Systemic Risk and Bank Business Models*

Maarten R.C. van Oordt†
De Nederlandsche Bank

Chen Zhou‡
De Nederlandsche Bank and Erasmus University Rotterdam

August 10, 2015

Abstract In this study we decompose banks' systemic risk on the cross-sectional level into two dimensions: the level of bank tail risk and the strength of its link to severe shocks in the financial system. We estimate a systemic risk measure based on extreme observations that can be decomposed into two subcomponents reflecting these dimensions. We analyze the relations between characteristics of bank business models and these dimensions. The balance between the two determines the relation between bank characteristics and systemic risk. Our analysis reveals differences in the scope and direction of policies following from the micro- and macroprudential objectives of regulation.

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

JEL Classifications: G10, G21, G28

*The authors are grateful to Valerie de Bruyckere for many insightful comments and for generously providing us with sample programs to read the data. The authors also thank participants in the BIS workshop '*Systemically important financial institutions: A research agenda*' (Beijing, 2014), the 6th IFABS Conference (Lisbon, 2014), the 4th International FEBS Conference (Guildford, 2014), the 7th IRMC (Warsaw, 2014), the 20th International CEF Conference (Oslo, 2014), the 29th Annual EEA Meeting (Toulouse, 2014), the Netherlands Economists Day (Amsterdam, 2014), the Conference of the Centre for Finance, Credit and Macroeconomics on '*Effective Macroprudential Instruments*' (Nottingham, 2014), the Financial Stability Conference of the Cleveland Fed (Washington, 2014), the joint conference of De Nederlandsche Bank and the European Banking Center on '*Macroprudential regulation: From theory to implementation*' (Amsterdam, 2015), the 64th Annual MFA Meeting (Chicago, 2015), the 51s Annual EFA Meeting (New Orleans, 2015), the 20th SMYE (Ghent, 2015), the IBEFA Summer Meeting (Honolulu, 2015), and participants in research seminars of the City University of London (2014), De Nederlandsche Bank (2014), the Federal Reserve Bank of Boston (2015), Bank of Canada (2015), Bank of England (2015), Norges Bank (2015) and the Deutsche Bundesbank (2015) for useful comments and suggestions. Views expressed do not necessarily reflect official positions of De Nederlandsche Bank.

†Email: M.R.C.van.Oordt@dnb.nl

‡Email: C.Zhou@dnb.nl, zhou@ese.eur.nl

1 Introduction

Before the global financial crisis, prudential regulation focused predominantly on the soundness of financial institutions taken in isolation. The weak performance of many 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 bank failures at the individual level is relevant for financial stability, but also whether bank failures tend to occur in clusters. 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.

Banks with certain business models may be associated with a higher level of systemic risk because of a higher overall level of risk, or because of a stronger link to the system in financial distress. This is a relevant distinction for understanding the interaction between the micro- and macroprudential objectives of regulation. Our goal is to improve the understanding of systemic risk by decomposing banks' systemic risk on the cross-sectional level into two dimensions: (1) the level of a bank's tail risk and (2) the strength of its link to severe shocks in the financial system.[1] This decomposition does not only allow us to assess whether certain characteristics of bank's business models are related to bank's systemic risk, but also via which of the two systemic risk dimensions.

Empirically, we document the following observations. First, the weak correlation between systemic risk and bank risk, as documented by, e.g., Acharya et al. (2009) and Adrian and Brunnermeier (2011), is because of the very low correlation between the level of bank risk and the strength of its link to severe shocks in the financial system. A prudential approach focusing solely on bank risk does not incorporate its impact on the link of banks to the system in case of financial distress. Consequently, such an approach may fall short in curtailing bank's systemic risk. Second, banks engaging in more nontraditional banking activities are generally associated with a higher level of systemic risk, because such banks are stronger linked to severe shocks in the financial system. Hence,

[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 Galati and Moessner (2013, Section 3.1).

these non-traditional activities are relevant from a macro-prudential perspective, even though there may seem little reason to be concerned about these activities from a purely microprudential point of view.

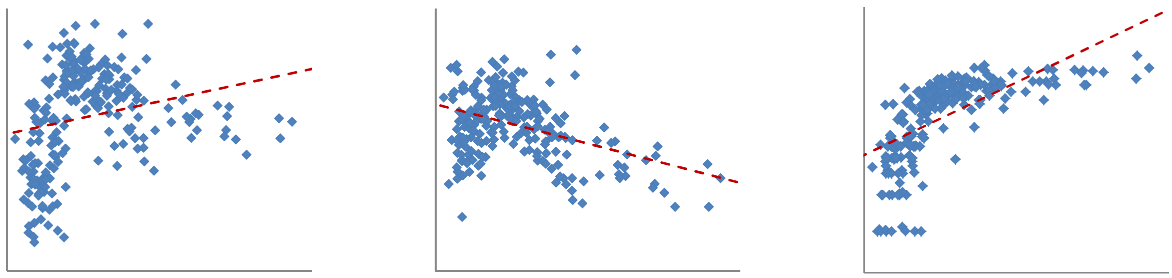
Third, evaluating systemic risk based on conventional measures, such as correlations and standard deviations, do not provide a full picture on how bank characteristics are related to systemic risk. This is mainly because correlations do not capture well the dependence structure for extremely adverse shocks in the financial system. By contrast, standard deviations seem to provide a reasonably well description of relative differences in tail risk. This stresses the importance of exploring new approaches to modeling the dependence structure among financial institutions in extreme events.

In our study, the systemic risk of financial institutions in the cross-section is conceptualized as their sensitivity to severe shocks in the financial system. Banks with a higher sensitivity to systemic shocks are expected to face larger losses in a banking crisis. For banks with the same level of total tail risk, a bank with a stronger link to the system during severe shocks in the financial system should be considered to be more systemically risky: compared to its peers, such a bank is expected to suffer larger losses in a systemic crisis. We call the strength of the link between a bank and the system during financial distress its 'systemic linkage'. It measures whether the risk of a bank is more likely to materialize during a financial crisis or at a different point in time. Conversely, for banks with the same level of systemic linkage, the one with a higher level of tail risk should be considered to be more systemically risky. Hence, two dimensions of banks' systemic risk arise: the level of a bank's tail risk and the bank's systemic linkage.

An illustration of the decomposition of systemic risk and its relation to bank characteristics is provided in Figure 1. Figure 1 plots banks' size against our systemic risk measure and the two subcomponents measuring bank tail risk and the link to the system, respectively. The log of the systemic risk measure equals the sum of the log of its two subcomponents. We observe downward and upward sloping trends in the size-tail risk and size-systemic linkage interrelationship, respectively. Since the latter dominates the former, larger banks exhibit a higher level of systemic risk. From this decomposition, one

Figure 1: Systemic risk and bank size

Systemic risk ($\log \hat{\beta}_i^T$)	=	Bank tail risk ($\log IR_i$)	+	Link to the system ($\log SL_i$)



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. The measures are defined in Eqs. (2.1) and (2.6).

may not only conclude that size relates positively to systemic risk, but also that this is 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 prudential 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).

The decomposition of systemic risk reveals a connection between the micro- and macroprudential objectives of regulation. While the microprudential objective considers only the level of bank risk, the macroprudential objective has to take into consideration both the level of risk and the link between a bank and the system in case of financial stress. In other words, "common exposures" and "interlinkages" across institutions, which may be irrelevant from a microprudential perspective, are important from a macroprudential point of view; see Borio (2003, 2014).

