMEL ratios are Capital (tier 1 risk-based capital ratio), Asset quality (non-performing loans ratio), Management (cost to income ratio), Earnings (return on equity) and Liquidity (liquid assets ratio). (ii) Indicators on bank's income sources (as a ratio to total income): non-interest income share, fiduciary activities income share, service charges on deposit accounts share, trading revenue share and other non-interest income share. (iii) Indicators on bank's loan decomposition: the loans to total assets ratio, the real estate loan share, the agricultural loan share, the commercial and industrial loan share, the consumer loan share and other loan share. Except the loans to total assets ratio, these indicators are calculated as shares of total loans. (iv) Indicators on bank's funding structure: deposits to total assets ratio, interest-bearing core deposits, large time deposits share and non-interest-bearing deposits

[8] Available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

share. Except the deposits to total assets ratio, these indicators are calculated as a share of total deposits.

For each Bank Holding Company in our sample, we match its stock market data with the corresponding characteristics of bank business models. The link between stock market data and the FR Y-9C reports is based on the match provided by the Federal Reserve Bank of New York in 2012.[9] Since the measures on systemic risk and its subcomponents are estimated from stock market data in a four-year moving window, we average the 16 quarterly observations on the characteristics of bank business models within each estimation window to construct the characteristics used in the regression analysis.[10] Consequently, the sample period for the regressions ranges from 1994Q4 until 2011Q4. In addition we exclude all observations corresponding to a zero estimates of $\hat{\beta}_{it}^T$, because our regression models requires taking logarithm of the estimated β_{it}^T.[11] We end up with 12,620 bank-quarter observations.

The first row in Table 1 shows the descriptive statistics on β^T and its subcomponents.[12] We observe that across all banks in all period, the average $\hat{\beta}^T$ is 0.92. In an extreme market downturn, the average loss in bank equity returns is thus comparable with the large loss in the system return. The coefficient $\hat{\beta}^T$ ranges from 0.13 to 3.71 which demonstrates large differences in the sensitivity of banks' capital losses to large shocks in the financial system. Therefore, it is important to investigate which bank characteristics help to differentiate the coefficient β^T in the cross-section. The component, ${\tau_i}^{1/\zeta_s}$, can be interpreted as the fraction of banks' tail risk that is associated with their systemic risk. We observe the fraction at 62% on average, while ranging from 0.18 to 0.92. This illustrates the role of systemic linkage plays in the variation in β_{it}^T. The other component, $\frac{VaR_i}{VaR_s}$, compares bank's individual risk to that of the system. On average, an investment in the stocks of a single banks has a VaR that is 51% higher an investment in

[9] Available at `http://www.ny.frb.org/research/banking_research/datasets.html`.

[10] In Section 5 we also provide results when regressing the estimated β_{it}^Ts on the bank characteristics from the quarter preceding the four-year moving window.

[11] In Section 5 we verify the impact of excluding observations corresponding to zero β_{it}^T estimates.

[12] Instead of reporting the descriptive statistics of the dependent variables in the regression models, we report those of the original measures β_{it}^T, τ^{1/ζ_s} and $\frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_s(k/n)}$ as discussed in Subsection 2.2. The reason is that because these three measures have a direct economic interpretation. In the panel regressions, we use the log transformation to ensure the additive feature of the regression coefficients in Eqs. (2.7)–(2.9).

a financial index. Again, differences in this component demonstrate the role of individual risk in the variation β_{it}^{T}.

The second to fourth row in Table 1 shows the descriptive statistics on the characteristics of bank business models we use in our panel regressions. To eliminate the potential impact of outliers, all variables are constructed after winsorizing at 1% and 99% quantiles of the whole sample. All variables except the total asset are in ratios. For the total asset, we take the logarithm transformation of its level in thousands of USD. To report the relation with bank size after controlling for endogeneity due to its relation with other firm characteristics, we first regress the logarithm of total assets on the other regressors, and then use the residual as as our right hand side variable for bank size.

4 Empirical results

In the baseline specification we estimate the relations in Eqs. (2.7)–(2.9) for the CAMEL ratios, bank size, asset growth, the non-interest income share, loans to assets and deposits to assets. Table 2 provides these baseline results. Tables 3–5 contain the estimates for models with respectively further decompositions into different income sources, different loan types and different types of deposits.

4.1 Size

The relation between size and systemic risk has been an important issue in the literature. Empirical studies generally report a positive relation between bank size and measures on systemic risk. López-Espinosa et al. (2012) and Girardi and Ergün (2013) find a weak positive relation between CoVaR and bank size. Brunnermeier et al. (2012) find that this positive relation is robust if CoVaR is replaced by MES. Vallascas and Keasey (2012) report that larger banks tend to have a stronger relation between shocks to their distance-to-default and that of the entire financial system. Stiroh (2006b) reports that banks with larger size tend to have higher sensitivity to market risk. Several other studies report nonlinear positive relations between size and measures; see e.g. Huang et al. (2012) and

Moore and Zhou (2012).

