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RESEARCH ARTICLE

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Systemic risk and bank business models

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Summary
In this paper, we decompose banks' systemic risk into two dimensions: the risk of a bank ("bank tail risk") and the link of the bank to the system in financial distress ("systemic linkage"). Based on extreme value theory, we estimate a systemic risk measure that can be decomposed into two subcomponents reflecting these dimensions. Empirically, we assess the relationships of bank business models to the two dimensions of systemic risk. The observed differences in these relationships partly explain why micro- and macroprudential perspectives sometimes have different implications for banking regulation.

1 | INTRODUCTION

Over the past decade, the emphasis of banking regulation has shifted from a microprudential approach towards a more macroprudential approach. Before the 2007–09 financial crisis, regulation focused predominantly on the soundness of financial institutions taken in isolation. Prudential regulation aimed at curbing excessive risk taking as a consequence of, for example, deposit insurance. In the crisis, a substantial fraction of the global financial system became severely distressed, which led to a sharp decline in real economic activity. This made it painfully clear that, besides the stability of individual banks, it is also important for financial stability whether bank failures tend to occur in clusters.

With the concern of system-wide distress in mind, the macroprudential objective of prudential regulation—that is, limiting systemic risk—gained traction on the regulatory agenda. The scope of interest for banking regulators has widened, since aspects such as "common exposures and interlinkages across institutions," which may be irrelevant from a microprudential perspectives, are important from a macroprudential point of view (see Borio, 2003, 2014). Such differences between the micro- and macroprudential perspective may lead to different priorities in, or even opposing policy implications for, banking regulation.

The origin of potentially conflicting views stemming from differences between the micro- and macroprudential perspectives can be clarified by a conceptual decomposition into two subcomponents of banks' systemic risk on the cross-sectional dimension.[1] The first component is the overall risk of a bank ("bank tail risk"). The higher the level of a bank's tail risk, the larger is the bank's unconditional probability of failure. The second component is the connection between an institution's extreme losses and systemic events ("systemic linkage"). It indicates whether the tail risk of a bank is more likely to materialize during a financial crisis. The stronger the systemic linkage, the larger is the proportion of a bank's overall tail risk associated with severely adverse shocks in the financial system. While the first component is relevant from both perspectives, it is only the macroprudential perspective that is concerned with the second component.

[1]Throughout the paper we focus on the cross-sectional dimension of systemic risk. See Galati and Moessner (2013, section 3.1) for an overview of the rich literature on systemic risk in the time dimension, or see, for example, De Bandt et al. (2010) for a general survey on systemic risk.