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. Note however that, regardless of the direction of the effect, stronger co-movement with severe shocks in the financial system indicates that an institution is more likely to face difficulties when it is most costly to the real economy, i.e., in case of a widespread disruption of the financial system.[2] Hence, from a regulator's point of view, even if a bank only passively suffers from large systemic shocks, it should be regulated more tightly, because such a bank imposes a larger expected cost on the real economy due to financial instability; see, e.g., Acharya and Yorulmazer (2007), Acharya (2009), Wagner (2010) and Korinek (2012).[3]

Our study contributes to three strands of literature. First, we contribute to the extant literature introducing measures to rank financial institutions in terms of systemic risk in the cross-section. 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).[4] It is not the purpose of the present paper to improve rankings of financial institutions in terms of systemic risk. Rather, we hope to provide more insight on the systemic risk of financial institutions by the aforementioned decomposition into bank's tail risk and systemic linkage.

We measure the systemic risk of financial institutions by estimating the sensitivity of banks' equity returns to severe shocks in the financial system. That is, 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 the Marginal Expected Shortfall (MES), which is the systemic risk measure proposed by Acharya et al. (2009, 2012). Theoretically, we show how it quantifies all cross-sectional variation in the MES. The benefit of our approach to estimating systemic risk is that it facilitates the decomposition into the 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 characteristics of bank business models and the two dimensions

[2]For empirical evidence on the real effects of financial crises we refer to Peek and Rosengren (2000), Boyd et al. (2005), Dell'Ariccia et al. (2008), Hall (2010) and the references therein. Implicitly we presume that it is important to avoid financial instability because of the cost it imposes on the real economy.

[3]The directionality of shock propagation is important if, e.g., it is the purpose to assess whether the bailout of one institution will reduce losses at other financial institutions.

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

of systemic risk.

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). On the systemic risk level, our results are not new in the sense that they merely confirm the relationships established in these earlier studies. However, what is new to our study is that we also identify whether these relationships are through the bank's tail risk or through the link between the bank and the system in financial stress. This insight is important to identify areas in which micro- and macroprudential objectives may potentially lead to differences in the scope and direction of regulation.

Third, we contribute to the literature on applying multivariate Extreme Value Theory (EVT) in the systemic risk context. Since the systemic risk measure employed in this study describes the sensitivity of the bank to large adverse shocks in the financial system, it has to be estimated from relatively few extreme observations. The problem of estimating the coefficient in a linear relation between a firm's and the in returns and extreme shocks in the financial system has been studied by Van Oordt and Zhou (2011). Their methodology relies on estimating both the level of tail risks and the level of tail dependence. Estimating tail dependence, which is based on joint tail probabilities, has been the focus of many studies to capture extreme dependencies in the context of banking; see, e.g., Hartmann et al. (2007), De Jonghe (2010), Zhou (2010), Weiß et al. (2014) and Balla et al. (2014). The present study shows how these earlier studies connect to the broader systemic risk literature by revealing the role of tail dependence in determining the level of systemic risk.

The paper is organized as follows. Section 2 discusses the methodology. Section 3 gives a description of the data. Section 4 presents our empirical results. Section 5 provides some concluding remarks and a graphical summary of our main results.

2 Methodology

In this section we discuss our framework on how to decompose banks' systemic risk into banks' tail risk and the linkage between 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), Knaup and Wagner (2012) and Fahlenbrach et al. (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.[5]

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

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

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

[5] In Subsection 4.5 we discuss the value-added of our approach vis-à-vis an unconditional linear model.

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 $R_s < -VaR_s(\bar{p})$.[6] Hence, our approach does not require any assumptions 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 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 $p < \bar{p}$,

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

where $ES_s(p)$ denotes the expected shortfall of R_s defined as $ES_s(p) = -\mathbb{E}[R_s | R_s \leq -VaR_s(p)]$.[7] Since the expected shortfall of the return on the financial system, $ES_s(p)$, is invariant across different banks, any dispersion in the MES_i measure across institutions is because of 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, $ES_s(p)$.[8]

---

[6] Hence, also the independence assumption between R_s and ε_i is only necessary for $R_s < -VaR_s(\bar{p})$, i.e., $\Pr(\varepsilon_i < t, R_s < u | R_s < -VaR_s(\bar{p})) = \Pr(\varepsilon_i < t | R_s < -VaR_s(\bar{p})) \Pr(R_s < u | R_s < -VaR_s(\bar{p}))$ for any $t \in \mathbb{R}$ and $u < -VaR_s(\bar{p})$.

[7] Having R_s representing the return on the financial index follows the conceptual discussion of Acharya et al. (2013, pp. 179–181). Moreover, following the "Component Expected Shortfall" definition of Banulescu and Dumitrescu (2015), this allows us to express the expected loss of bank i as a share of the total losses in the system in case of financial stress as $\beta_i^T MV_i / MV_s$, where MV_i and MV_s are the market capitalizations of bank i and the entire financial system, respectively.

[8] Allen et al. (2012) provide evidence that the level of tail risk in the financial system based on stock returns helps to forecast macroeconomic downturns, while the tail risk among nonfinancial firms has no marginal predictive ability. Similarly, Giglio et al. (forthcoming) observe return volatility in the financial sector to be a significant predictor of macroeconomic tail-risk, while non-financial volatility is not.

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 applying conventional methods such as an OLS regression on a small number of observations to estimate β_i^T; see, e.g., Mikosch and De Vries (2013). Instead, we estimate β_i^T using 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. 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.

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). Let R_i and R_s follow heavy-tailed distributions with tail indices ζ_i and ζ_s, respectively.[9] 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

[9] 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.[10] The coefficient β_i^T is then estimated by

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

where the tail index $\hat{\zeta}_s$ is the estimator proposed in Hill (1975); $\widehat{VaR}_i(k/n)$ and $\widehat{VaR}_s(k/n)$ are estimated by the $(k+1)$th worst return on the bank's stock and the financial index; and $\hat{\tau}_i(k/n)$ 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 and asymptotically normal, 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 bank risk, respectively. From Eq. (2.3), we observe that the sensitivity to extreme shocks is determined by two components, $VaR_i(p)/VaR_s(p)$ and $\tau_i(p)^{1/\zeta_s}$.

The first component, $VaR_i(p)/VaR_s(p)$, is the ratio between the VaR of bank i and that of 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. Hence, this component measures the level of tail risk at a particular bank, but carries no information on whether the tail risk of that bank is related to severe shocks in the financial system. In our sample, this component bears the value 1.65 on average. This means that an equity investment in a single institution bears on average 65% more tail risk than the same investment in the financial index.

The second component, $\tau_i(p)^{1/\zeta_s}$, measures the relation between the tail risk of an

[10]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 $k/n \approx 4\%$. The baseline results in Table 2 are hardly affected by choosing $k = 30$ or $k = 50$ instead.

individual bank and severe shocks in the financial system. Cross-sectional differences 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.[11] 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 risk at 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.[12] In our sample, this fraction is 60% on average.

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 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

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

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 tail risk of bank i. In total, the log of the estimated systemic risk measure, $\hat{\beta}_i^T$, equals the sum of the log of the systemic linkage measure and the log of the bank's tail risk measure.

[11]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. For example, with $R_B = 2R_A$, we have $VaR_B(p) = 2VaR_A(p)$, which implies $\tau_A(p) = \Pr(R_A < -VaR_A(p)|R_s < -VaR_s(p)) = \Pr(2R_A < -2VaR_A(p)|R_s < -VaR_s(p)) = \Pr(R_B < -VaR_B(p)|R_s < -VaR_s(p)) = \tau_B(p)$.

