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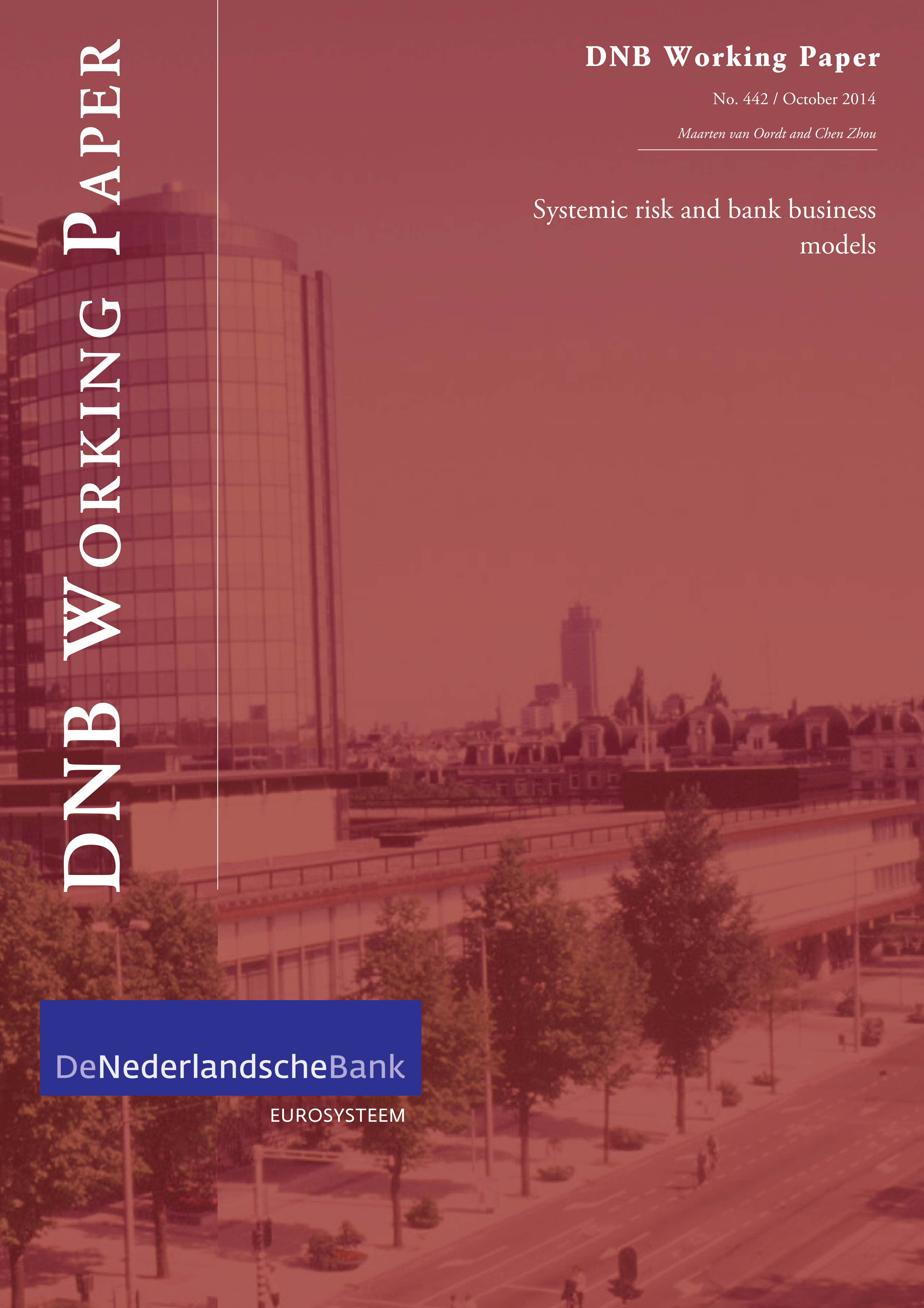

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Systemic risk and bank business models [*]

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Abstract

In this study we disentangle two dimensions of banks' systemic risk: the level of bank tail risk and the linkage between a bank's tail risk and severe shocks in the financial system. We employ a measure of 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 interrelationship 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 direction and scope of policy under the micro- and macro-prudential objectives of regulation.

Keywords: Financial institutions, financial stability, tail risk, macroprudential regulation, non-interest income.
JEL Classifications: G10, G21, G28

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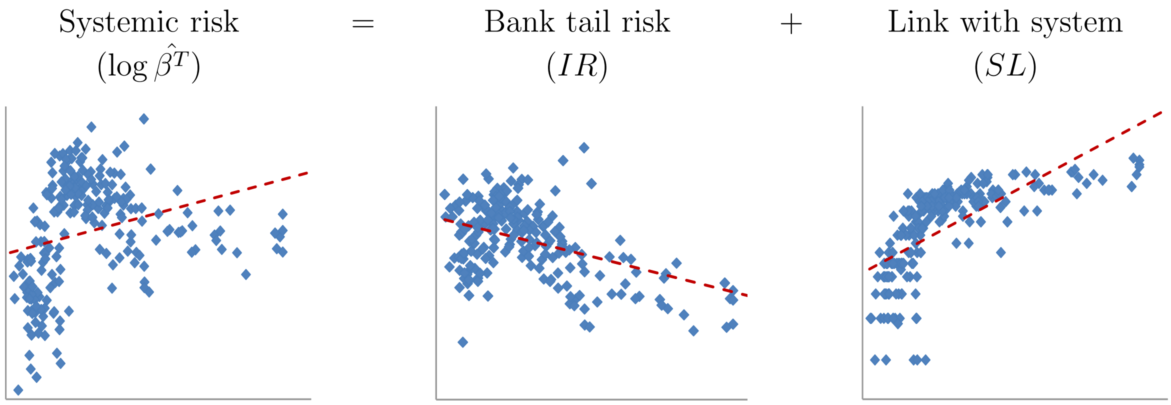
1 Introduction

Before the global financial crisis, prudential regulation focused predominantly on the soundness of financial institutions taken in isolation. 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 bank failures occur simultaneously. With the concern of system-wide distress in mind, the debate on banking regulation has been broadened towards a macroprudential approach: limiting banks' systemic risk. In this paper, we decompose banks' systemic risk on the cross-sectional level into two dimensions: the level of a bank's tail risk and the linkage between the bank's tail risk and severe shocks in the financial system.[1] This is important for understanding the interaction between micro- and macroprudential regulation: estimating banks' systemic risk and its subcomponents is a first step towards identifying how the characteristics of bank business models are related to systemic risk via these two dimensions. Empirically, some characteristics that are irrelevant to bank tail risk turn out to be important for banks' 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. Banks' 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 to be 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 con-

[1] Throughout the paper we focus on systemic risk in the cross-section. We refer to De Bandt et al. (2010) for a general survey on systemic risk. For an overview of the rich literature on systemic risk in the time dimension; see Gabriele and Moessner (2013, Section 3.1).