In line with the findings of these studies, we find that larger banks tend to exhibit significant higher sensitivities to severe shocks in the financial system. The findings in Table 2, Model (1) support an increase in this sensitivity of about 8% for banks with twice as much total assets. In line with the findings of Stiroh (2006b) and Pais and Stork (2011), we find that this increase is not due to a positive association between size and the riskiness of individual banks. We observe a small but significant negative association between size and the riskiness on individual banks. Banks with twice as much assets tend to have a level of tail risk that is on average approximately 4% lower; see Table 2, Model (3). Our finding is also consistent with the results of Tabak et al. (2013), who find no support for the hypothesis that large banks behave imprudently in a sample of Latin American banking systems. Instead, it is the stronger dependence among the large banks and the financial system in case of tail events that induces a positive association between size and the sensitivity to severe shocks in the financial system, a relation which was previously documented by De Jonghe (2010) and Pais and Stork (2011). The results in Table 2, Model (2) support a 12% higher level of tail dependence for banks with twice as much assets.

4.2 Capital buffers

Most empirical studies establish a negative relation between systemic risk and bank's capital ratios (or a positive relation with its reciprocal, leverage). Vallascas and Keasey (2012) find a significant negative relation between systemic risk and bank capital. This negative relation is further supported by evidence of a positive relation between leverage and systemic risk in the study of Brunnermeier et al. (2012) and weak evidence in the studies of López-Espinosa et al. (2012) and Girardi and Ergün (2013). Stiroh (2006b) documents an insignificant relation between bank capital ratios and their market betas.

Our findings are consistent with the general pattern. We find that banks with higher capital ratios are associated with a significantly lower sensitivity to extreme shocks in the financial system. An increase of the capital tier 1 ratio with 1%-point is associated with

a significant decrease of the sensitivity to extreme shocks by about 1.5%. The driver of this decrease in sensitivity to extreme shocks is that banks with high capital ratios are associated with a weaker linkage to the system in case of tail events. This is consistent with the findings of Vallascas and Keasey (2012) on coexceedences and the findings of De Jonghe (2010) on tail dependence. Although Stiroh (2006a,b) reports a lower level of volatility for banks with higher capital ratios, we find that banks with higher capital ratios bear (slightly) more tail risks. Also Ellul and Yerramilli (2013) observe such a positive relation between bank capital and tail risk. Nevertheless, the positive relation with tail risk is strongly dominated in terms of magnitude by the negative relation between capital buffers and the dependence between a bank and the system in case of tail events.

From the results we also observe that banks that are able to generate more profits, and therefore have better ability to build up new capital buffers from retained earnings, are considered as bearing less tail risk by investors. An increase in return-on-equity by 1%-point generally tends to reduce the perceived individual risk and the bank's sensitivity to large shocks in the financial system by 1.5%. The negative relation between bank profitability and tail risk is further supported by the findings of Ellul and Yerramilli (2013). Moreover, the results are somewhat in line with the positive relation between competition (and hence, fewer profit opportunities) and both individual and systemic risk as documented by Anginer et al. (2014).[13] Both the actual capital buffers and the profitability are negatively related to systemic risk. However, the relations with the different dimensions of systemic risk differ. Apparently, banks with higher actual capital buffers are perceived as bearing more tail risk by investors, while banks with the ability to build new capital buffers are evaluated as being less risky to investors. Nevertheless, both are associated with a lower sensitivity of banks to large shocks in the financial system.

4.3 Non-interest income

We find a strong positive relation between reliance of banks on the non-interest income and their sensitivity to severe shocks in the financial system. An increase in the non-

[13] We refer to the study of Boyd and De Nicolo (2005) for a discussion of the literature on this topic.

interest income share by 1%-point corresponds to an increase in the sensitivity to severe shocks in the financial system by approximately 0.7%. This positive relation is in line with the findings of Brunnermeier et al. (2012) and Vallascas and Keasey (2012) on systemic risk. Also Stiroh (2006b) reports a positive relation between the reliance on non-interest income and the market betas of financial firms.

The observed positive relation between the non-interest income share and the sensitivity to severe financial shocks is mainly due to a stronger linkage in stress events. Previously, De Jonghe (2010) and Vallascas and Keasey (2012) have documented a similar positive relation between tail dependence and the reliance on non-interest income. We do not observe a significant positive relation between non-interest income share and the tail risk of individual institutions, although several studies report a positive relation between volatility and non-interest income; see e.g. Stiroh (2006a) and Lepetit et al. (2008). A difference is that our measure for individual risk focuses explicitly on adverse tail risk, which may be different from the global risk measures such as volatility.

4.4 Traditionality of balance sheets

In the traditional business model of bank, banks attract deposits and invest in loans. Following this traditional banking model, banks' balance sheets are thus usually characterized by relatively high loans-to-assets and high deposit-to-assets ratios.