[12]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".

2.4 Regression models

To explore the empirical relation between systemic risk and characteristics of bank business models, we estimate three regression models using our estimates of systemic risk, systemic linkage and bank tail risk as dependent variables. Formally, with the bank characteristics of bank i in the quarter directly preceding the 16 quarter estimation window of $\hat{\beta}_{it}^{T}$, denoted as X_{it-16}, we estimate the coefficients in the following models from panel data on bank holding companies

$$\log \hat{\beta}_{it}^{T} = \alpha_{1t} + X_{it-16}\theta + \upsilon_{it}, \tag{2.7}$$

$$\log SL_{it} = \alpha_{2t} + X_{it-16}\delta + \xi_{it}, \tag{2.8}$$

$$\log IR_{it} = \alpha_{3t} + X_{it-16}\gamma + \nu_{it}, \tag{2.9}$$

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. Following De Jonghe (2010), to take full advantage of the cross-sectional dispersion across the financial institutions in our panel, we do not include bank fixed effects.[13] To deal with the serial correlation among observations of the error terms over time and the cross-sectional correlation of the error terms at the same point in time we estimate standard errors that are clustered on both the bank and time level.

With the estimated coefficients $\hat{\gamma}$ and $\hat{\delta}$ it is possible to assess via which dimensions bank characteristics are related to a bank's sensitivity to extreme shocks in the financial system. According to Eq. (2.6), the dependent variable in the model in (2.7) equals the sum of those in (2.8) and (2.9). Theoretically it holds that $\theta = \gamma + \delta$. 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. Therefore, we can also assess how the interrelationships with the two dimensions of systemic risk balance quantitatively in the relation between bank characteristics and the level of systemic risk.

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

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 1992 to 2011. At the end of each quarter, we use four years of historical daily equity returns to estimate the three dependent variables, the $\hat{\beta}_{it}^{T}$ and its two subcomponents. To guarantee the quality of the data and the liquidity of the stocks on the equity market, the selected bank have total assets of at least USD 500 million and non-zero returns on at least 60% of the days in the estimation window. We use a broad financial index based on the daily value weighted returns of firms with SIC-codes between 6000 and 6999 which covers firms in banking, insurance, real estate and trading.[14]

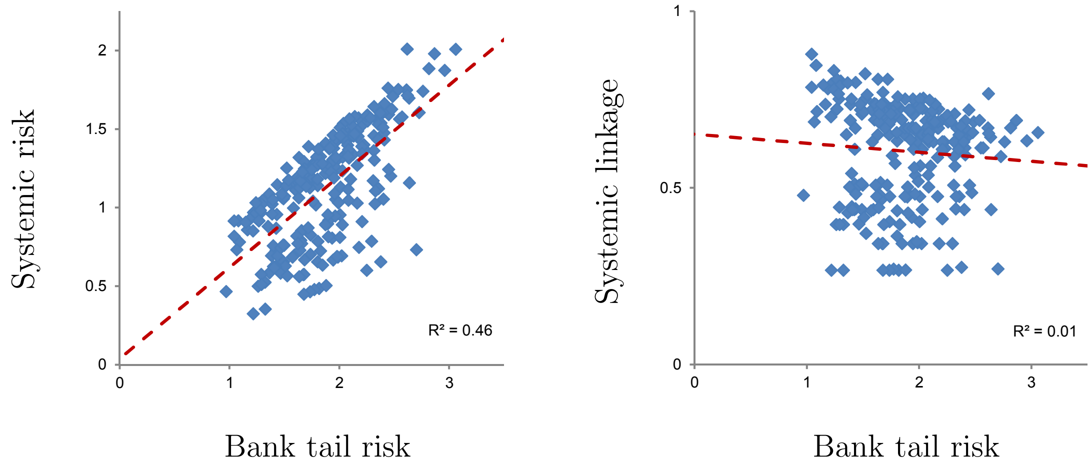
Descriptive statistics on β_{it}^{T} and its subcomponents are presented in Table 1, panel (a).[15] We observe that across all banks in all periods, the average $\hat{\beta}_{it}^{T}$ is 0.97. In an extreme market downturn, the average loss in bank equity returns is thus comparable with the loss in the financial index. The coefficient $\hat{\beta}_{it}^{T}$ ranges from 0.14 to 3.58, 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_{it}^{T} in the cross-section. The SL_{it}, which measures the strength of the link between the bank and the system in case of widespread financial distress, ranges from 0.19 to 0.92. This illustrates the role that systemic linkage plays in the variation of β_{it}^{T}. The other component, IR_{it}, compares banks' risk to that of the system. More than 90% of the observations for this component are larger than 1. Hence, usually, an investment in the stock of a single bank bears more tail risk than an investment in the financial index. Again, differences in this component demonstrate the role of the risk level in the variation of β_{it}^{T}.

An illustration of the relation between bank tail risk and banks' systemic risk is

[14] Available on the website of Kenneth French via the link "38 Industry Portfolios" at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[15] Instead of reporting the descriptive statistics of the dependent variables in the regression models, we report those of the original measures β_{it}^{T}, SL_{it} and IR_{it} as defined in Eq. (2.6). 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. Banks' systemic risk is measured as β_i^T. Bank tail risk and banks' systemic linkage are measured as IR_i and SL_i; for the definitions see Eq. (2.6).

presented in Figure 2, panel (a). 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. The difference between bank tail risk and 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. This hints that sometimes different steps may be necessary to pursue the micro- and macroprudential objectives of regulation. Moreover, 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).[16] 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

[16]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). Two exceptions are that we estimate our models with the tangible equity ratio and a more narrow definition of liquid assets (US treasuries, currency, noninterest bearing balances and interest bearing balances).

the logarithm of total assets, the CAMEL ratios and the growth rate of total assets.[17] (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 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) an indicators of banks' funding structure: deposits to total assets ratio.

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.[18] 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.[19] The estimation windows for the left hand side variables range from 1992Q3–1996Q2 to 2008Q1–2011Q4. In addition, we exclude all observations corresponding to a zero estimate of $\hat{\beta}^T_{it}$, because our regression models require taking logarithm of the estimated β^T_{it}.[20] We end up with 13,498 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 impact of potential outliers, all variables are constructed after winsorizing at 1% and 99% quantiles of the whole sample. Return on Equity is annualized. 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

[17]Here the CAMEL ratios are Capital (tangible equity capital ratio), Asset quality (non-performing loans ratio), Management (cost to income ratio), Earnings (return on total equity) and Liquidity (liquid assets ratio).

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

[19]In Subsection 4.6 we provide results when regressing the estimated β^T_{it}s on bank characteristics averaged over the 16 quarterly observations within the four-year estimation window and on bank characteristics in two quarters before the estimation window.

[20]In Subsection 4.6 we verify the impact of excluding observations corresponding to zero β^T_{it} estimates.

regress the logarithm of total assets on the other regressors, and then use the residual 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 presents the baseline results. Tables 3–4 contain estimates for models with further decompositions into different sources of non-interest income and different loan types, respectively. Table 5 shows the results while controlling for conventional risk measures.

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., Shaffer (1994) and 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. (2014).