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. Bank size is measured by log(Total Assets). The dashed lines show fitted linear trend lines.

sidered to be more systemically risky. To conclude, from our discussion two dimensions of banks' systemic risk arise: the level of a bank's tail risk and the bank's systemic linkage.

The decomposition of systemic risk reveals a connection between microprudential and macroprudential regulation. While microprudential regulation considers only the banks' tail risk, macroprudential regulation has to take both banks' tail risk and banks' systemic linkage into consideration. In other words, "correlations and common exposures" across institutions, which are irrelevant to microprudential regulation, are important for macroprudential regulation; see Borio (2003, Table 1). Macroprudential regulators have to pay attention to both dimensions and balance banks' tail risk and banks' systemic linkage according to their importance.

Our conceptualizations of systemic risk and systemic linkage do not have a directional flavor: they simply measure the co-movement, regardless of 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 such banks are more likely to fail along with a large part of the financial system, 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 tail risk and systemic linkage. The systemic risk measure equals the sum of its two subcomponents. We observe downward and upward trends in the size-tail risk and size-systemic linkage interrelationship, respectively. Since the latter dominates the former, on the aggregate level, larger banks exhibit 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 a consequence of the relation to the systemic linkage dimension. On the tail risk dimension, large banks taken in isolation would appear to be less risky. This decomposition might partly explain why microprudential regulation was hardly 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 decompositions for other characteristics of bank business models, providing more insight as to how these characteristics are related to systemic risk.

Empirically, we measure the systemic risk of financial institutions by estimating the sensitivity of banks' 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 a 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 coefficient we estimate 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 of examining the interrelationship between bank characteristics and the two dimensions of systemic risk.

Since the coefficient describes the relation between the bank and system-wide shocks 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).[2] Van Oordt and Zhou (forthcoming) 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).[3] 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.

Second, we contribute to the literature on identifying which bank characteristics are related to systemic risk. For macroprudential policy purposes, it is useful to measure systemic risk and identify indicators of systemic risk at the bank level. Academic literature has provided several measures of 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

[2] Early applications of multivariate EVT on the financial system focus on estimating tail dependence; see e.g. Hartmann et al. (2007), De Jonghe (2010) and Zhou (2010).

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

gain a better understanding of the connection between microprudential and macroprudential regulation. It also helps to identify areas in which micro- and macroprudential objectives may potentially lead to differences in the direction and scope 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. Section 5 provides some concluding remarks.

2 Methodology

In this section we discuss our framework on how to decompose banks' systemic risk into banks' tail risk and the linkage between the banks' 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 their sensitivity to shocks in the financial system. A natural measure for this would be the coefficient from a linear relation between indicators of the status of one bank and the system; see e.g. Nijskens and Wagner (2011). However, the relation between financial institutions and the financial system may be quite different for small fluctuations and severe shocks; see e.g. Bartram et al. (2007) and Knaup and Wagner (2012). Usually, systemic risk in the banking literature refers to large, adverse shocks in the financial system, and not to the everyday occurrence of small fluctuations. Therefore, we consider a linear relation between the equity returns of a financial institution and the financial system conditional upon extremely adverse shocks in the financial system.

Let R_i and R_s denote the stock return of bank i and the return on an equity investment in the financial system. 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 about 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 larger capital losses in case of an extremely adverse shock in the financial system. Here we do not distinguish whether these shocks are from outside the system or endogenously developed within 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). With MES_i defined as the expected return of bank i conditional upon a severe shock to the financial system, it is straightforward to get from the assumed linear tail model in Eq. (2.1) that, for $p < \bar{p}$,

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

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_i 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_i, 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 $\bar{p}$, only a few observations correspond 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 using conventional methods such as 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.

We assume the heavy-tailedness of financial returns as documented in the literature; see e.g. Jansen and De Vries (1991) and Embrechts et al. (1997). Assume R_i and R_s follow heavy-tailed distributions with tail indices ζ_i and ζ_s, respectively.[4] 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

[4] A distribution is called heavy-tailed if it decays at 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 $t > 1$.

worst observations.[5] 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 represent measures of systemic linkage and individual risk, respectively. From Eq. (2.3), we observe that the sensitivity to extreme shocks is determined by two components, $\frac{VaR_i(p)}{VaR_s(p)}$ and $\tau_i(p)^{1/\zeta_s}$.

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. This component measures the level of bank tail risk without carrying information on whether the tail risk of a particular bank is related to severe shocks in the financial system. In our sample, this component bears the value 1.51 on average. This means that an equity investment in an average institution bears 51% more tail risk than the same investment in the financial index. Since the denominator $VaR_s(p)$ is homogeneous across all financial institutions, the cross-sectional variation in this 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 tail risk of an individual bank and severe shocks in the financial system. Cross-sectional differences

[5] 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 use an estimation window of four years of daily returns and fix $k = 40$. This corresponds to $k/n \approx 4\%$.

in this component are solely due to the variation across different banks in the measure of tail dependence, the $\tau_i(p)$s. Similar to the correlation coefficient, the level of $\tau_i(p)$ is independent of the distribution of the bank's tail risk, i.e., the distribution of R_i.[6] Therefore, it contains information only on the dependence between extreme shocks in the financial system and severe losses suffered by a particular bank, without being affected by the level of individual risk of that bank. Hence, it bears 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.[7]

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

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

From the discussion above, the subcomponent SL_i measures the systemic linkage of bank i to the system while the 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 the sum of the systemic linkage measure and the bank's tail risk measure.