From Table 2, Model (1) we observe in general a weak negative link between loans-to-assets ratios and the sensitivity of institutions to severe shocks in the financial system. However, the relation is not robustly significant across all specifications. The decomposition of systemic risk provides more insight on the relation with the loan-to-assets ratio. Banks that concentrate their business models towards lending are significantly associated with higher levels of tail risk, but with a lower level of dependence with the financial system in stress events. Banks with a 10%-point higher loans-to-assets ratio are associated with a 1.5% higher level of tail risk and with a 2.4% lower level of systemic linkage. The balance of the two relations explains why banks with high loans-to-assets ratios tend to be relatively insensitive to severe shocks in the financial system. The relation with tail

risk is further lifted out by the coefficient on the non-performing-loans ratio as a proxy of the riskiness of the loan portfolio. In line with the positive association between non-performing-loans ratios and the level of volatility documented by e.g. Stiroh (2006a), we find that higher non-performing-loans ratios are associated with higher levels of bank tail risk. Nevertheless, this proxy of risk is significantly negatively related to the measure on systemic linkage.

Similar results on the relation with systemic linkage also hold true for banks with high deposits-to-assets ratios. Banks with a 10%-point higher deposits-to-assets ratios are associated with a 2.5% lower level of tail dependence with the financial system. The deposits-to-assets ratio seems to be unrelated to the level of tail risk at individual institutions. In sum, banks with higher levels of deposits-to-assets ratios exhibit a lower level of sensitivity to severe shocks in the financial system. This result is also consistent with the study of López-Espinosa et al. (2012) who document that short-term wholesale funding increases systemic risk as measured by ΔCoVaR. Hence, we conclude that institutions with more traditional balance sheets (higher loans-to-assets and deposits-to-assets ratios) in general tend to be less sensitive to severe shocks in the financial system.

Tables 4 and 5 show estimated models with further decompositions of the loan portfolio and the deposit base, respectively. The coefficients for loan types in Table 4 report the effect relative to the impact of loans secured real estate, which account on average for 65% of the loan portfolios. The regression results show that agricultural loans are the safest loan type. Banks with relatively large investments in agricultural loans as a substitute for real estate loans tend to have lower tail risk and tend to be relatively independent of shocks in the banking system. Investment in commercial and industrial loans tends to be associated with the largest increase in the sensitivity to severe shocks in the financial system. The coefficients for different types of deposits in Table 5 report the effect relative to the impact of interest bearing deposits, which account on average for 67% of the deposits. The results for Model (1) show that banks with more non-interest bearing deposits tend to be more sensitive to large shocks in the financial system, while the share of large deposits does not seem to play a role. The latter is a result of the

relation with the two dimensions of systemic risk. Banks with a smaller share of large deposits tend to exhibit less tail risk, while their relation with the financial system in case of tail events tends to be less intense.

To assess the impact of the speed of bank balance sheet expansion, we include asset growth in the model. The evidence in the literature gives a somewhat mixed view of the impact of expansionary strategies by banks on their risk. For example, Foos et al. (2010) document a positive relation between loan growth and subsequent loan loss provisions, while López-Espinosa et al. (2013) do not find a significant relation between loan growth and CDS spreads. Vallascas and Keasey (2012) and López-Espinosa et al. (2013) report a positive association between loan growth and systemic risk. Our results provide some additional evidence: A 1%-point increase in the growth rate of assets is associated with an increase to the sensitivity to large shocks in the financial system of approximately 1.0%. This increase is mainly due to the relation with bank tail risk: A 1%-point higher growth rate of assets is associated with an approximately 1.4% higher level of bank tail risk.

5 Robustness

In this section we discuss several alterations in our baseline methodology. The results from the robustness checks are provided in Table 6. We show alternative results for the model specification in Table 2, Model (1).

In Table 6, Model (1) we provide the estimation results after replacing the bank characteristics averaged over the four-year estimation horizon of the systemic risk measure by the bank characteristics in the quarter preceding the estimation horizon. The appeal of this specification is that it shows how current bank characteristics relate to future systemic risk in our dataset. The most notable changes following this alternative specification are the smaller positive coefficient of past profitability and smaller negative impact of past asset growth on systemic risk relative to there concurrent counterparts.

We further assess the impact of excluding observations corresponding to zero β_{it}^{T}

estimates in Table 6, Models (2) and (3). Given that empirical estimates on the level of bank's tail risk are always nonzero, having a zero $\hat{\beta}_{it}^{T}$ is equivalent to having a zero estimate for the systemic linkage measure, SL. Such estimates occur in practice for approximately 1.3% of the observations. Taking natural logarithms of the regressors leads to the exclusion of those observations. Truncation of the dependent variable theoretically may bias the estimated coefficients towards zero. To verify the significance of this bias for our results, we repeat the estimation of the model for $\hat{\beta}_{it}^{T}$ without taking logs. In Models (2) and (3) we provide results when respectively excluding and including zero estimates for β_{it}^{T}. Except for the coefficient for liquid assets, which turns insignificant, the estimated coefficients remain practically unchanged when zero estimates are included.