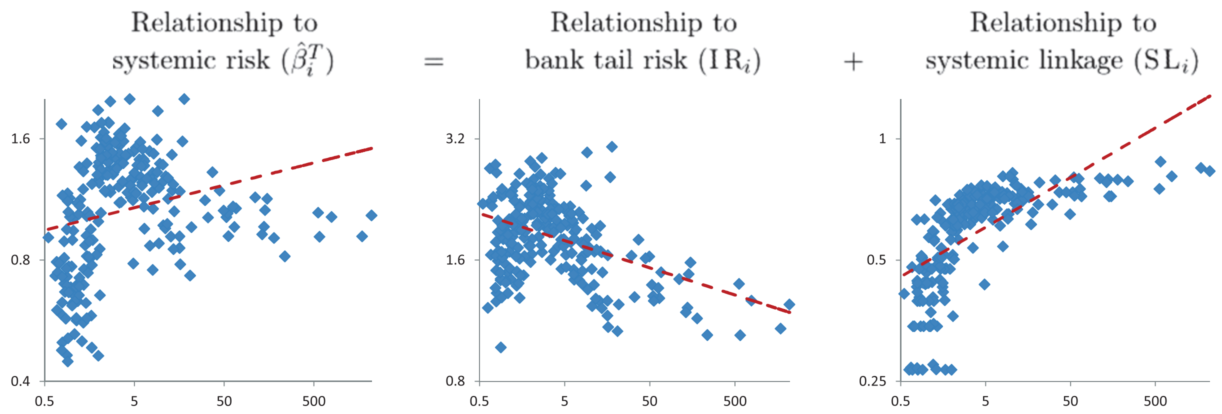

FIGURE 1 Systemic risk and bank size. The figure shows the relationship between different dimensions of systemic risk (vertical axes) and bank size (on the horizontal axis) in 2007:Q4. Bank size is measured by total assets (USD billions). The dashed lines show fitted linear trends. The measures are defined in Equations 1 and 5 [Colour figure can be viewed at wileyonlinelibrary.com]

The main contribution of this paper is the empirical decomposition of banks' systemic risk into these two components using extreme value theory (EVT). We apply the EVT approach of Van Oordt and Zhou (2017) to estimate the systemic risk of a bank as the sensitivity of a bank's stock returns to extremely adverse shocks in the financial system based on a few tail observations. The subcomponents of this estimator have a natural economic interpretation as the level of a bank's tail risk (based on the bank's value-at-risk) and its systemic linkage (based on the bank's tail dependence with the system). To demonstrate this empirically, we decompose the systemic risk of US bank holding companies (BHCs). We use this decomposition to estimate how banks' business models affect systemic risk through each of the two subcomponents.

An example of how the decomposition can provide deeper insight into the interrelationships of bank characteristics to systemic risk is provided in Figure 1. The figure plots banks' size against estimates of the systemic risk measure and the two subcomponents measuring bank tail risk and systemic linkage, respectively.[2] We observe downward and upward sloping trends in the size-tail risk and size-systemic linkage interrelationships, respectively. Since the latter dominates the former, larger banks exhibit higher levels of systemic risk. From this decomposition, we may conclude not only that size relates positively to systemic risk, but also that this is a result of larger banks exhibiting a stronger link to the system in financial distress.

Research on systemic risk has intensified over the past decade. Benoit et al. (2017) provided a careful review of the recent systemic risk literature in a broader context. They distinguished two approaches to measuring systemic risk in the literature: a "source-specific approach" and a "global approach." Papers that follow the source-specific approach to systemic risk consider specific sources of systemic risk, such as contagion risk, liquidity crises or correlated risk taking. These sources of systemic risk are often identified in the context of a theoretical model. Regulators have introduced several tools to monitor these different channels of systemic risk. Papers that follow the global approach aim to derive global measures of systemic risk, potentially encompassing all the mechanisms studied in the first group of papers. Benoit et al. (2017) categorize commonly applied measures such as marginal expected shortfall (MES) (Acharya et al., 2009, 2017), SRISK (Acharya et al., 2017), and CoVaR (Adrian & Brunnermeier, 2016) into this second group. The systemic risk measure used in the present paper best fits within this second category.[3] Theoretically, it is closely related to MES, and we will also discuss its theoretical relationship to several other measures that follow a global approach to systemic risk.

Our study contributes to three strands of literature. First, our systemic risk measure and its decomposition help to a establish a connection between studies applying tail dependence as a proxy of systemic risk (De Jonghe, 2010, Hartmann et al., 2007) and those applying other measures such as MES, SRISK and Exposure CoVaR. The systemic linkage component quantifies all cross-sectional variation in the tail dependence, as tail dependence abstracts from a bank's marginal risk. The sensitivity of banks to large shocks in the financial system depends both on the tail dependence and the levels of banks' marginal risk. It is straightforward to derive that this measure quantifies all cross-sectional variation in the MES, which is defined as the expected loss of a bank conditional upon an extremely adverse shock. In other words, the

[2]The log of the systemic risk measure equals the sum of the log of its two subcomponents.