2.4 Regression models

To explore the empirical relation between systemic risk and bank characteristics, we estimate three regression models using the measures of systemic risk, systemic linkage and bank tail risk as dependent variables. Formally, with the bank characteristics of bank

[6] It is easily verified that the level of $\tau_i(p)$ in Eq. (2.4) is unaffected by any monotonic transformation (with a strictly increasing function) of the marginal distribution of the bank returns, the R_is.

[7] 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 "quantity of banks' 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 banks' tail risk $\widehat{VaR_i}(k/n)$ can be interpreted as the "quantity of banks' tail risk that is associated with severe shocks in the financial system".

i preceding period t denoted as X_{it-1}, we estimate the coefficients in the following models from panel data on bank holding companies

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

$$SL_{it} = \alpha_{2t} + X_{it-1}\delta + \xi_{it}, \quad (2.8)$$

$$IR_{it} = \alpha_{3t} + X_{it-1}\gamma + \nu_{it}, \quad (2.9)$$

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.[8] 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 (2.7) is the sum of those in (2.8) and (2.9). Hence, theoretically it holds that the coefficients for the relation between a certain bank's characteristics and the log of β_{it}^{T}, the θ, equals the sum of the coefficients for the relation between bank characteristics and the bank's tail risk, the γ, and the coefficients for the relation to systemic linkage, the δ.[9] With the estimated coefficients $\hat{\gamma}$ and $\hat{\delta}$ it is possible to assess via which dimensions bank characteristics are related to an individual institution's sensitivity to extreme shocks in the financial system. In addition, we can assess how these two interrelationships 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 the end of each quarter, we use four years of historical daily equity

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

[9] This relation also holds empirically, i.e., $\hat{\theta} = \hat{\gamma} + \hat{\delta}$, because we estimate the models in Eqs. (2.7)–(2.9) equation-by-equation using least squares (panel) regressions.

returns to estimate the three dependent variables, the $\hat{\beta}_{it}^T$ and its two subcomponents. To guarantee that selected banks are liquidly traded on the equity market, each selected bank must have at least 60% non-zero daily returns in all estimation windows. The financial index covers firms in banking, insurance, real estate and trading, and is collected from the website of Kenneth French.[10]

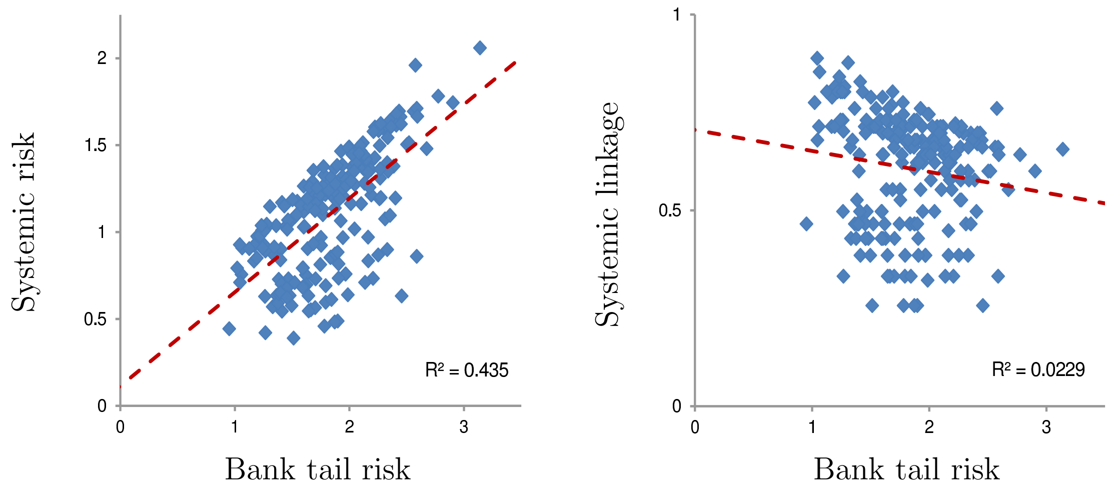
Panel (a) in Table 1 shows the descriptive statistics on β^T and its subcomponents.[11] We observe that across all banks in all periods, the average $\hat{\beta}^T$ is 0.91. In an extreme market downturn, the average loss in bank equity returns is thus comparable with the loss in the financial index. The coefficient $\hat{\beta}^T$ ranges from 0.13 to 3.71, demonstrating 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 this fraction at 63% on average, while ranging from 18% to 92%. This illustrates the role that systemic linkage plays in the variation of β_{it}^T. The other component, $\frac{VaR_i}{VaR_s}$, compares banks' individual risk to that of the system. More than 90% of the observations for this component is larger than 1. Hence, usually, an investment in the stock of a single bank has bears more tail risk than an investment in the financial index. Again, differences in this component demonstrate the role of individual risk in the variation of β_{it}^T.

Figure 2, panel (a) provides an illustration of the relation between bank tail risk and banks' systemic risk. Although the relation between bank tail risk and systemic risk is positive, a large fraction of the variation in systemic risk is not explained by the level of bank tail risk alone. This shows that the two provide different information on bank risk, which hints that sometimes different steps may be necessary to pursue the micro- and macroprudential objectives of regulation. The difference between bank tail risk and

[10] Available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`; "38 Industry Portfolios". The financial index provides daily value weighted returns and is based on firms with SIC-codes 6000–6999.

[11] 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. This is 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).

Figure 2: Bank tail risk and systemic risk



The figures show the relation between bank tail risk and respectively systemic risk (left panel) and systemic linkage (right panel) in 2007Q4. Bank tail risk is measured by $\frac{\widehat{VaR}_i(k/n)}{\widehat{VaR}_s(k/n)}$. Banks' systemic risk is measured by β_i^T. Banks' systemic linkage component is measured by τ^{1/ζ_s}.

systemic risk depends on the linkage between bank tail risk and severe shocks in the financial system. Figure 2, panel (b) shows that the relation between bank tail risk and systemic linkage is relatively weak. In other words, the two subcomponents provide almost orthogonal information regarding banks' systemic risk: it cannot be taken for granted that bank characteristics related to bank tail risk are related to systemic linkage in the same way.