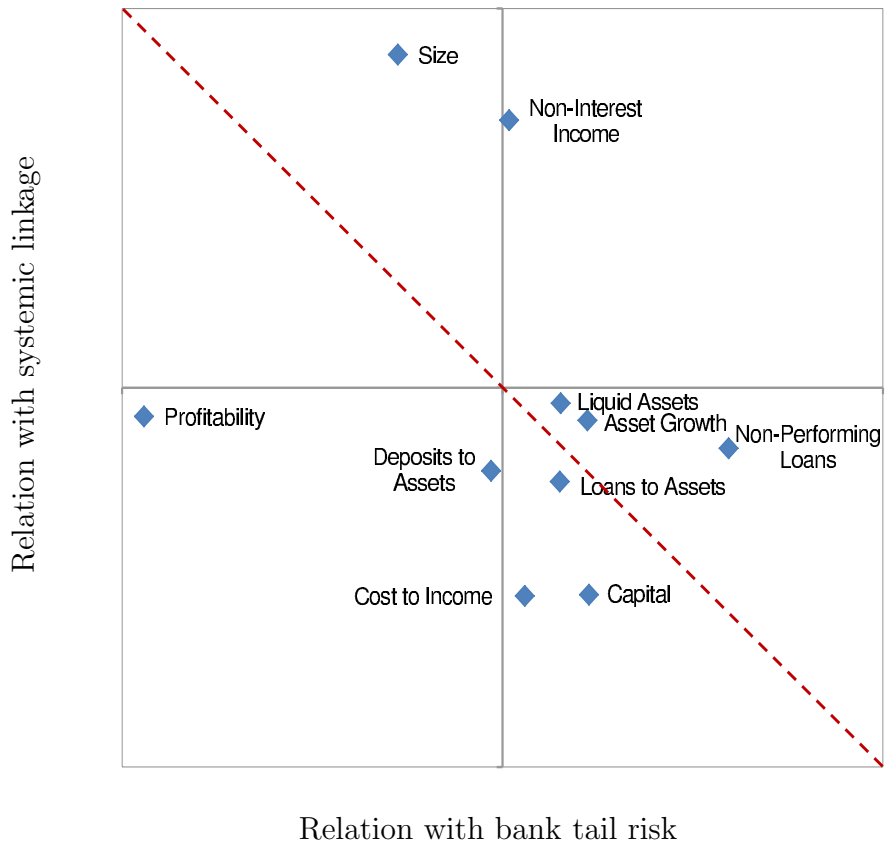
6 Concluding remarks

In this paper, we analyze how bank characteristics are related to systemic risk through two distinguished dimensions: systemic linkage and tail risk. By employing a novel systemic risk measure, the coefficient β_{i}^{T}, we decompose systemic risk into two subcomponents reflecting these two dimensions. By running panel regressions on the measures of systemic risk and its two subcomponents, we identify several characteristics of bank business models that are related to systemic risk and assess how this relation is established via the two dimensions.

Figure 2 illustrates both, the benefits of decomposing systemic risk into the two dimensions, and some of our main empirical findings. The figure shows a scatter based on the estimated coefficients in Table 2, models (2) and (3). Each dot represents a single bank characteristic. The horizontal location of a bank characteristic depends on the standardized coefficient in the model for bank tail risk, its vertical location depends on the standardized coefficient in the model for the linkage between severe shocks in the financial system and bank's tail risk.[14] Hence, a characteristic with a dot far away from (close to) the vertical axis indicates that the underlying bank characteristic is strongly related (un-

[14] Due to the standardization, a larger distance with respect to one of the axis means a larger expected change in the corresponding dependent variable with respect to a one standard deviation shock in the underlying bank characteristic.

Figure 2: Bank characteristics and systemic risk



The figure shows the relation between different bank characteristics and systemic risk. Dots further to the right (left) of the vertical axis imply a stronger positive (negative) relation between that particular characteristic and individual bank tail risk. Dots further above the dashed diagonal signify a positive (negative) relation between that particular characteristic and systemic risk. A larger distance from the diagonal signifies a stronger relation.
The figure is based on a scatter of the estimated coefficients in Table 2, models (2) and (3). On the vertical and horizontal axes are the coefficients for SL in Model (2) and the coefficient for IR in Model (3), respectively. The magnitude of the coefficients is normalized by the standard deviation of the relevant variable.

related) to bank tail risk. Similarly, dots that are far away (close to) from the horizontal axis correspond to characteristics that are strongly related (unrelated) to the systemic linkage. In addition, we draw the diagonal $x + y = 0$ (dashed line), which refers to the positions in the diagram in which the two relations precisely counterbalance each other in determining the level of systemic risk. Dots far away from the diagonal correspond to characteristics that have a relatively strong relation with systemic risk: A position in the northeastern (southwestern) half of the plane indicates a positive (negative) relation.

The scatter plot in Figure 2 helps to select relevant bank characteristic as indicators

for bank's tail risk and bank's systemic risk. From a purely microprudential point of view, the effective indicators are far away from the vertical axis. Those indicators have the strongest relation with the tail risk of a bank taken in isolation. Hence, a high non-performing loan ratio and a structural low profitability are effective indicators of a high level of tail risk. Further, from a purely microprudential point of view, bank characteristics close to the vertical axis are somewhat irrelevant for regulation. However, from a macroprudential point of view it is also important whether indicators are far away from the diagonal. For example, non-interest income is very close to the vertical axis and would not be considered as an effective indicator for differentiating banks' tail risks. Moreover, large banks are generally associated with less tail risk. However, in Figure 2, both indicators are far above the diagonal. Consequently, non-interest income and bank size have a relatively strong positive relation with banks' systemic risk.