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 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 link to the system that induces higher sensitivity of large banks to severe shocks in the financial system. The positive relation between bank size and the dependence between banks and the financial system in tail events 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 systemic linkage 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 10%-point corresponds to an increase in the sensitivity to severe shocks in the financial system by approximately 5.8%. 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).[21] 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 a 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, banks with more trading revenue and other non-interest income are much stronger related to the system in case of financial stress. Therefore, these activities are strongly positively related to banks' systemic risk; see also Brunnermeier et al. (2012). Hence, whether banks are involved in 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 characterized by relatively high loans-to-assets financed with deposits. 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.

First we consider the loans-to-assets ratio as a proxy of the traditionality of the bank balance sheets. From Table 2, Model (1) we observe that banks with a 10%-point higher loans-to-assets ratio are associated with a 2.0% lower level of systemic linkage. The decomposition of systemic risk provides more insight into the relation to the loans-to-

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

assets ratio. Banks that concentrate their business models towards traditional lending are associated with a weaker link to the financial system in stress events. However, the relation to systemic risk is not significant, among others because of a weak positive relation between the loans-to-assets ratio and bank tail risk. Whether the loan business is associated with higher systemic risk may also depend on the riskiness of the loan portfolio. By considering the non-performing-loans ratio as a proxy of the loan portfolio's riskiness, we find that higher level of risk in the loan portfolio is associated with higher levels of bank tail risk. This is in line with the positive association between non-performing-loans ratios and the level of volatility documented by, e.g., Stiroh (2006a). The positive relation to bank risk drives the positive association between non-performing-loans ratios and systemic risk.

The model with a further decompositions of the loan portfolio is presented in Table 4. The coefficients for loan types report the effect relative to the impact of loans secured with real estate, which account for 64% of the loan portfolios on average. The regression results show that banks with relatively large investments in agricultural loans as a substitute for real estate loans tend to be relatively independent of shocks in the banking system. Investment in commercial and industrial loans tends to be associated with the most significant increase in the sensitivity to severe shocks in the financial system.

In the traditional business model lending activities are funded with deposits. The deposit funding gap, i.e., the difference between the loans-to-assets ratio and the deposits-to-assets ratio, is an indicator to what extent banks rely on other funding sources for their lending business. From Table 2, Model (1), we observe that banks with a 10%-point larger deposit funding gap are associated with a 2.4% stronger link to financial system and a 1.9% higher level of sensitivity to severe shocks in the financial system. This result is consistent with the study of López-Espinosa et al. (2012), who document that short-term wholesale funding increases systemic risk as measured by ΔCoVaR. Similarly, Bologna (2015) documents that financial institutions with higher deposit funding gaps were more likely to fail during the 2007-2009 crisis period. Hence, we conclude that institutions with more traditional funding profile tend to be less sensitive to severe shocks in the system because of a weaker link to the system in the case of financial stress.

Finally, to assess the relation with the conservativeness of banks' 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: banks with a 10%-point higher growth rate of assets are associated with 2.6% higher sensitivity to large shocks in the financial system. This is due to the relation to bank tail risk: a 10%-point higher growth rate of assets is associated with an approximately 2.1% 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 the actual market risks. Further, higher capital may have the unintended effect of enabling banks to take more tail risk; see Perotti et al. (2011). Consequently, the empirical interrelationship between bank capital and systemic risk may 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 the relation between capital buffers and 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 1%-point higher tangible equity ratio is with an approximately 2.9% lower sensitivity to extreme shocks. The driver of this relation 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, Ellul and Yerramilli (2013) observe a positive relation between bank capital and tail risk. We observe an insignificant negative relation between bank capital and bank tail risks.

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. The estimation results show that a 1%-point higher Return-on-Equity is associated with a 0.4% lower level of bank risk and a 0.4% lower sensitivity to large shocks in the financial system. The negative relation between bank profitability and tail risk is also 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).[22] Both the actual capital buffers and the profitability are negatively related to systemic risk. However, the interrelationship with the different dimensions of systemic risk differs. Banks with higher actual capital buffers are less sensitive to large shocks because of a weaker link to the system in case of financial stress, while banks with the ability to build new capital buffers are perceived as less systemically risky because of a lower overall level of risk.

[22] We refer to the study of Boyd and De Nicoló (2005) for a discussion of the relation between bank risk and competition.

4.5 Systemic risk and conventional risk measures

The contribution of our paper is to demonstrate how systemic risk – when measured from a few tail observations only – can be decomposed into bank tail risk and the strength of the link between the bank and the system in financial distress. Although it is new to the literature to provide an empirical and theoretical decomposition when estimating systemic risk from a few tail observations, the idea of decomposing systemic risk does appear in the literature. For example, Acharya et al. (2009) show that, under the assumption of multivariate normality, the systemic risk of a bank depends on its standard deviation and its correlation with the system. Moreover, Nijskens and Wagner (2011) attribute changes in the systematic risk of banks to changes in standard deviations and changes in correlation. However, the decompositions in these studies are based on conventional risk measures such as correlation and standard deviations. A remaining empirical question is whether the assessment of systemic risk based on extremes may provide different insights. We address this question by adding conventional risk measures to our baseline models.

Measuring systemic risk based on extremes is important because the dependence structure and risks may change in case of large negative shocks in the financial system. By contrast, using conventional risk measures, such as standard deviation and correlation, requires assuming similar dynamics for large negative shocks and moderate shocks. For example, if the linear relation $R_i = \beta_i R_s + \varepsilon$ holds independently of whether R_s is extremely negative or not, then we would have $\beta_i^T = \beta_i$. In this case, estimating β_i instead of β_i^T would also provide a good description of the sensitivity of bank i to large adverse shocks in the financial system. Applying ordinary least squares gives $\hat{\beta}_i = \hat{\rho}_i \times (\hat{\sigma}_i/\hat{\sigma}_s)$, where $\hat{\rho}_i$ is the correlation between R_i and R_s and $\hat{\sigma}_i/\hat{\sigma}_s$ is the ratio of their standard deviations. Hence, a decomposition of $\hat{\beta}_i$ on the log level arises as $\log \hat{\beta}_i = \log \hat{\rho}_i + \log(\hat{\sigma}_i/\hat{\sigma}_s)$. If the estimation based on extremes provides no new information on the sensitivity of banks to large adverse shocks in the financial system, adding $\log \hat{\rho}_i$ and $\log(\hat{\sigma}_i/\hat{\sigma}_s)$ as additional explanatory variables for systemic risk and its subcomponents is expected to render most, if not all, coefficients insignificant.

The estimation results after adding the conventional risk measures to our baseline specification are presented in Table 5. A first observation is that the model for systemic linkage puts a relatively strong positive weight on the correlation, while the model for bank tail risk puts a relatively strong positive weight on the ratio between the standard deviations. Moreover, the explanatory power of both models increases considerably, especially for the model on bank tail risk. This means that the standard deviation and correlation carry a considerable amount of information on the two components of systemic risk that are estimated based on extreme observations only. Apparently, conventional risk measures may provide a relatively strong signal about the potential values of extreme risk measures in the context of systemic risk.

The relationships between bank characteristics and the subcomponents of systemic risk while controlling for the relation with conventional risk measures follows from their coefficients in Table 5, Model (2) and (3). Most of the coefficients in the model using bank tail risk as dependent variable turn insignificant. These bank characteristics thus provide little information on the level of bank tail risk in addition to the information carried in the conventional risk measures. By contrast, many coefficients remain significant after adding the conventional risk measures to the model for systemic linkage. Hence, bank characteristics do provide additional information on the dependence between the bank and the system in financial distress which is not carried in the correlation coefficient. In particular, banks with larger size, lower capital buffers and less non-interest income have a stronger link to the system in financial distress than what their correlations would suggest.