The characteristics of bank business models are constructed from the publicly available FR Y-9C reports in line with the definitions of Baele et al. (2014).[12] More specifically, at the end of each quarter we calculate the following indicators 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.[13] (ii) Indicators of banks' 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 of banks' loan

[12] For a detailed description of the construction of the bank characteristics with references to the labels of each item in the FR Y-9C reports; see Baele et al. (2014, Appendix A).

[13] 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 total equity) and Liquidity (liquid assets ratio).

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 of banks' funding structure: deposits to total assets ratio, interest-bearing core deposits, large time deposits share and non-interest-bearing deposits 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.[14] We regress the systemic risk measure and its subcomponents on the characteristics of bank business models in the quarter preceding the four-year estimation window.[15] The estimation windows for the left hand side variables range from 1991Q3–1995Q2 to 2008Q1–2011Q4. In addition, we exclude all observations corresponding to a zero estimate of $\hat{\beta}_{it}^{T}$, because our regression models require taking logarithm of the estimated β_{it}^{T}.[16] We end up with 11,597 bank-quarter observations.

Table 1, panels (b) – (d) report the descriptive statistics on the characteristics of bank business models used in our panel regressions. In general, the descriptive statistics look similar to those of the sample used by Baele et al. (2014). 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 total assets are in ratios. For total assets, we take the logarithmic transformation of its level in thousands of USD. Following Baele et al. (2014, Appendix A), to estimate each model after controlling for the endogeneity of bank size due to its relation to other bank characteristics, we first regress the logarithm of total assets on the other regressors (except its own growth rate), and then use the residual as our right-hand side variable for bank size.

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

[15] In Subsection 4.5 we provide results when regressing the estimated β_{it}^{T}s on bank characteristics averaged over the 16 quarterly observations within the four-year estimation window.

[16] In Subsection 4.5 we verify the impact of excluding observations corresponding to zero β_{it}^{T} estimates.

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 further decompositions into different sources of non-interest income, different loan types and different types of deposits, respectively.

4.1 Size

The relation between size and systemic risk has been an important issue in the literature. Theoretically, the relation is ambiguous. Large banks may be associated with lower risk because of better diversification; see e.g. Demsetz and Strahan (1997). However, even if better diversified banks face lower risks individually, they may ultimately be associated with more systemic risk; see e.g. Wagner (2010). Further, investors in "too-big-to-fail" institutions may enjoy (implicit) guarantees, which may encourage large banks to take more risks. Such institutions may also weight their investment portfolios towards risks which are expensive to insure privately (systematic risks); see e.g. Penati and Protopapadakis (1988). However, these incentives may be absent for very large institutions, because bailing them out may not feasible, especially if public finances are weak; see e.g. Demirgüç-Kunt and Huizinga (2013) and Acharya et al. (forthcoming).

Empirical studies generally report a positive relation between bank size and measures of 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 larger-sized banks tend to have higher sensitivity to market risk. Several other studies report a nonlinear positive relation between size and systemic risk measures; see e.g. Huang et al. (2012) and Moore and Zhou (2012).

In line with these studies, we find that larger banks tend to exhibit significantly higher sensitivities to severe shocks in the financial system. The findings in Table 2, Model (1) support an increase in this sensitivity of about 6%($\approx 2^{0.080} - 1$) for banks with twice as many total assets. In line with the findings of Stiroh (2006b), Pais and Stork (2013) and Tabak et al. (2013), we find that this increase is not due to a positive association between size and bank tail risk. We observe a small but significant negative association between size and individual banks' riskiness. Banks with twice as many assets tend to have a level of tail risk that is, on average, approximately 2% lower; see Table 2, Model (3). Instead, it is the stronger dependence between 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 (2013). The results in Table 2, Model (2) support an 8% higher level of tail dependence for banks with twice as many assets.

4.2 Non-interest income

We find a strong positive relation between banks' reliance on non-interest income and their sensitivity to severe shocks in the financial system. An increase in the non-interest income share by 1%-point corresponds to an increase in the sensitivity to severe shocks in the financial system by approximately 0.4%. This positive relation is in line with the findings of Brunnermeier et al. (2012) and Vallascas and Keasey (2012) on systemic risk. Moreover, Stiroh (2006b) reports a positive relation between financial firms' reliance on non-interest income and their market betas ('systematic risk').

The observed positive relation between 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) documented a similar positive relation between tail dependence and the reliance on non-interest income.

We do not observe a positive relation between the non-interest income share and the level of bank tail risk, while several other studies report a positive relation between non-interest income and volatility; see e.g. Stiroh (2006a) and Lepetit et al. (2008).[17] In Table 3 we explore a decomposition of non-interest income. The results for Model (3) show that service charges to deposit accounts and income from fiduciary activities, such as wealth management, are responsible for the negative relation between the non-interest income share and bank tail risk. In contrast, we observe no significant relation between bank tail risk and trading revenue or bank tail risk and other non-interest income, which includes, for example, investment banking, venture capital revenues and net gains on loans sales. Nevertheless, the tail risks of banks with more trading revenue and other non-interest income are much stronger related to large shocks in the financial system. Therefore, these activities are strongly positively related to banks' systemic risk; see also Brunnermeier et al. (2012). Hence, whether banks involve into these activities is relevant from a macroprudential point of view, which is the basic principle for the introduction of the "Volcker Rule" to curb risks from proprietary trading or positions in hedge funds and private equity funds at US banks.

4.3 Traditionality of balance sheets

In the traditional business model, 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 deposits-to-assets ratios. If traditional activities are more isolated from the risk in the financial system, then the traditionality of bank balance sheets would be associated with a lower systemic linkage, and potentially, with lower systemic risk.

From Table 2, Model (1) we observe in general a weak negative link between institutions' loans-to-assets ratios and their sensitivity to severe shocks in the financial system. However, the relation is not significant. The decomposition of systemic risk provides more insight into the relation to the loans-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 on the financial system in stress events. Banks with

[17] A difference is that our individual risk measure focuses explicitly on downward tail risk, which may be different from risk measures based on the entire distribution, such as volatility.

a 10%-point higher loans-to-assets ratio are associated with a 2.5% higher level of tail risk and with a 2.7% 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 to tail risk is further emphasized by the coefficient of the non-performing-loans ratio as a proxy of the loan portfolio's riskiness. 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 of systemic linkage.