[3]The measures of systemic risk and systemic linkage do not have a directional flavor: They measure the comovement, regardless of the underlying cause of shock propagation. Statistically, one could measure the sensitivity of the system to extreme shocks of an institution instead. Although this would change the statistical direction of the conditioning event, it does not change the direction of the underlying cause of the comovement; for an excellent discussion see, for example, Adrian and Brunnermeier (2016, subsections II.C and II.D).

two result in equivalent rankings of systemic risk across financial institutions. Moreover, we show how the Exposure CoVaR relates to our systemic risk measure and the tail dependence. In other words, it can be regarded as an alternative way to aggregate the systemic linkage and individual risk components into a systemic risk measure. To summarize, the present study demonstrates the theoretical connection across the existing systemic risk measures by demonstrating how they aggregate information differently regarding tail dependence and banks' marginal risk.

Second, 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 besides the aforementioned measures, see 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). It is not the purpose of the present paper to improve rankings of financial institutions in terms of systemic risk. Instead, we provide more insight into systemic risk by the aforementioned decomposition into bank tail risk and systemic linkage.

Third, 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 its indicators 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., Anginer et al., 2014; Brunnermeier et al., 2012; Girardi & Ergün, 2013; López-Espinosa et al., 2012; López-Espinosa et al., 2013; Vallascas and Keasey, 2012). On the systemic risk level, most of our results are not novel in the sense that they confirm empirical relationships to systemic risk established in earlier studies. However, what is new is that we also identify whether these relationships are through the bank's tail risk or the systemic linkage dimension. This distinction is important in the regulatory arena. While the level of bank tail risk is relevant for both the micro- and macroprudential objectives of regulation, systemic linkage is relevant for the macroprudential objective only. The distinction therefore helps to identify areas in which micro- and macroprudential objectives may lead to differences in the scope or direction of regulation. Moreover, depending on the weights given to both objectives, the two components should receive different weights in the regulatory debate.

From our empirical exercise we document the following observations. First, evaluating systemic risk based on conventional measures, such as correlations and standard deviations, does not provide a full picture of 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 good description of relative differences in bank tail risk. This stresses the importance of exploring new approaches to modeling the dependence structure among financial institutions in extreme events.

Second, the weak correlation between systemic risk and bank tail risk, as documented by Acharya et al. (2009) and Adrian and Brunnermeier (2016), for example, is a consequence of the very low correlation between the level of bank tail risk and systemic linkage. A prudential approach focusing solely on bank risk does not incorporate the impact on systemic linkages. Consequently, such an approach falls short in curtailing a bank's systemic risk.

Third, banks engaging in more nontraditional banking activities are generally associated with a higher level of systemic risk, because such banks are linked more strongly to the system in financial distress. Hence these nontraditional activities are relevant from a macroprudential perspective, even though there may seem little reason to be concerned about these activities from a purely microprudential point of view.

2 | DECOMPOSITION OF SYSTEMIC RISK

In this section we discuss our framework for decomposing banks' systemic risk into bank tail risk and systemic linkage. The subsections discuss successively the systemic risk measure, its estimation methodology, its decomposition of systemic risk into bank tail risk and systemic linkage, and its relationship to several other systemic risk measures.

2.1 | 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 relationship between indicators of the status of one bank and the system (see, e.g., Nijskens & Wagner, 2011). However, the relationship 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 & Wagner, 2012; 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 relationship between the equity returns of a financial institution and the financial system conditional upon extremely adverse shocks in the financial system.[4]

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 the systemic risk of bank i by the coefficient β_i^T in the following linear tail model:

$$R_i = \beta_i^T R_s + \varepsilon_i, \quad \text{for} \quad R_s < -\text{VaR}_s(\bar{p}), \tag{1}$$

where $\text{VaR}_s(\bar{p})$ is the "value-at-risk" of an equity investment in the financial system, which is defined as the loss on a dollar investment that is exceeded with some small probability $\bar{p}$—that is, $\text{VaR}_s(\bar{p}) := -\sup\{c : \Pr(R_s \leq c) \leq \bar{p}\}$, and where ε_i represents the shocks from other sources which are assumed to be independent of the shocks in the financial system represented by R_s. The index T indicates that coefficient β_i^T describes the relationship between bank i and the financial system only in the event of extremely adverse shocks in the financial system—that is, only if $R_s < -\text{VaR}_s(\bar{p})$. Hence the linear tail model in Equation 1 does not make any assumptions on the relationship between the bank and the financial system under normal conditions.