The relation between bank characteristics and systemic risk while controlling for conventional risk measures follows from the extent to which these measures capture bank tail risk and systemic linkage. Table 5, Model (1) shows that many coefficients remain significant in the model for systemic risk. With the aforementioned results for the subcomponents, the main reason is because of the systemic linkage dimension. This suggests that conventional analysis does not capture the relation with systemic risk well because of a different dependence structure in case of extreme shocks in the financial system. This analysis further supports the importance of broad efforts to properly handle the dependence structure under extreme market conditions. Examples on this direction are quantile regressions to estimate CoVaR (Adrian and Brunnermeier (2011)), dynamic conditional correlation models to estimate SRISK (Brownlees and Engle (2015)) and extreme value approaches to estimating MES (Acharya et al. (2009) and Cai et al. (2015)).

4.6 Robustness checks

In this subsection we discuss several departures from our baseline methodology. Table 6 presents robustness checks for the baseline model specification in Table 2, Model (1).

The relationship between systemic risk and lagged bank characteristics is expected to be weaker than the contemporaneous relationship. In Table 6, 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 model is estimated using GMM with instrumental variables to avoid additional endogeneity issues as a result of using simultaneous regressors. The instruments are the explanatory variables in the quarter preceding the four-year estimation window from the model specifications in Table 3. Over-identification is not rejected based on the Hansen J-test statistic, while under-identification is rejected based on the Kleibergen-Paap rk LM-statistic. The most notable changes in this specification are the larger impact of profitability and asset growth on systemic risk. A potential explanation is that the contemporaneous profitability and asset growth are associated with systemic risk, but that their past values are noisy proxies for their future values.

Another potential concern is that the bank characteristics in the predictive regressions do not really precede the estimation horizon of the systemic risk measures, because FR Y-9C reports are released with a small time lag. To address this concern we regress the systemic risk measure and its subcomponents on bank characteristics two quarters before the four-year estimation window (unreported). Our baseline results are hardly affected by this change.[23] This raises confidence that our results are not strongly affected by this issue.

[23] The significant coefficient on profitability in the model with systemic risk in Table 2 becomes weakly significant when regressing on bank characteristics two quarters before the four-year estimation window.

Model (2) includes bank fixed effects. The consequence is that some of 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 coefficients for asset growth and return on equity turn insignificant. Hence, although banks with structurally lower profitability and structurally higher growth are associated with a higher level of systemic risk, we do not find statistical evidence that changes in these bank characteristics result in changes in their systemic risk.

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 1.5% 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 (3). Although the coefficient does not change much, the deposit funding gap turns significant from weakly significant. Moreover, bank profit turns insignificant, which suggests that caution is required when using high bank profit as an indicator of low systemic risk.

Systemic risk may be nonlinearly related to bank size. This is somewhat suggested by the pattern in Figure 1. Therefore, we separately estimate the relation for smaller and larger banks. Model (4) is estimated based on bank-year observations for banks with total assets less than USD 10 billion, Model (5) includes only bank-year observations for banks with total assets more than USD 10 billion. 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 and insignificant among larger banks, which is line with the nonlinear relation between bank size and risk documented by De Nicoló (2000). Similar observations hold true for bank capital, bank profitability, cost-to-income and asset growth.

As a further robustness check, we include the log of the number of full-time equivalent employees as an alternative measure for bank size in Model (6). Similarly, we estimate a specification while directly including log(Assets) (unreported). Both models change the interpretation of the coefficients of the other variables relative to the baseline specification. In the baseline specification, the coefficients show the relation between bank characteristics and systemic risk if bank size is assumed to respond to changes in the other variables. Specifications with log(Number of Employees) and log(Assets) estimate the interrelationships with the other variables if bank size is assumed to be fixed. Most coefficients in the model do not change, although the magnitude of some coefficients change. Most notable are the smaller coefficients for the capital ratio, the deposit funding gap and non-interest income. This suggests that part of the relation between systemic risk and these bank characteristics is due to the fact that banks with lower capital ratios, larger deposit funding gaps and a larger share of non-interest income tend to have larger size. Nevertheless, except for the deposit funding gap, the coefficients remain significant. This shows that the relations to bank size does not account completely for the relations of the capital ratio and non-interest income to systemic risk.

5 Concluding remarks

In this paper, we analyze how characteristics of bank business models are related to systemic risk through its two dimensions: systemic linkage and tail risk. We employ an EVT approach to estimate a systemic risk measure which facilitates the empirical decomposition of 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 obtain further insight on how this relation is established via the two dimensions.

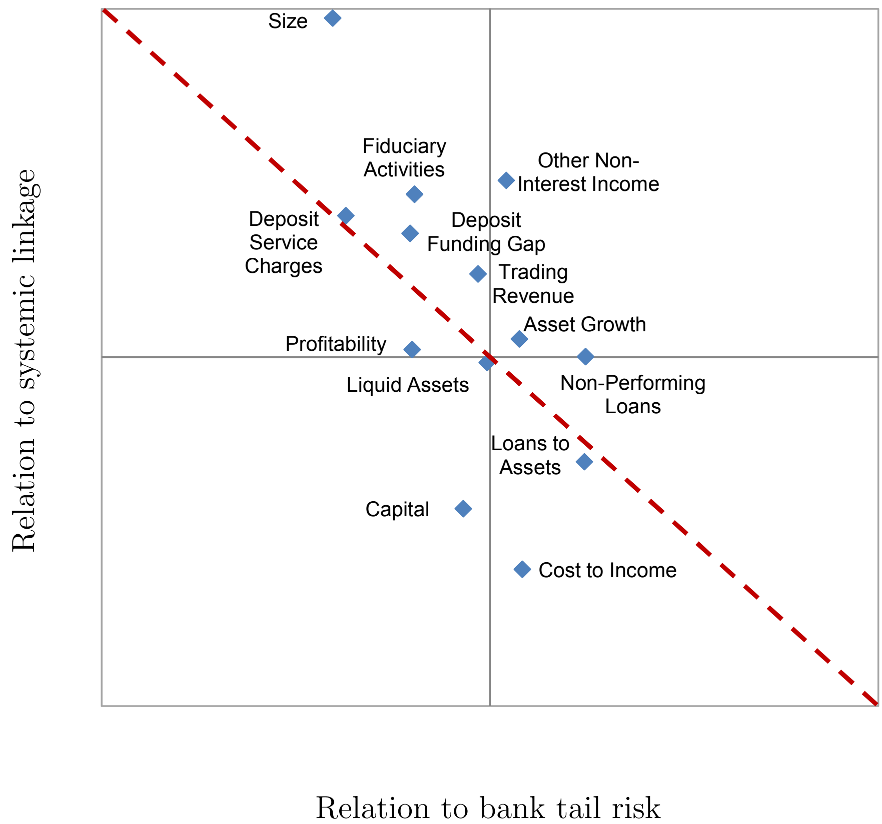
Our main empirical findings are illsutrated in Figure 3. The figure shows a scatter based on the estimated coefficients in the models for systemic linkage and bank risk; see Table 3, Models (2) and (3), respectively. Each dot represents a single bank characteristic. The horizontal location of a bank characteristic depends on the standardized coefficient in Model (2), its vertical location depends on the standardized coefficient in Model (3).[24] Hence, a characteristic located far away from the vertical axis indicates that the characteristic is strongly related to bank tail risk. Similarly, characteristics far away from the horizontal axis correspond to characteristics that are strongly related to systemic linkage. In addition, the dashed diagonal refers to the positions in the diagram at which the two relations precisely cancel 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 characteristics of banks' business models 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 stronger relations to the tail risk of a bank taken in isolation. Moreover, from a purely microprudential point of view, bank characteristics close to the vertical axis are somewhat irrelevant for regulation. From a macroprudential point of view the important bank characteristics are far away from the diagonal as those have stronger relations to systemic risk.