For the deposits-to-assets ratio we find similar result on the relation to systemic linkage. Banks with a 10%-point higher deposits-to-assets ratio are associated with a 2.5% lower level of tail dependence on the financial system and a 1.5% lower level of tail risk at individual institutions. In sum, banks with higher 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 with real estate, which account for 63% of the loan portfolios on average. The regression results show that agricultural loans can be considered to be having the most conservative risk profile. 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 for 67% of the deposits on average. The results for Model (1) show that banks with more non-interest bearing deposits and large time deposits tend to be more sensitive to large shocks in the financial system, although via different dimensions. Banks with a larger share of large deposits tend to exhibit more tail risk, while their interrelationship 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 banks' expansionary strategies 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 10%-point increase in the growth rate of assets is associated with an increase of the sensitivity to large shocks in the financial system by approximately 1.9%. This increase is due to the relation to bank tail risk: a 10%-point higher growth rate of assets is associated with an approximately 2.4% higher level of bank tail risk.

4.4 Capital buffers

Bank capital may act as a loss-absorbing buffer. Given the risk of the asset portfolio, higher capital ratios are thus likely to be associated with lower bank tail risk. Nevertheless, with capital regulations based on risk-weighted assets, Rochet (1992) shows that the interrelationship between bank capital and bank risks can be ambiguous if the risk weights on the assets are not proportional to their actual market risks. Further, higher capital may have an unintended effect of enabling banks to take more tail risk; see Perotti et al. (2011). Consequently, the interrelationship between bank capital and systemic risk may also be ambiguous.

Most empirical studies establish a negative relation between systemic risk and banks' capital ratios (or a positive relation to 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 banks' capital ratios and their market betas.

Our findings on systemic risk are consistent with the general pattern in the empirical literature. 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 by 1%-point is associated with a significant decrease of the sensitivity to extreme shocks by about 1.8%. 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 coexceedances 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 higher tail risks. Also Ellul and Yerramilli (2013) observe such a positive relation between bank capital and tail risk. Nevertheless, the positive relation to 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 by investors to be bearing less tail risk. 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 0.4%. 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).[18] Both the actual capital buffers and the profitability are negatively related to systemic risk. However, the interrelationhip with

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

the different dimensions of systemic risk differs. Apparently, investors perceive banks with higher actual capital buffers as bearing more tail risk and evaluate banks with the ability to build new capital buffers as being less risky. Nevertheless, both are associated with a lower sensitivity to large shocks in the financial system.

4.5 Robustness checks

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

In Model (1) we replace the bank characteristics in the quarter preceding the estimation horizon by bank characteristics averaged over the four-year estimation horizon of the systemic risk measure. The most notable change following this alternative specification is the larger impact of profitability and asset growth on systemic risk. A potential explanation is that contemporaneous profitability and asset growth are associated with systemic risk, but their past values are noisy proxies for their future values.

In the baseline analysis, we exclude observations corresponding to zero beta estimates because we take the natural logarithm of this variable. Such estimates occur in practice for approximately 1.2% of the observations. Truncation of the dependent variable theoretically may bias the estimated coefficients towards zero. As a robustness check we repeat the estimation of the model for $\hat{\beta}_{it}^{T}$ without taking logs while including the zero estimates in Model (2). Except for the coefficient for liquid assets, which turns out almost insignificant, the coefficients remain qualitatively unchanged when zero estimates are included.

In Model (3) we include bank fixed effects. The consequence is that the cross-sectional dispersion across the banks is captured by the fixed effects. This may be problematic for the estimation of the coefficients for the bank characteristics if the dependent variables have limited variation over time. Once fixed effects are included in the regression with $\hat{\beta}_{it}^{T}$ as dependent variable, the main difference is that the coefficient for total assets growth turns out insignificant. This suggests that caution is required when regarding asset growth as an indicator of systemic risk.

As a further robustness check, we directly include log(Assets) as an explanatory variable in Model (4). This changes the interpretation of the coefficients of the other variables relative to the baseline specification. In the baseline specification, the coefficients report the relation between bank characteristics and systemic risk if bank size is assumed to respond to changes in the other variables. The specification with log(Assets) shows the relation if bank size is assumed to be fixed. The results are qualitatively unchanged, although the magnitude of the coefficients change. Most notable are the smaller coefficients for non interest income and the capital ratio. This suggests that a considerable part of the relation of systemic risk to non interest income and capital ratios is because banks with lower capital ratios and higher non interest income share larger size tends to have larger size. Nevertheless, the coefficients remain significant (weakly significant in case of the capital ratio), which shows that the relations to bank size do not account completely for their relations to systemic risk.

Finally, Figure 1 shows that systemic risk may be nonlinearly related to size, which is line with the finding of De Nicoló (2000) on bank size and risk. Therefore, we estimate the relation for small and large banks separately. Model (5) excludes bank-year observations for banks with the magnitude of total assets belonging to the top 20% in that particular year. Model (6) is estimated with bank-year observations for banks with a magnitude of total assets belonging to the top 20%. For most variables we observe a smaller impact on systemic risk among larger banks. For example, the positive relation between size and systemic risk is less pronounced among larger banks. The same holds true for bank capital, bank profitability, cost-to-income and non-interest income. A few variables have a stronger relation to systemic risk among large banks. The size of the loan book has a significantly positive relation to systemic risk among larger banks, while it is insignificant among smaller banks.