To summarize, if it is the purpose of regulation to safeguard both, the stability of banks taken in isolation, and the stability of the financial system as a whole, then the focus should not be on bank characteristics related to bank's individual tail risk only, but also on characteristics related to bank's systemic linkage. Whether bank characteristics are relevant to bank's systemic risk depends on how their relation with bank's tail risk and their relation with systemic linkage precisely balance. This paper provides a framework to assess this issue. Moreover, we illustrate the methodology with an analysis of the relation between systemic risk and some main bank characteristics. The summary of our analysis in Figure 2 shows that some characteristics have a similar relation with both, tail risk and systemic risk. For those characteristics, micro- and macroprudential objectives have similar implications. However, the analysis also reveals that differences in policy implications and difference in the scope of regulation may arise due to the two regulatory objectives. In these cases it will be necessary for the regulator to choose the right balance between the micro- and macroprudential objective of regulation.

Appendix: Data definitions

See Table 7.

References

V. Acharya, L. Pedersen, T. Philippon, and M. Richardson. Regulating systemic risk. In *Restoring financial stability: How to repair a failed system*, pages 283–304. Wiley, 2009.

V. Acharya, R. Engle, and M. Richardson. Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review: Papers & Proceedings*, 102 (3):59–64, 2012.

V.V. Acharya. A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255, 2009.

V.V. Acharya and T. Yorulmazer. Too many to fail–an analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation*, 16(1):1–31, 2007.

T. Adrian and M.K. Brunnermeier. Covar. Technical report, National Bureau of Economic Research, 2011.

D. Anginer, A. Demirgüç-Kunt, and M. Zhu. How does competition affect bank systemic risk? *Journal of Financial Intermediation*, 23(1):1–26, 2014.

M. Billio, M. Getmansky, A.W. Lo, and L. Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 2012.

D. Bisias, M. Flood, A.W. Lo, and S. Valavanis. A survey of systemic risk analytics. *Annual Review of Financial Economics*, 4:255–296, 2012.

J.H. Boyd and G. De Nicolo. The theory of bank risk taking and competition revisited. *Journal of Finance*, 60(3):1329–1343, 2005.

M.K. Brunnermeier, G. Dong, and D. Palia. Banks non-interest income and systemic risk. *Working Paper*, 2012.

J.A. Chan-Lau. Regulatory capital charges for too-connected-to-fail institutions: A practical proposal. *Financial Markets, Institutions & Instruments*, 19(5):355–379, 2010.

O. De Jonghe. Back to the basics in banking? a micro-analysis of banking system stability. *Journal of Financial Intermediation*, 19(3):387–417, 2010.

M. Drehmann and N. Tarashev. Measuring the systemic importance of interconnected banks. *Journal of Financial Intermediation*, 22(4):586 – 607, 2013.

A. Ellul and V. Yerramilli. Stronger risk controls, lower risk: Evidence from us bank holding companies. *Journal of Finance*, 68(5):1757–1803, 2013.

P. Embrechts, L. de Haan, and X. Huang. Modelling multivariate extremes. In *Extremes and integrated risk management*, pages 59–67. Risk Waters Group, 2000.

D. Foos, L. Norden, and M. Weber. Loan growth and riskiness of banks. *Journal of Banking & Finance*, 34(12):2929–2940, 2010.

FSB. Policy measures to address systemically important financial institutions. *Financial Stability Board*, 2011.

G. Girardi and A.T. Ergün. Systemic risk measurement: Multivariate garch estimation of covar. *Journal of Banking & Finance*, forthcoming, 2013.

B.M. Hill. A simple general approach to inference about the tail of a distribution. *Annals of Statistics*, 3(5):1163–1174, 1975.

X. Huang, H. Zhou, and H. Zhu. Systemic risk contributions. *Journal of Financial Services Research*, 42:55–83, 2012.

Xin Huang, Hao Zhou, and Haibin Zhu. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11):2036–2049, 2009.

M. Knaup and W. Wagner. Forward-looking tail risk exposures at us bank holding companies. *Journal of Financial Services Research*, 42(1-2):35–54, 2012.

A. Lehar. Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, 29(10):2577–2603, 2005.

L. Lepetit, E. Nys, Ph. Rous, and A. Tarazi. Bank income structure and risk: An empirical analysis of european banks. *Journal of Banking & Finance*, 32(8):1452–1467, 2008.

G. López-Espinosa, A. Moreno, A. Rubia, and L. Valderrama. Short-term wholesale funding and systemic risk: A global covar approach. *Journal of Banking & Finance*, 36:3150–3162, 2012.

G. López-Espinosa, A. Rubia, L. Valderrama, and M. Antón. Good for one, bad for all: Determinants of individual versus systemic risk. *Journal of Financial Stability*, 13(3): 287–299, 2013.

K. Moore and C. Zhou. Identifying systemically important financial institutions: Size and other determinants. *DNB Working Paper*, (347), 2012.

R. Nijskens and W. Wagner. Credit risk transfer activities and systemic risk: How banks became less risky individually but posed greater risks to the financial system at the same time. *Journal of Banking & Finance*, 35(6):1391–1398, 2011.

A. Pais and P.A. Stork. Bank size and systemic risk. *European Financial Management*, forthcoming, 2011.

K.J. Stiroh. New evidence on the determinants of bank risk. *Journal of Financial Services Research*, 30(3):237–263, 2006a.