The micro- and macroprudential objectives for regulation may differ in scope. For example, trading revenue and other non-interest income are very close to the vertical axis and would not be regarded as effective indicators for differentiating banks' tail risks. However, these indicators are located above and away from the diagonal. Consequently, trading revenue and other non-interest income, including, for example, investment banking, venture capital revenues and net gains on loans sales, have positive relations to banks' systemic risk. In addition, the policy implications of the micro- and macroprudential objectives may differ in direction. For example, large banks are generally associated with less tail risk. However, in Figure 3 bank size is located far above the diagonal, which implies that its relation to systemic risk has an opposite sign. Discouraging large banks may

[24] Due to the standardization, a larger distance with respect to one of the axes means a larger expected difference in the corresponding dependent variable with respect to a standard deviation difference 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 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 $\log SL_{it}$ in Model (2) and the coefficient for $\log IR_{it}$ in Model (3), respectively. The magnitude of the coefficients is normalized by the standard deviation of the relevant variable.

help to enhance stability of the financial system, but may also increase risk at individual institutions by reducing diversification possibilities within each bank.

To conclude, 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 only be on characteristics related to bank risk at an individual level, but also on characteristics related to bank's systemic linkage. Whether bank characteristics are relevant to systemic risk depends on how the two relations to bank tail risk and systemic linkage precisely balance. This study is a first step to assess this issue in the context of extremely adverse shocks. 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 policy implications following from the two regulatory objectives may differ in scope and direction. In the latter case it will be the difficult task of the regulator to search for the right balance between the micro- and macroprudential objectives of regulation.

References

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.

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

V.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, L.H. Pedersen, T. Philippon, and M. Richardson. How to calculate systemic risk surcharges. In J.G. Haubrich and A.W. Lo, editors, *Quantifying systemic risk*, pages 175–212. University of Chicago Press, 2013.

V.V. Acharya, I. Drechsler, and Ph. Schnabl. A pyrrhic victory? Bank bailouts and sovereign credit risk. *Journal of Finance*, 69(6):2689–2739, 2014.

T. Adrian and M.K. Brunnermeier. CoVaR. *NBER Working Paper*, 17454, 2011.

L. Allen, T.G. Bali, and Y. Tang. Does systemic risk in the financial sector predict future economic downturns? *Review of Financial Studies*, 25(10):3000–3036, 2012.

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

L. Baele, V. De Bruyckere, O. De Jonghe, and R. Vander Vennet. Do stock markets discipline US bank holding companies: Just monitoring, or also influencing? *North American Journal of Economics and Finance*, 29:124–145, 2014.

E. Balla, I. Ergen, and M. Migueis. Tail dependence and indicators of systemic risk for large US depositories. *Journal of Financial Stability*, 15:195–209, 2014.

G.D. Banulescu and E.I. Dumitrescu. Which are the SIFIs? A Component Expected Shortfall approach to systemic risk. *Journal of Banking & Finance*, 50:575–588, 2015.

S.M. Bartram, G.W. Brown, and J.E. Hund. Estimating systemic risk in the international financial system. *Journal of Financial Economics*, 86(3):835–869, 2007.

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*, 104(3):535–559, 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.

P. Bologna. Structural funding and bank failures. *Journal of Financial Services Research*, 47:81–113, 2015.

C. Borio. Towards a macroprudential framework for financial supervision and regulation? *CESifo Economic Studies*, 128(9):181–215, 2003.

C. Borio. The international monetary and financial system: Its Achilles heel and what to do about it. *BIS Working Papers*, 456, 2014.

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

J.H. Boyd, S. Kwak, and B. Smith. The real output losses associated with modern banking crises. *Journal of Money, Credit, and Banking*, 37(6):977–999, 2005.

C. Brownlees and R. Engle. SRISK: A conditional capital shortfall index for systemic risk measurement. *Working Paper*, 2015.

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

J.-J. Cai, J.H.J. Einmahl, L. Haan, and C. Zhou. Estimation of the marginal expected shortfall: the mean when a related variable is extreme. *Journal of the Royal Statistical Society: Series B*, 77(2):417–442, 2015.

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 Bandt, P. Hartmann, and J.L. Peydró. Systemic risk in banking: An update. In A.N. Berger, P. Molyneux, and J.O.S. Wilson, editors, *The Oxford Handbook of Banking*, pages 633–672. Oxford University Press, 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.

G. De Nicoló. Size, charter value and risk in banking: An international perspective. *Board of Governors of the Federal Reserve System International Finance Discussion Paper*, 689, 2000.

G. Dell'Ariccia, E. Detragiache, and R. Rajan. The real effect of banking crises. *Journal of Financial Intermediation*, 17(1):89–112, 2008.

A. Demirgüç-Kunt and H. Huizinga. Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads. *Journal of Banking & Finance*, 37(3):875–894, 2013.

R.S. Demsetz and P.E. Strahan. Diversification, size, and risk at bank holding companies. *Journal of Money, Credit and Banking*, 29(3):300–313, 1997.

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, C. Klüppelberg, and T. Mikosch. *Modelling extremal events for insurance and finance*, volume 33. Springer Verlag, 1997.

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

R. Fahlenbrach, R. Prilmeier, and R.M. Stulz. This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *Journal of Finance*, 67(6):2139–2185, 2012.

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.

E.B.G. Galati and R. Moessner. Macroprudential policy: A literature review. *Journal of Economic Surveys*, 27(5):846–878, 2013.

S. Giglio, B. Kelly, and S. Pruitt. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, forthcoming.

G. Girardi and A.T. Ergün. Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance*, 37(8):3169–3180, 2013.

R.E. Hall. Why does the economy fall to pieces after a financial crisis? *Journal of Economic Perspectives*, 24(4):3–20, 2010.

P. Hartmann, S. Straetmans, and C.G. de Vries. Banking system stability: A cross-Atlantic perspective. In M. Carey and R.M. Stulz, editors, *The Risks of Financial Institutions*, pages 133–192. University of Chicago Press, 2007.

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. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11):2036–2049, 2009.

X. Huang, H. Zhou, and H. Zhu. Systemic risk contributions. *Journal of Financial Services Research*, 42(1-2):55–83, 2012.

D.W. Jansen and C.G. De Vries. On the frequency of large stock returns: Putting booms and busts into perspective. *Review of Economics and Statistics*, 73(1):18–24, 1991.

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. Korinek. Systemic risk-taking: Amplicifcation effects, externalities and regulatory responses. *Working Paper*, 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(12):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.

T. Mikosch and C.G. De Vries. Heavy tails of OLS. *Journal of Econometrics*, 172(2): 205–221, 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*, 19(3):429–451, 2013.

J. Peek and E.S. Rosengren. Collateral damage: Effects of the Japanese bank crisis on real activity in the United States. *American Economic Review*, 90(1):30–45, 2000.