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 the event of an extremely adverse shock in the financial system. As mentioned before, this measure does not reveal the underlying cause of the comovement. Note, however, that, regardless of the underlying cause, stronger comovement 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—that is, in the event of a widespread disruption of the financial system.[5] Hence the regulator may even be concerned with banks suffering passively from systemic shocks, because such banks impose a larger expected cost on the real economy in a potential crisis (see, e.g., Acharya & Yorulmazer, 2007; Acharya et al., 2017; Dàvila & Korinek, 2018; Wagner, 2010).[6]

2.2 | Estimation

The main difficulty in estimating coefficient β_i^T is the small number of observations corresponding to extremely adverse shocks in the financial system. Given some low probability $\bar{p}$, only a few observations correspond to the tail scenario $R_s \leq -\text{VaR}_s(\bar{p})$. Therefore, there is a risk of large estimation uncertainty when estimating β_i^T from a small subset of observations by applying conventional methods such as an ordinary least squares (OLS) regression (see, e.g., Mikosch & De Vries, 2013). Instead, we estimate β_i^T using an EVT approach. Van Oordt and Zhou (2017) 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 (2016) 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., Embrechts et al., 1997; Jansen & De Vries, 1991). Let R_i and R_s follow heavy-tailed distributions with tail indices ζ_i and ζ_s, respectively.[7] Under mild conditions, Van Oordt and Zhou (2017) derive for $\beta_i^T \geq 0$ that

$$\beta_i^T = \lim_{p \to 0} \tau_i(p)^{1/\zeta_s} \frac{\text{VaR}_i(p)}{\text{VaR}_s(p)}, \tag{2}$$

where $\text{VaR}_i(p)$ and $\text{VaR}_s(p)$ are the value-at-risks 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

$$\tau_i(p) := \Pr(R_i < -\text{VaR}_i(p) | R_s < -\text{VaR}_s(p)). \tag{3}$$

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

[5] 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 references therein. Implicitly, we presume that it is important to avoid financial instability because of the cost it imposes on the real economy.

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

[7] 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 $t > 1$.

Empirically, all components in Equation 2 can be estimated by existing estimators in EVT. The estimator of β^T is thus given by combining the estimators of its components, as follows. With n observations on the pair (R_i, R_s), we consider the tail region as the k worst observations. The coefficient β_i^T is then estimated by

$$\hat{\beta}_i^T := \hat{\tau}_i(k/n)^{1/\hat{\zeta}_s} \frac{\widehat{\mathrm{VaR}}_i(k/n)}{\widehat{\mathrm{VaR}}_s(k/n)}, \tag{4}$$

where the tail index $\hat{\zeta}_s$ is the estimator proposed in Hill (1975), $\widehat{\mathrm{VaR}}_i(k/n)$ and $\widehat{\mathrm{VaR}}_s(k/n)$ 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 nonparametric 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, provided that k is a sequence depending on n such that $k := k(n) \to +\infty$ and $k(n)/n \to 0$ as $n \to +\infty$ (see Van Oordt & Zhou, 2017). In practice, samples are finite and k is fixed at a certain level. The choice of a low k results in a large estimation uncertainty, while choosing a high k results in a potential estimation bias. The results that we present below are not very sensitive to the choice of k. In our baseline results, we fix $k = 40$ using an estimation window of 4 years of daily returns. This corresponds to $k/n \approx 4\%$, which is similar to the level of k/n in other studies.[8] Our results and the micro- and macroprudential implications are robust to equivalent realistic choices of k. More specifically, the estimation results do not change much when setting a level of k in the range from 20 to 80 instead (available in the Supporting Information Appendix), but the explained variance and statistical significance of the regression models drop when setting k as low as 10 (such a low level of k results in a relatively high level of estimation uncertainty).[9]