5 Conclusion

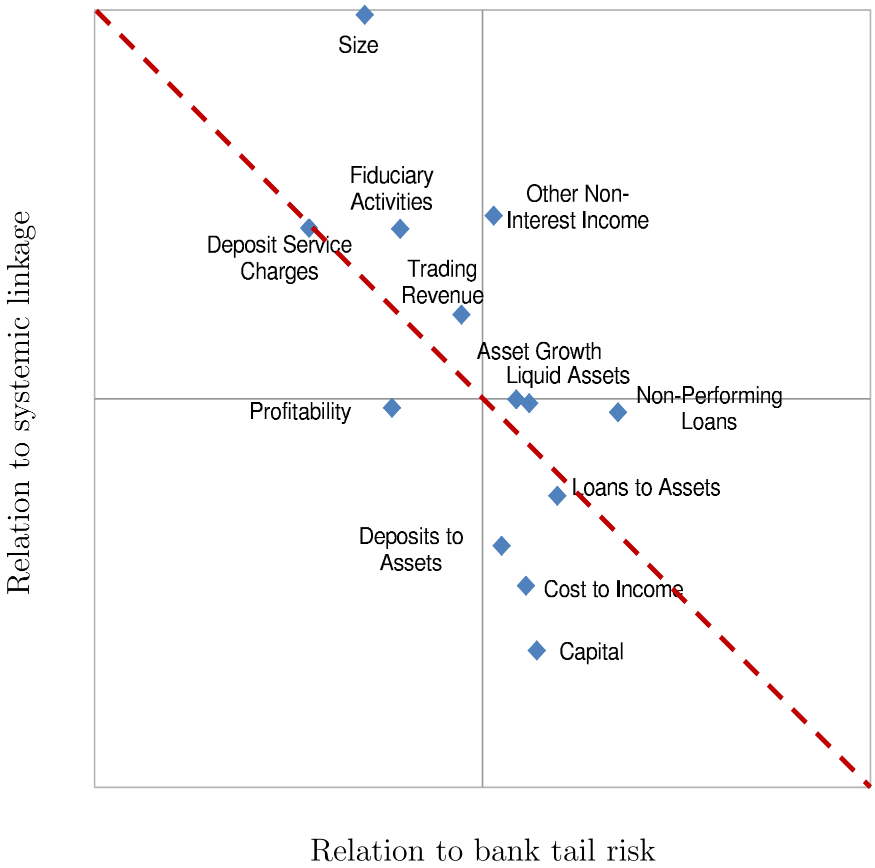
In this paper, we analyze how bank characteristics are related to systemic risk through two distinguished dimensions: systemic linkage and tail risk. By employing a novel systemic risk measure, the coefficient β_i^T, we decompose systemic risk into two subcomponents reflecting these two dimensions. By running panel regressions on the systemic risk measure 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 3 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 3, 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 tail risk.[19] Hence, a characteristic with a dot far away from (close to) the vertical axis indicates that the underlying bank characteristic is strongly related (unrelated) to bank tail risk. Similarly, dots that are far away from (close to) the horizontal axis correspond to characteristics that are strongly related (unrelated) to the systemic linkage. In addition, the dashed diagonal refers to the positions in the diagram in which the two relations precisely cancel each other out in determining the level of systemic risk. Dots far away from the diagonal correspond to characteristics that have a relatively strong relation to systemic risk: a position in the northeastern (southwestern) half of the plane indicates a positive (negative) relation.

The scatter plot in Figure 3 helps to select relevant bank characteristic as indicators for banks' tail risk and banks' 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 to the tail risk of a bank taken in isolation. Hence, a high non-performing loan

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

Figure 3: 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 (below) 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 3, 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.

ratio and a structurally 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, trading revenue and other non-interest income are very close to the vertical axis and would not be regarded as an effective indicator for differentiating banks' tail risks. Moreover, large banks are generally associated with lower tail risk. However, in Figure 3, these indicators are far above the diagonal. Consequently, trading revenue, other non-interest income and bank size have a relatively strong positive relation to banks' systemic risk.

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, the focus should not be on bank characteristics related to a bank's individual tail risk only, but also on characteristics related to the bank's systemic linkage. Whether bank characteristics are relevant to a bank's systemic risk depends on how their relation to the bank's tail risk and their relation to systemic linkage precisely balance. This study is a first step in a research agenda to assess this issue. We illustrate the framework with an analysis of the interrelationship between systemic risk and some main bank characteristics. The summary of our analysis in Figure 3 shows that some characteristics have a similar relation to 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 differences 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 objectives of regulation.

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Tables

Table 1: Descriptive statistics

VARIABLES	Mean	Sd	Min	p10	p90	Max
PANEL A						
Systemic risk						
Systemic Risk: $\hat{\beta}^T$	0.911	0.305	0.127	0.547	1.304	3.711
Systemic Linkage: $\exp(SL)$	0.625	0.143	0.179	0.432	0.808	0.923
Bank Tail Risk: $\exp(IR)$	1.485	0.503	0.469	0.992	2.110	8.525
PANEL B						
Main characteristics						
ln(Total Assets)	15.306	1.531	13.179	13.667	17.589	20.450
Tier 1 Risk-Based Capital Ratio (%)	11.744	3.101	5.410	8.463	15.624	24.614
Non-Performing Loans Ratio	0.011	0.013	0.000	0.002	0.022	0.121
Cost to Income	0.631	0.119	0.369	0.499	0.754	1.609
Return on Equity	0.132	0.076	-1.071	0.076	0.194	0.278
Liquid Assets	0.036	0.088	-0.184	-0.058	0.143	0.347
Growth in Total Assets	0.030	0.057	-0.080	-0.016	0.082	0.332
PANEL C						
Income streams						
Non-Interest Income Share	0.270	0.139	-0.001	0.131	0.437	0.790
Srvc Charges on Deposit Accounts Shr	0.077	0.038	0.000	0.030	0.126	0.194
Fiduciary Activities Income Share	0.042	0.069	0.000	0.000	0.092	0.471
Trading Revenue Share	0.007	0.021	-0.015	0.000	0.019	0.133
Other Non-Interest Income Share	0.142	0.115	-0.077	0.047	0.263	0.712
PANEL D						
Loan portfolio						
Loans to Total Assets	0.642	0.132	0.014	0.477	0.780	0.944
Real Estate Loan Share	0.631	0.187	0.041	0.391	0.851	0.979
Commercial and Industrial Loan Shr	0.188	0.116	0.005	0.070	0.341	0.631
Consumer Loan Share	0.122	0.102	0.001	0.014	0.254	0.495
Agricultural Loan Share	0.009	0.018	0.000	0.000	0.028	0.108
Other Loan Share	0.044	0.066	0.000	0.001	0.105	0.479
PANEL E						
Funding structure						
Deposits to Total Assets	0.747	0.114	0.243	0.609	0.868	0.910
Interest-Bearing Core Deposits Share	0.668	0.113	0.275	0.516	0.797	0.881
Large Time Deposits Share	0.205	0.109	0.034	0.088	0.342	0.657
Non-Interest-Bearing Deposits Share	0.127	0.066	0.011	0.046	0.203	0.351

Descriptive statistics of the bank-year observations used for the estimation of the models in Tables 2–5.