A. Penati and A. Protopapadakis. The effect of implicit deposit insurance on banks' portfolio choices with an application to international 'overexposure'. *Journal of Monetary Economics*, 21(1):107–126, 1988.

E.C. Perotti, L. Ratnovski, and R.E. Vlahu. Capital regulation and tail risk. *International Journal of Central Banking*, 7(4):123–163, 2011.

J.C. Rochet. Capital requirements and the behaviour of commercial banks. *European Economic Review*, 36(5):1137–1170, 1992.

S. Shaffer. Pooling intensifies joint failure risk. *Research in Financial Services: Private and Public Policy*, 6:249–280, 1994.

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 (6):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.

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

G.N.F. Weiß, S. Neumann, and D. Bostandzic. Systemic risk and bank consolidation: International evidence. *Journal of Banking & Finance*, 40:165–181, 2014.

C. Zhou. Are banks too big to fail? Measuring systemic importance of financial institutions. *International Journal of Central Banking*, 6(4):205–250, 2010.

Tables

Table 1: Descriptive statistics

VARIABLES	Mean	Sd	Min	p10	p90	Max
PANEL A						
Systemic risk						
Systemic Risk: $\hat{\beta}_{it}^{T}$	0.965	0.319	0.140	0.577	1.382	3.575
Systemic Linkage: SL_{it}	0.599	0.146	0.193	0.399	0.784	0.917
Bank Tail Risk: IR_{it}	1.648	0.552	0.512	1.116	2.268	7.716
PANEL B						
Main characteristics						
ln(Total Assets)	14.838	1.464	13.150	13.354	17.054	19.668
Tangible Equity Ratio	7.367	2.083	2.922	4.873	9.907	14.252
Non-Performing Loans Ratio	0.010	0.010	0.000	0.002	0.019	0.061
Cost to Income	0.626	0.105	0.368	0.498	0.752	0.972
Return on Equity	0.135	0.052	-0.058	0.077	0.194	0.269
Liquid Assets	0.069	0.061	0.011	0.022	0.151	0.337
Deposit Funding Gap	-0.111	0.138	-0.634	-0.290	0.050	0.377
Growth in Total Assets	0.033	0.064	-0.066	-0.015	0.087	0.392
PANEL C						
Non-interest income						
Non-Interest Income Share	0.260	0.138	0.052	0.123	0.429	0.763
Srvc Charges on Deposit Accounts Shr	0.076	0.038	0.000	0.028	0.125	0.192
Fiduciary Activities Income Share	0.039	0.066	0.000	0.000	0.085	0.470
Trading Revenue Share	0.006	0.018	-0.010	0.000	0.014	0.116
Other Non-Interest Income Share	0.138	0.117	0.014	0.044	0.260	0.702
PANEL D						
Loan portfolio						
Loans to Total Assets	0.643	0.128	0.145	0.484	0.781	0.872
Real Estate Loan Share	0.640	0.184	0.033	0.407	0.856	0.986
Commercial and Industrial Loan Shr	0.186	0.116	0.000	0.068	0.338	0.642
Consumer Loan Share	0.119	0.103	0.001	0.013	0.252	0.514
Agricultural Loan Share	0.010	0.020	0.000	0.000	0.032	0.110
Other Loan Share	0.039	0.062	-0.009	0.000	0.095	0.439

Descriptive statistics of the 13,498 bank-year observations used for the estimation of the models in Tables 2–4.

Table 2: Baseline results on systemic risk

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^T$	$\log SL_{it}$	$\log IR_{it}$
Bank Size (reslnTA)	0.072***	0.121***	-0.049***
	(0.013)	(0.007)	(0.011)
Tangible Equity Ratio	-0.029***	-0.028***	-0.001
	(0.005)	(0.003)	(0.004)
Non-Performing Loans Ratio	3.223***	-0.211	3.434***
	(0.905)	(0.746)	(0.721)
Cost to Income Ratio	-0.631***	-0.742***	0.111
	(0.126)	(0.069)	(0.107)
Return on Equity	-0.462**	-0.055	-0.408**
	(0.197)	(0.113)	(0.185)
Liquid Assets	-0.054	0.114	-0.168
	(0.185)	(0.151)	(0.179)
Deposit Funding Gap	0.190*	0.242***	-0.052
	(0.103)	(0.068)	(0.093)
Loans to Total Assets	-0.091	-0.197**	0.106
	(0.103)	(0.082)	(0.085)
Non-Interest Income Share	0.585***	0.668***	-0.084
	(0.084)	(0.055)	(0.075)
Growth in Total Assets	0.264***	0.057	0.207***
	(0.061)	(0.040)	(0.048)
Constant	0.775***	-0.005	0.780***
	(0.146)	(0.088)	(0.126)
Observations	13,498	13,498	13,498
Number of banks	510	510	510
R-squared	0.319	0.491	0.363
Partial R-squared	0.178	0.454	0.083
Time fixed effects	Yes	Yes	Yes
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	$\log \hat{\beta}^T_{it}$	$\log SL_{it}$	$\log IR_{it}$
Bank Size (reslnTA)	0.070***	0.120***	-0.050***
	(0.013)	(0.007)	(0.010)
Tangible Equity Ratio	-0.029***	-0.025***	-0.004
	(0.005)	(0.004)	(0.004)
Non-Performing Loans Ratio	3.066***	0.028	3.038***
	(0.874)	(0.740)	(0.685)
Cost to Income Ratio	-0.600***	-0.694***	0.095
	(0.129)	(0.068)	(0.106)
Return on Equity	-0.414**	0.052	-0.466**
	(0.198)	(0.115)	(0.182)
Liquid Assets	-0.043	-0.028	-0.015
	(0.189)	(0.159)	(0.176)
Deposit Funding Gap	0.141	0.335***	-0.194**
	(0.110)	(0.071)	(0.090)
Loans to Total Assets	-0.049	-0.260***	0.211***
	(0.109)	(0.083)	(0.081)
Growth in Total Assets	0.244***	0.100**	0.143***
	(0.058)	(0.039)	(0.045)
Fiduciary Activities Income Share	0.496***	0.849***	-0.353***
	(0.142)	(0.091)	(0.127)
Srvc Charges on Dep Accnts Shr	0.114	1.294***	-1.180***
	(0.253)	(0.191)	(0.203)
Trading Revenue Share	1.377***	1.583***	-0.206
	(0.456)	(0.334)	(0.381)
Other Non-Interest Income Share	0.565***	0.522***	0.043
	(0.101)	(0.066)	(0.071)
Constant	0.746***	-0.043	0.789***
	(0.148)	(0.089)	(0.120)
Observations	13,498	13,498	13,498
Number of banks	510	510	510
R-squared	0.321	0.502	0.386
Partial R-squared	0.180	0.466	0.117
Time fixed effects	Yes	Yes	Yes
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 4: Systemic risk and different loan types