2.3 | Decomposition

We assess how bank characteristics are related to a bank's sensitivity to severe shocks in the financial system, in particular, by being related to a bank's tail risk and/or to a bank's systemic linkage. We address such a distinction by decomposing the systemic risk measure β_i^T and its estimator into two components that represent measures of bank tail risk and systemic linkage, respectively. Consider the logarithmic transformation of the estimator of β_i^T in Equation 2 as

$$\log \hat{\beta}_i^T = \log \hat{\tau}_i(k/n)^{1/\hat{\zeta}_s} + \log \frac{\widehat{\mathrm{VaR}}_i(k/n)}{\widehat{\mathrm{VaR}}_s(k/n)} =: \log \mathrm{SL}_i + \log \mathrm{IR}_i. \tag{5}$$

Hence the sensitivity to extreme shocks is determined by two components: $\mathrm{IR}_i = \mathrm{VaR}_i(p)/\mathrm{VaR}_s(p)$ and $\mathrm{SL}_i = \tau_i(p)^{1/\zeta_s}$. The discussion below shows that these two components measure the two dimensions of systemic risk.

The first component, IR_i, is the ratio between the VaR of bank i and that of the financial index. Since the denominator $\mathrm{VaR}_s(p)$ 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 $\mathrm{VaR}_i(p)$s. Hence this component measures the level of bank tail risk, 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, implying 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, SL_i, measures the strength of the link between the bank and the system in financial distress. 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—that is, the distribution of R_i.[10] 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 bank tail risk. Hence it bears information on systemic linkage only. Moreover, a simple interpretation of the systemic

[8] See, for example, Jansen and De Vries (1991) ($k/n = 260/6,000$ and $12/294$) and Longin and Solnik (2001) (k/n around 4–5%).

[9] The level of n is determined by the length of the estimation window. Our choice for the length of the estimation window is in line with the common practice in the EVT literature of using a relatively long estimation horizon to achieve a relatively low estimation uncertainty (e.g., 4 or 5 years). Nevertheless, the results remain qualitatively unchanged when using an estimation window of 2 years instead (see the Supporting Information Appendix).

[10] It is easily verified that the level of $\tau_i(p)$ in Equation 3 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 $\mathrm{VaR}_B(p) = 2\mathrm{VaR}_A(p)$, which implies $\tau_A(p) = \Pr(R_A < -\mathrm{VaR}_A(p) | R_s < -\mathrm{VaR}_s(p)) = \Pr(2R_A < -2\mathrm{VaR}_A(p) | R_s < -\mathrm{VaR}_s(p)) = \Pr(R_B < -\mathrm{VaR}_B(p) | R_s < -\mathrm{VaR}_s(p)) = \tau_B(p)$.

linkage, SL_i, is the fraction of banks' tail risk that is associated with severe shocks in the financial system.[11] In our sample, this fraction is 60% on average.

From the discussion above, the subcomponent IR_i measures the tail risk of bank i, while the subcomponent SL_i measures the systemic linkage 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.

2.4 | Relationship to other measures

In a broader context, the β_i^T closely relates to several other measures that, based on the categorization of Benoit et al. (2017), follow a global approach to measuring systemic risk, such as MES, SRISK and Exposure CoVaR.

We start with a comparison to the tail dependence measure, $\tau_i(p)$, defined in Equation 3. Several papers directly rely on tail dependence as a proxy of systemic risk (see, e.g., Balla et al., 2014; De Jonghe, 2010; Hartmann et al., 2007; Weiß et al., 2014; Zhou, 2010).[12] The level of tail dependence is only related to one of the two subcomponents of β_i^T as discussed in the previous subsection. As a consequence, two banks with the same levels of tail dependence but different levels of marginal risk may exhibit considerable differences in their responses to severe shocks in the financial system.