K.J. Stiroh. A portfolio view of banking with interest and noninterest activities. *Journal of Money, Credit and Banking*, 38(5):1351–1361, 2006b.

B.M. Tabak, D.M. Fazio, and D.O. Cajueiro. Systemically important banks and financial stability: The case of latin america. *Journal of Banking & Finance*, 37(10):3855–3866, 2013.

F. Vallascas and K. Keasey. Bank resilience to systemic shocks and the stability of banking systems: Small is beautiful. *Journal of International Money and Finance*, 31: 1745–1776, 2012.

M.R.C. Van Oordt and C. Zhou. Systematic risk under extremely adverse market conditions. *DNB Working Paper*, 281, 2011.

M.R.C. Van Oordt and C. Zhou. Systematic tail risk. *Journal of Financial and Quantitative Analysis*, (forthcoming), 2013.

W. Wagner. Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation*, 19(3):373–386, 2010.

Tables

Table 1: Descriptive statistics

Variable	Mean	Sd	Min	p10	p90	Max
PANEL A						
Systemic risk						
Systemic Risk: $\hat{\beta}^T$	0.916	0.312	0.127	0.549	1.317	3.711
Systemic Linkage: $\exp(SL)$	0.620	0.143	0.179	0.423	0.804	0.923
Bank Tail Risk: $\exp(IR)$	1.510	0.534	0.469	1.001	2.155	8.696
PANEL B						
Bank strategy variables						
ln(Total Assets)	15.439	1.540	13.147	13.783	17.723	20.399
Tier 1 Risk-Based Capital Ratio (%)	11.696	2.686	6.014	8.800	15.002	24.614
Non-Performing Loans Ratio	0.014	0.013	0.000	0.004	0.029	0.121
Cost to Income	0.642	0.104	0.369	0.523	0.769	1.314
Return on Equity	0.110	0.081	-0.482	0.024	0.181	0.278
Liquid Assets	0.027	0.077	-0.184	-0.056	0.114	0.347
Growth in Total Assets	0.026	0.019	-0.059	0.004	0.050	0.332
PANEL C						
Revenue streams						
Non-Interest Income Share	0.274	0.133	0.013	0.142	0.430	0.790
Srvc Charges on Deposit Accounts Shr	0.078	0.037	0.000	0.032	0.124	0.194
Fiduciary Activities Income Share	0.041	0.068	0.000	0.000	0.086	0.471
Trading Revenue Share	0.007	0.019	-0.011	0.000	0.017	0.132
Other Non-Interest Income Share	0.146	0.106	-0.047	0.058	0.258	0.712
PANEL D						
Asset mix						
Loans to Total Assets	0.648	0.125	0.142	0.495	0.780	0.884
Real Estate Loan Share	0.647	0.185	0.041	0.405	0.862	0.979
Commercial and Industrial Loan Shr	0.184	0.113	0.005	0.070	0.327	0.631
Consumer Loan Share	0.111	0.098	0.001	0.012	0.243	0.495
Agricultural Loan Share	0.009	0.017	0.000	0.000	0.026	0.108
Other Loan Share	0.044	0.063	0.000	0.002	0.102	0.479
PANEL E						
Funding structure						
Deposits to Total Assets	0.738	0.108	0.243	0.615	0.851	0.910
Interest-Bearing Core Deposits Share	0.670	0.104	0.275	0.536	0.788	0.881
Large Time Deposits Share	0.211	0.100	0.034	0.103	0.334	0.657
Non-Interest-Bearing Deposits Share	0.118	0.062	0.011	0.044	0.189	0.351

Table 2: Baseline results on systemic risk

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	SL_{it}	IR_{it}
Bank Size (reslnTA)	0.079***	0.115***	-0.036***
	(0.009)	(0.004)	(0.007)
Tier 1 Risk-Based Cap. Ratio	-0.014***	-0.024***	0.010***
	(0.002)	(0.002)	(0.002)
Non-Performing Loans Ratio	3.942***	-1.449***	5.392***
	(0.405)	(0.233)	(0.377)
Cost to Income Ratio	-0.567***	-0.635***	0.068
	(0.072)	(0.045)	(0.047)
Return on Equity	-1.521***	-0.113*	-1.408***
	(0.088)	(0.059)	(0.063)
Liquid Assets	0.174**	-0.063	0.236***
	(0.076)	(0.044)	(0.049)
Loans to Total Assets	-0.093*	-0.238***	0.145***
	(0.052)	(0.032)	(0.035)
Deposits to Total Assets	-0.277***	-0.244***	-0.033
	(0.054)	(0.034)	(0.058)
Non-Interest Income Share	0.655***	0.640***	0.016
	(0.043)	(0.030)	(0.041)
Growth in Total Assets	0.849***	-0.531***	1.380***
	(0.209)	(0.131)	(0.193)
Constant	0.657***	0.296***	0.361***
	(0.079)	(0.048)	(0.071)
Observations	12,620	12,620	12,620
Number of banks	480	480	480
R-squared	0.436	0.549	0.560
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	No	No	No
Clustering at bank level	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes

The definitions of the dependent variables are provided in Eqs. (2.5) and (2.6). The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The independent variables are averages over quarterly observations from the same time window. The independent variables are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 3: Systemic risk and sources of non-interest income

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	SL_{it}	IR_{it}
Bank Size (reslnTA)	0.077***	0.115***	-0.038***
	(0.009)	(0.004)	(0.007)
Tier 1 Risk-Based Cap. Ratio	-0.015***	-0.022***	0.007***
	(0.002)	(0.002)	(0.002)
Non-Performing Loans Ratio	3.813***	-1.196***	5.009***
	(0.390)	(0.229)	(0.341)
Cost to Income Ratio	-0.566***	-0.596***	0.030
	(0.075)	(0.045)	(0.047)
Return on Equity	-1.513***	-0.047	-1.466***
	(0.089)	(0.060)	(0.064)
Liquid Assets	0.175**	-0.009	0.183***
	(0.071)	(0.047)	(0.046)
Loans to Total Assets	-0.127**	-0.168***	0.041
	(0.053)	(0.037)	(0.035)
Deposits to Total Assets	-0.258***	-0.392***	0.134**
	(0.064)	(0.043)	(0.055)
Growth in Total Assets	0.802***	-0.246*	1.049***
	(0.205)	(0.131)	(0.195)
Fiduciary Activities Income Share	0.599***	0.714***	-0.115*
	(0.084)	(0.053)	(0.064)
Srvc Charges on Dep. Accnts Shr	0.506***	1.309***	-0.802***
	(0.137)	(0.111)	(0.102)
Trading Revenue Share	0.703**	1.235***	-0.531**
	(0.322)	(0.198)	(0.269)
Other Non-Interest Income Share	0.686***	0.499***	0.187***
	(0.047)	(0.027)	(0.038)
Constant	0.682***	0.251***	0.430***
	(0.077)	(0.051)	(0.066)
Observations	12,620	12,620	12,620
Number of banks	480	480	480
R-squared	0.434	0.557	0.572
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	No	No	No
Clustering at bank level	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes

The definitions of the dependent variables are provided in Eqs. (2.5) and (2.6). The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The independent variables are averages over quarterly observations from the same time window. The independent variables are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors in the baseline specification in Table 2. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 4: Systemic risk and different loan types

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	SL_{it}	IR_{it}
Bank Size (reslnTA)	0.081***	0.119***	-0.038***
	(0.009)	(0.004)	(0.007)
Tier 1 Risk-Based Cap. Ratio	-0.013***	-0.020***	0.007***
	(0.003)	(0.002)	(0.002)
Non-Performing Loans Ratio	4.144***	-1.111***	5.255***
	(0.392)	(0.222)	(0.365)
Cost to Income Ratio	-0.484***	-0.494***	0.010
	(0.073)	(0.047)	(0.049)
Return on Equity	-1.433***	0.003	-1.436***
	(0.093)	(0.068)	(0.069)
Liquid Assets	0.147*	-0.130***	0.277***
	(0.075)	(0.039)	(0.060)
Loans to Total Assets	-0.082	-0.159***	0.076**
	(0.052)	(0.028)	(0.038)
Deposits to Total Assets	-0.250***	-0.236***	-0.014
	(0.057)	(0.032)	(0.056)
Non-Interest Income Share	0.611***	0.517***	0.093**
	(0.041)	(0.028)	(0.041)
Growth in Total Assets	0.951***	-0.232*	1.183***
	(0.211)	(0.120)	(0.179)
Agricultural Loan Share	-1.470***	-0.821***	-0.649***
	(0.289)	(0.151)	(0.186)
Commercial and Industrial Loan Shr	0.194***	0.352***	-0.158***
	(0.051)	(0.027)	(0.041)
Consumer Loan Share	0.105*	0.240***	-0.135**
	(0.054)	(0.016)	(0.056)
Other Loan Share	-0.018	0.190***	-0.208
	(0.147)	(0.044)	(0.132)
Constant	0.500***	-0.023	0.524***
	(0.090)	(0.047)	(0.076)
Observations	12,620	12,620	12,620
Number of banks	480	480	480
R-squared	0.444	0.575	0.566
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	No	No	No
Clustering at bank level	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes

The definitions of the dependent variables are provided in Eqs. (2.5) and (2.6). The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The independent variables are averages over quarterly observations from the same time window. The independent variables are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors in the baseline specification in Table 2. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 5: Systemic risk and types of depositors