Table 2: Baseline results on systemic risk

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	SL_{it}	IR_{it}
Bank Size (reslnTA)	0.080***	0.114***	-0.034***
	(0.010)	(0.003)	(0.009)
Tier 1 Risk-Based Cap. Ratio	-0.018***	-0.025***	0.007***
	(0.002)	(0.001)	(0.002)
Non-Performing Loans Ratio	2.875***	-0.547**	3.422***
	(0.329)	(0.239)	(0.260)
Cost to Income Ratio	-0.356***	-0.454***	0.098**
	(0.055)	(0.029)	(0.048)
Return on Equity	-0.380***	-0.079**	-0.301***
	(0.070)	(0.035)	(0.067)
Liquid Assets	0.168***	-0.044	0.212***
	(0.056)	(0.035)	(0.040)
Loans to Total Assets	-0.023	-0.274***	0.251***
	(0.051)	(0.028)	(0.050)
Deposits to Total Assets	-0.395***	-0.247***	-0.148**
	(0.051)	(0.030)	(0.063)
Non-Interest Income Share	0.448***	0.564***	-0.116***
	(0.037)	(0.021)	(0.043)
Growth in Total Assets	0.187***	-0.052	0.238***
	(0.053)	(0.033)	(0.046)
Constant	0.522***	0.236***	0.285***
	(0.076)	(0.038)	(0.076)
Observations	11,597	11,597	11,597
Number of banks	461	461	461
R-squared	0.373	0.518	0.409
Partial R-squared	0.196	0.492	0.090
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 explanatory variables are observations from the quarter preceding the estimation horizon. They are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors. The "partial R-squared" is calculated as $1 - \frac{1-R^2}{1-R_D^2}$, where R^2 is the R-squared in the table and where R_D^2 is the R-squared from a regression with only dummies for the fixed effects. 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	$\log \hat{\beta}^T_{it}$	SL_{it}	IR_{it}
Bank Size (reslnTA)	0.079***	0.114***	-0.035***
	(0.009)	(0.004)	(0.008)
Tier 1 Risk-Based Cap. Ratio	-0.018***	-0.023***	0.005**
	(0.002)	(0.001)	(0.002)
Non-Performing Loans Ratio	2.690***	-0.304	2.994***
	(0.323)	(0.229)	(0.260)
Cost to Income Ratio	-0.342***	-0.446***	0.104**
	(0.056)	(0.029)	(0.047)
Return on Equity	-0.372***	-0.035	-0.337***
	(0.072)	(0.039)	(0.067)
Liquid Assets	0.136***	-0.016	0.151***
	(0.051)	(0.036)	(0.034)
Loans to Total Assets	-0.048	-0.209***	0.161***
	(0.052)	(0.034)	(0.046)
Deposits to Total Assets	-0.319***	-0.367***	0.048
	(0.053)	(0.033)	(0.053)
Growth in Total Assets	0.163***	-0.005	0.169***
	(0.054)	(0.032)	(0.046)
Fiduciary Activities Income Share	0.357***	0.694***	-0.336***
	(0.059)	(0.041)	(0.063)
Srvc Charges on Dep Accnts Shr	-0.023	1.280***	-1.303***
	(0.111)	(0.100)	(0.101)
Trading Revenue Share	0.856***	1.139***	-0.283
	(0.211)	(0.133)	(0.210)
Other Non-Interest Income Share	0.478***	0.450***	0.028
	(0.039)	(0.020)	(0.032)
Constant	0.509***	0.198***	0.311***
	(0.075)	(0.040)	(0.068)
Observations	11,597	11,597	11,597
Number of banks	461	461	461
R-squared	0.375	0.532	0.434
Partial R-squared	0.206	0.522	0.103
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 explanatory variables are observations from the quarter preceding the estimation horizon. They are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors. The "partial R-squared" is calculated as $1 - \frac{1-R^2}{1-R^2_D}$, where R^2 is the R-squared in the table and where R^2_D is the R-squared from a regression with only dummies for the fixed effects. 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***	0.116***	-0.035***
	(0.010)	(0.003)	(0.009)
Tier 1 Risk-Based Cap. Ratio	-0.017***	-0.021***	0.005**
	(0.002)	(0.001)	(0.002)
Non-Performing Loans Ratio	2.849***	-0.324	3.173***
	(0.311)	(0.209)	(0.252)
Cost to Income Ratio	-0.315***	-0.376***	0.061
	(0.053)	(0.028)	(0.046)
Return on Equity	-0.338***	-0.006	-0.332***
	(0.071)	(0.040)	(0.063)
Liquid Assets	0.138**	-0.103***	0.241***
	(0.057)	(0.031)	(0.046)
Loans to Total Assets	-0.019	-0.204***	0.185***
	(0.048)	(0.027)	(0.048)
Deposits to Total Assets	-0.352***	-0.213***	-0.139**
	(0.056)	(0.030)	(0.061)
Non-Interest Income Share	0.429***	0.466***	-0.037
	(0.035)	(0.018)	(0.037)
Growth in Total Assets	0.194***	-0.009	0.203***
	(0.054)	(0.031)	(0.045)
Agricultural Loan Share	-1.352***	-0.930***	-0.422***
	(0.211)	(0.135)	(0.158)
Commercial and Industrial Loan Shr	0.167***	0.323***	-0.156***
	(0.046)	(0.023)	(0.032)
Consumer Loan Share	0.016	0.238***	-0.222***
	(0.046)	(0.016)	(0.052)
Other Loan Share	0.005	0.227***	-0.221*
	(0.126)	(0.042)	(0.117)
Constant	0.413***	-0.031	0.445***
	(0.081)	(0.040)	(0.080)
Observations	11,597	11,597	11,597
Number of banks	461	461	461
R-squared	0.380	0.547	0.417
Partial R-squared	0.199	0.506	0.128
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 explanatory variables are observations from the quarter preceding the estimation horizon. They are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors. The "partial R-squared" is calculated as $1 - \frac{1-R^2}{1-R_D^2}$, where R^2 is the R-squared in the table and where R_D^2 is the R-squared from a regression with only dummies for the fixed effects. 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)	0.080***	0.116***	-0.036***