There is a strong analogy between β_i^T and the MES measure of Acharya et al. (2009, 2017). With the MES_i defined as the expected loss of bank i conditional upon a severe shock in the financial system, it is straightforward to derive from the assumed linear tail model in Equation 1 that, for $p < \bar{p}$,

$$\mathrm{MES}_i(p) := -\mathbb{E}[R_i | R_s \leq -\mathrm{VaR}_s(p)] = -\beta_i^T \mathbb{E}[R_s | R_s \leq -\mathrm{VaR}_s(p)] = \beta_i^T \mathrm{ES}_s(p), \tag{6}$$

where $\mathrm{ES}_s(p)$ denotes the expected shortfall of R_s defined as $\mathrm{ES}_s(p) = -\mathbb{E}[R_s | R_s \leq -\mathrm{VaR}_s(p)]$. The expected shortfall of the financial system, $\mathrm{ES}_s(p)$, is the same for each and every bank. Hence any dispersion in the MES_i across institutions is because of cross-sectional differences in β_i^T. In other words, the β_i^T provides a full description of the cross-sectional variation in 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, $\mathrm{ES}_s(p)$.

The β_i^T is also related to the SRISK measure of Brownlees and Engle (2017) as a consequence of the relationship between SRISK and MES.[13] Let c denote the minimum market-based capital ratio at which the bank is believed to be in a sufficiently good shape. Then SRISK is defined as the expected shortfall relative to that minimum level, conditional upon a systemic event. With the systemic event defined as an adverse shock in the financial system[14] that occurs with probability p, we have

$$\mathrm{SRISK}_i(p) := -\mathbb{E}\left[c\,(D_i + W_i) - W_i | R_s^{\mathrm{LR}} \leq -\mathrm{VaR}_s^{\mathrm{LR}}(p)\right], \tag{7}$$

where the book value of debt is denoted by D_i, the market capitalization is denoted by W_i, and the superscript LR denotes the fact that SRISK usually conditions upon a long-run stress event, such as 6 months. Acharya et al. (2012) estimate the long-run MES (LRMES) from the daily $\mathrm{MES}_i(p)$ by applying a scaling factor C^{LR} as $\mathrm{LRMES}_i(p) \approx C^{\mathrm{LR}} \times \mathrm{MES}_i(p)$. Following this approximation, the relationship of SRISK to β_i^T can be expressed as

$$\mathrm{SRISK}_i(p) \approx cD_i - (1-c)\left(1 - \beta_i^T C^{\mathrm{LR}} \mathrm{ES}_s(p)\right) W_i. \tag{8}$$

Hence, compared with MES_i, the cross-sectional variation in the level of $SRISK_i$ depends not only on the cross-sectional variation in β_i^T but, by definition, also on the differences in bank size and financial leverage.

[11] Suppose the tail risk of bank 1 is completely associated with severe shocks in the financial system (and no other sources of risk). Then $\mathrm{VaR}_1(p) = \beta_1^T \mathrm{VaR}_s(p)$. Hence, in general, $\beta_i^T \mathrm{VaR}_s(p)$ could be interpreted as the "quantity of banks' tail risk that is associated with severe shocks in the financial system." From Equation 4 we have $\hat{\tau}_i(k/n)^{1/\hat{\xi}_s} \widehat{\mathrm{VaR}}_i(k/n) = \hat{\beta}_i^T \widehat{\mathrm{VaR}}_s(k/n)$. Hence the "fraction" $\hat{\tau}_i(k/n)^{1/\hat{\xi}_s}$ of banks' tail risk $\widehat{\mathrm{VaR}}_i(k/n)$ meets this interpretation.