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	SL_{it}	IR_{it}
Bank Size (reslnTA)	0.079***	0.115***	-0.035***
	(0.009)	(0.004)	(0.007)
Tier 1 Risk-Based Cap. Ratio	-0.014***	-0.024***	0.010***
	(0.002)	(0.002)	(0.002)
Non-Performing Loans Ratio	3.887***	-1.340***	5.226***
	(0.416)	(0.213)	(0.380)
Cost to Income Ratio	-0.582***	-0.681***	0.099**
	(0.069)	(0.045)	(0.046)
Return on Equity	-1.581***	-0.238***	-1.344***
	(0.085)	(0.058)	(0.064)
Liquid Assets	0.120	-0.201***	0.322***
	(0.080)	(0.046)	(0.053)
Loans to Total Assets	-0.102*	-0.267***	0.165***
	(0.053)	(0.031)	(0.035)
Deposits to Total Assets	-0.292***	-0.301***	0.009
	(0.053)	(0.037)	(0.055)
Non-Interest Income Share	0.642***	0.626***	0.016
	(0.043)	(0.028)	(0.040)
Growth in Total Assets	0.937***	-0.264**	1.202***
	(0.200)	(0.126)	(0.187)
Non-Interest-Bearing Deposits Share	0.311***	0.507***	-0.196***
	(0.043)	(0.065)	(0.072)
Large Time Deposits Share	-0.004	-0.138***	0.134***
	(0.056)	(0.028)	(0.048)
Constant	0.646***	0.344***	0.301***
	(0.083)	(0.053)	(0.069)
Observations	12,620	12,620	12,620
Number of banks	480	480	480
R-squared	0.438	0.562	0.563
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	No	No	No
Clustering at bank level	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes

The definitions of the dependent variables are provided in Eqs. (2.5) and (2.6). The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The independent variables are averages over quarterly observations from the same time window. The independent variables are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors in the baseline specification in Table 2. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 6: Robustness checks

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\log \hat{\beta}_{it}^T$	$\hat{\beta}_{it}^T$	$\hat{\beta}_{it}^T$	$\log \hat{\beta}_{it}^T$	$\log \hat{\beta}_{it}^T$
Bank Size (reslnTA)	0.080***	0.057***	0.059***	0.044**	
	(0.010)	(0.007)	(0.007)	(0.020)	
log(Total Assets)					0.074***
					(0.008)
Tier 1 Risk-Based Cap. Ratio	-0.018***	-0.011***	-0.014***	-0.013**	0.001
	(0.002)	(0.002)	(0.002)	(0.006)	(0.003)
Non-Performing Loans Ratio	2.869***	4.308***	4.061***	3.621***	4.044***
	(0.329)	(0.623)	(0.625)	(0.638)	(0.429)
Cost to Income Ratio	-0.358***	-0.375***	-0.342***	-0.145	-0.339***
	(0.055)	(0.060)	(0.067)	(0.142)	(0.068)
Return on Equity	-0.382***	-1.161***	-1.105***	-0.953***	-1.421***
	(0.071)	(0.075)	(0.087)	(0.129)	(0.089)
Liquid Assets	0.165***	0.195**	0.099	0.487***	0.106
	(0.056)	(0.081)	(0.084)	(0.144)	(0.067)
Loans to Total Assets	-0.035	-0.081*	-0.081*	-0.114	0.059
	(0.053)	(0.047)	(0.047)	(0.130)	(0.058)
Deposits to Total Assets	-0.389***	-0.247***	-0.279***	-0.696***	0.020
	(0.052)	(0.057)	(0.052)	(0.136)	(0.047)
Non-Interest Income Share	0.446***	0.523***	0.556***	0.403***	0.349***
	(0.036)	(0.038)	(0.039)	(0.127)	(0.045)
Growth in Total Assets	0.186***	0.595***	0.653***	-0.579**	1.231***
	(0.053)	(0.213)	(0.233)	(0.258)	(0.213)
Constant	0.530***	1.486***	1.434***	0.422**	-1.106***
	(0.076)	(0.072)	(0.068)	(0.169)	(0.177)
Observations	11,597	12,620	12,791	12,620	12,620
Number of banks	461	480	482	480	480
R-squared	0.373	0.453	0.395	0.383	0.436
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	No	No	No	Yes	No
Clustering at bank level	Yes	Yes	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes	Yes	Yes

This table provides the estimation results for Model (1) in Table 2 after several alterations of our baseline methodology. In this table, Model (1) provides the estimation results if we replace the right hand side variables by the bank characteristics in the quarter preceding the estimation horizon of 16 quarters for the measure on systemic risk. Model (2) provides the estimation results if the left hand side variable $\log \hat{\beta}_{it}^T$ is replaced by $\hat{\beta}_{it}^T$, while using exactly the same sample as in the original specification. Model (3) includes observations with $\hat{\beta}_{it}^T = 0$ (in the baseline methodology these observations are removed due to the natural logarithm). Bank fixed effects are included in Model (4). In Model (5) we interact bank size by a dummy for which takes value 1 if the bank belongs to the 20% largest banks. we replace the original variable for bank size by 'log(Total Assets)'. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 7: Data definitions

VARIABLES	DEFINITION	
Total Assets	bhck2170, deflated to 2007:Q4 dollars (in thousands)	
	bhck2170	TOTAL ASSETS
Tier 1 Risk-Based Capital Ratio	100 * bhck8274 / bhcka223, (from 1996)	
	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 Ratio	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
Loans to Total Assets	bhck2122 / Total Assets	
	bhck2122	TOTAL LOANS AND LEASES, NET OF UNEARNED INCOME
Deposits to Total Assets	(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 Income Share	bhck4079 / (bhck4074 + bhck4079)	
	bhck4074	NET INTEREST INCOME
	bhck4079	TOTAL NONINTEREST INCOME
(...)		
Etc.	To be continued...	