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	$\log SL_{it}$	$\log IR_{it}$
Bank Size (reslnTA)	0.071***	0.120***	-0.050***
	(0.013)	(0.007)	(0.011)
Tangible Equity Ratio	-0.028***	-0.026***	-0.002
	(0.005)	(0.003)	(0.004)
Non-Performing Loans Ratio	3.160***	-0.179	3.339***
	(0.854)	(0.661)	(0.719)
Cost to Income Ratio	-0.578***	-0.667***	0.089
	(0.124)	(0.068)	(0.106)
Return on Equity	-0.416**	0.012	-0.428**
	(0.198)	(0.110)	(0.186)
Liquid Assets	-0.155	-0.022	-0.133
	(0.186)	(0.140)	(0.176)
Deposit Funding Gap	0.159	0.221***	-0.062
	(0.105)	(0.064)	(0.092)
Loans to Total Assets	-0.042	-0.162**	0.121
	(0.104)	(0.078)	(0.085)
Non-Interest Income Share	0.500***	0.552***	-0.052
	(0.090)	(0.054)	(0.080)
Growth in Total Assets	0.269***	0.073**	0.195***
	(0.060)	(0.037)	(0.048)
Agricultural Loan Share	-0.512	-0.829**	0.317
	(0.537)	(0.329)	(0.385)
Commercial and Industrial Loan Shr	0.228**	0.359***	-0.132*
	(0.090)	(0.050)	(0.073)
Consumer Loan Share	0.035	0.189***	-0.154
	(0.103)	(0.060)	(0.097)
Other Loan Share	0.289	0.266**	0.024
	(0.228)	(0.120)	(0.175)
Constant	0.654***	-0.176**	0.831***
	(0.150)	(0.089)	(0.125)
Observations	13,498	13,498	13,498
Number of banks	510	510	510
R-squared	0.328	0.520	0.367
Partial R-squared	0.188	0.486	0.0892
Time fixed effects	Yes	Yes	Yes
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: Results after controlling for normal risk measures

	(1)	(2)	(3)
VARIABLES	$\log \hat{\beta}_{it}^{T}$	$\log SL_{it}$	$\log IR_{it}$
$\log \rho_{it}$	0.168***	0.171***	-0.003
	(0.010)	(0.010)	(0.003)
$\log(\sigma_{it}/\sigma_{st})$	0.933***	-0.035*	0.968***
	(0.020)	(0.020)	(0.013)
Bank Size (reslnTA)	0.033***	0.036***	-0.003
	(0.006)	(0.005)	(0.002)
Tangible Equity Ratio	-0.012***	-0.013***	0.001
	(0.002)	(0.002)	(0.001)
Non-Performing Loans Ratio	-0.120	0.140	-0.260
	(0.408)	(0.400)	(0.192)
Cost to Income Ratio	-0.217***	-0.228***	0.011
	(0.047)	(0.044)	(0.019)
Return on Equity	-0.134	-0.162**	0.029
	(0.083)	(0.072)	(0.035)
Liquid Assets	-0.009	0.017	-0.026
	(0.094)	(0.099)	(0.033)
Deposit Funding Gap	0.121***	0.141***	-0.021
	(0.041)	(0.037)	(0.020)
Loans to Total Assets	-0.075	-0.112***	0.037*
	(0.048)	(0.041)	(0.020)
Non-Interest Income Share	0.257***	0.263***	-0.006
	(0.038)	(0.038)	(0.016)
Growth in Total Assets	0.000	-0.006	0.007
	(0.025)	(0.023)	(0.013)
Constant	-0.102**	-0.024	-0.078***
	(0.051)	(0.047)	(0.028)
Observations	13,293	13,293	13,293
Number of banks	506	506	506
R-squared	0.807	0.713	0.943
Partial R-squared	0.767	0.691	0.917
Time fixed effects	Yes	Yes	Yes
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 correlation is the correlation between R_i and R_s estimated over the same horizon. The ρ_{it}, σ_{it} and σ_{st} are respectively the correlation between R_i and R_s, and the standard deviations of R_i and R_s estimated over the same horizon. All other 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

	IV-GMM (1)	FE (2)	Zero β^Ts (3)	Small (4)	Large (5)	FTEs (6)
VARIABLES	$\log \hat{\beta}_{it}^T$	$\log \hat{\beta}_{it}^T$	$\hat{\beta}_{it}^T$	$\log \hat{\beta}_{it}^T$	$\log \hat{\beta}_{it}^T$	$\log \hat{\beta}_{it}^T$
Bank Size (reslnTA)	0.065***	0.051**	0.061***	0.110***	0.028	
	(0.012)	(0.020)	(0.011)	(0.021)	(0.020)	
Log(Number of Employees)						0.063***
						(0.011)
Tangible Equity Ratio	-0.018***	-0.019***	-0.026***	-0.036***	-0.011	-0.019***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.011)	(0.005)
Non-Performing Loans Ratio	3.533**	7.111***	3.499***	3.865***	3.205**	3.190***
	(1.683)	(1.362)	(1.196)	(1.068)	(1.330)	(0.896)
Cost to Income Ratio	-0.573***	-0.303**	-0.440***	-0.786***	-0.157	-0.431***
	(0.198)	(0.146)	(0.116)	(0.152)	(0.178)	(0.115)
Return on Equity	-1.001**	-0.120	-0.249	-0.544**	-0.252	-0.382**
	(0.471)	(0.170)	(0.195)	(0.218)	(0.246)	(0.194)
Liquid Assets	0.225	0.261	-0.122	-0.090	0.042	-0.188
	(0.221)	(0.234)	(0.192)	(0.213)	(0.334)	(0.182)
Deposit Funding Gap	0.218*	0.223	0.209**	0.314**	0.413**	-0.000
	(0.126)	(0.164)	(0.097)	(0.135)	(0.180)	(0.101)
Loans to Total Assets	-0.161	-0.445**	-0.125	-0.152	-0.237	0.023
	(0.114)	(0.206)	(0.097)	(0.131)	(0.147)	(0.101)
Non-Interest Income Share	0.489***	0.356**	0.545***	0.706***	0.506***	0.229**
	(0.117)	(0.157)	(0.082)	(0.120)	(0.146)	(0.098)
Growth in Total Assets	3.275**	0.019	0.239***	0.301***	0.147**	0.287***
	(1.330)	(0.044)	(0.062)	(0.069)	(0.066)	(0.061)
$\log(\hat{\beta}_{it-16}^T)$	0.286***					
	(0.033)					
Constant	0.186	0.069	1.403***	0.895***	0.208	0.089
	(0.180)	(0.176)	(0.134)	(0.183)	(0.170)	(0.146)
Hansen J statistic (p value)	1.7 (0.65)					
Kleibergen-Paap LM (p value)	46.1 (0.00)					
Observations	9,799	13,498	13,704	11,138	2,360	13,498
Number of banks	428	510	511	464	96	510
R-squared	0.379	0.577	0.288	0.318	0.281	0.315
Partial R-squared	0.256	0.051	0.161	0.134	0.216	0.173
Time fixed effects	Yes	No	Yes	Yes	Yes	Yes
Clustering at bank level	Yes	Yes	Yes	Yes	Yes	Yes
Clustering at time level	No	Yes	Yes	Yes	Yes	Yes

Estimates for $\hat{\beta}_{it}^T$ after several departures from our baseline methodology in Table 2. Model (1) provides estimated coefficients for contemporaneous bank characteristics, measured as the average over the 16 quarterly observations within the four-year estimation window of $\hat{\beta}_{it}^T$. Model (1) is estimated using GMM with instrumental variables. The instruments are the explanatory variables in Table 3 in the quarter preceding the four-year estimation window. Model (2) includes bank fixed effects. Model (3) 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). Model (4) only includes bank-year observations for banks with total assets smaller than USD 10 billion. Model (5) is estimated with bank-year observations for banks with total assets larger USD 10 billion. In Model (7) we replace the original variable for bank size by 'log(Number of Employees)'. 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.