	(0.010)	(0.003)	(0.009)
Tier 1 Risk-Based Cap. Ratio	-0.018***	-0.024***	0.006***
	(0.002)	(0.001)	(0.002)
Non-Performing Loans Ratio	2.644***	-0.467**	3.111***
	(0.355)	(0.194)	(0.237)
Cost to Income Ratio	-0.341***	-0.491***	0.150***
	(0.053)	(0.032)	(0.046)
Return on Equity	-0.385***	-0.126***	-0.259***
	(0.070)	(0.034)	(0.066)
Liquid Assets	0.201***	-0.183***	0.385***
	(0.059)	(0.040)	(0.050)
Loans to Total Assets	-0.010	-0.299***	0.289***
	(0.052)	(0.029)	(0.049)
Deposits to Total Assets	-0.363***	-0.312***	-0.051
	(0.048)	(0.030)	(0.056)
Non-Interest Income Share	0.433***	0.541***	-0.108***
	(0.036)	(0.020)	(0.037)
Growth in Total Assets	0.169***	-0.017	0.186***
	(0.051)	(0.032)	(0.043)
Non-Interest-Bearing Deposits Share	0.148***	0.504***	-0.356***
	(0.017)	(0.056)	(0.046)
Large Time Deposits Share	0.158***	-0.145***	0.303***
	(0.047)	(0.029)	(0.053)
Constant	0.437***	0.286***	0.151**
	(0.075)	(0.042)	(0.066)
Observations	11,597	11,597	11,597
Number of banks	461	461	461
R-squared	0.375	0.536	0.423
Partial R-squared	0.199	0.510	0.111
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 explanatory variables are observations from the quarter preceding the estimation horizon. They are all ratios, except bank size. Bank size is the residual from a regression of the logarithm of total assets on the other regressors. The "partial R-squared" is calculated as $1 - \frac{1-R^2}{1-R_D^2}$, where R^2 is the R-squared in the table and where R_D^2 is the R-squared from a regression with only dummies for the fixed effects. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 6: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	$\hat{\beta}_{it}^{T}$	$\log \hat{\beta}_{it}^{T}$	$\log \hat{\beta}_{it}^{T}$	$\log \hat{\beta}_{it}^{T}$	$\log \hat{\beta}_{it}^{T}$
Bank Size (reslnTA)	0.079***	0.059***	0.061***		0.116***	0.034***
	(0.009)	(0.007)	(0.015)		(0.017)	(0.008)
Log(Total Assets)				0.070***		
				(0.009)		
Tier 1 Risk-Based Cap. Ratio	-0.014***	-0.016***	-0.017***	-0.004*	-0.025***	-0.008**
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.004)
Non-Performing Loans Ratio	3.942***	3.433***	2.354***	2.891***	3.682***	2.302***
	(0.405)	(0.508)	(0.486)	(0.315)	(0.398)	(0.450)
Cost to Income Ratio	-0.567***	-0.260***	-0.206***	-0.172***	-0.431***	-0.057
	(0.072)	(0.051)	(0.065)	(0.046)	(0.074)	(0.050)
Return on Equity	-1.521***	-0.383***	-0.215***	-0.291***	-0.373***	-0.285***
	(0.088)	(0.100)	(0.062)	(0.073)	(0.076)	(0.086)
Liquid Assets	0.174**	0.106*	0.438***	0.107**	0.187***	0.247**
	(0.076)	(0.058)	(0.093)	(0.049)	(0.067)	(0.098)
Loans to Total Assets	-0.093*	-0.021	0.056	0.115*	-0.059	0.230***
	(0.052)	(0.046)	(0.087)	(0.060)	(0.063)	(0.078)
Deposits to Total Assets	-0.277***	-0.342***	-0.669***	-0.096***	-0.510***	-0.584***
	(0.054)	(0.041)	(0.106)	(0.036)	(0.078)	(0.087)
Non-Interest Income Share	0.655***	0.416***	0.242***	0.176***	0.547***	0.330***
	(0.043)	(0.034)	(0.086)	(0.052)	(0.061)	(0.074)
Growth in Total Assets	0.849***	0.141**	-0.009	0.245***	0.191***	0.133**
	(0.209)	(0.063)	(0.033)	(0.056)	(0.055)	(0.061)
Constant	0.657***	1.411***	0.433***	-1.131***	0.723***	0.291***
	(0.079)	(0.062)	(0.108)	(0.159)	(0.129)	(0.072)
Observations	12,620	11,740	11,597	11,597	9,233	2,364
Number of banks	480	461	461	461	419	108
R-squared	0.436	0.361	0.727	0.368	0.376	0.303
Partial R-squared	0.267	0.186	0.039	0.191	0.135	0.216
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	No	No	Yes	No	No	No
Clustering at bank level	Yes	Yes	Yes	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes	Yes	Yes	Yes

This table provides the estimation results for Model (1) in Table 2 after several departures from our baseline methodology. In this table, Model (1) provides the results when regressing the estimated β_{it}^{T}s on bank characteristics averaged over the 16 quarterly observations within the four-year estimation window. 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 including 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 (3). In Model (4) we replace the original variable for bank size by 'log(Total Assets)'. Model (5) excludes bank-year observations for banks with the magnitude of total assets belonging to the top 20% in that particular year. Model (6) is estimated only on bank-year observations for banks with the magnitude of total assets belonging to the top 20%. The "partial R-squared" is calculated as $1 - \frac{1-R^2}{1-R_D^2}$, where R^2 is the R-squared in the table and where R_D^2 is the R-squared from a regression with only dummies for the fixed effects. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

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