[12] For two early applications in the context of asset return linkages; see Hartmann et al. (2004) and Straetmans et al. (2008).

[13] Another measure that is closely related to the MES is the component expected shortfall (CES) of Banulescu and Dumitrescu (2015). The CES_i is defined as the expected loss of bank i as a share of the total losses in the system conditional upon a severe shock in the financial system. It relates to β_i^T as $\beta_i^T W_i / W_s$, where W_i and W_s are the market capitalizations of bank i and the entire financial system, respectively.

[14] Having R_s representing the return on the financial index follows the conceptual discussion of Acharya et al. (2013, pp. 179–181). Allen et al. (2012) provide evidence that the level of tail risk in the financial system based on stock returns helped to forecast macroeconomic downturns, while the tail risk among nonfinancial firms had no marginal predictive ability. Similarly, Giglio et al. (2016) observed return volatility in the financial sector to be a significant predictor of macroeconomic tail risk, whereas nonfinancial volatility was not. Alternatively, R_s could represent the return on a broader market index.

Finally, we discuss the relationship to the Exposure CoVaR measure of Adrian and Brunnermeier (2016). The Exposure CoVaR is computed as the banks' VaR conditional upon the system suffering a loss equal to the system's own VaR. Formally, for a given probability level p, the Exposure CoVaR of bank i is implicitly defined as

$$\Pr(R_i < -\text{Exposure CoVaR}_i(p) | R_s = -\text{VaR}_s(p)) = p. \tag{9}$$

The following lemma shows how the Exposure CoVaR$_i$ relates to β_i^T and its two subcomponents.

Lemma 1. *Assume that the linear model in Equation 1 holds true for all R_s, that both R_s and ε_i follow a heavy-tailed distribution with tail index ξ_s, and that $\tau_i = \lim_{p\to 0}\tau_i(p)$. Then, as $p \to 0$, we have*

$$\textit{Exposure CoVaR}_i(p) \sim \left(\tau_i^{1/\xi_s} + (1-\tau_i)^{1/\xi_s}\right)\text{VaR}_i(p) \sim \beta_i^T \text{VaR}_s(p) T(\tau_i, \xi_s), \tag{10}$$

where

$$T(\tau_i, \xi_s) = 1 + \left(\frac{1}{\tau_i} - 1\right)^{1/\xi_s}. \tag{11}$$

Lemma 1 reveals that the Exposure CoVaR$_i$ is not a monotonic increasing function with respect to τ_i.[15] For a given VaR$_i(p)$, it increases on $[0, 1/2]$, whereas it decreases on $[1/2, 1]$. For both $\tau_i = 0$ and $\tau_i = 1$, the Exposure CoVaR$_i$ will equal the bank's VaR.

Moreover, the level of bank-specific risk turns out to be relevant for the level of Exposure CoVaR$_i$. Equation 10 shows that the Exposure CoVaR$_i$ increases in the level of VaR$_i(p)$ even if $\tau_i = 0$. This is in contrast to β_i^T and MES$_i$, which are both independent of the level of bank-specific risk.

Finally, the empirical relationships of bank characteristics to β_i^T or MES$_i$ can be different from their relationships to Exposure CoVaR$_i$. The level of Exposure CoVaR$_i$ not only depends on the level of β_i^T but also on an additional transformation of the level of tail dependence—that is, $T(\tau_i, \xi_s)$ in Equation 11. The relationship of bank characteristics to Exposure CoVaR$_i$ can be weaker or stronger depending on how bank characteristics relate to $T(\tau_i, \xi_s)$. We will assess this relationship in the empirical analysis.

3 | EMPIRICAL METHODOLOGY

To explore the empirical relationship between systemic risk and characteristics of bank business models, we estimate three regression models using as dependent variables our estimates of, respectively, systemic risk, systemic linkage, and bank tail risk.

3.1 | Regression models

The dependent variables in the regression models are estimated for each bank i using daily data from 16-quarter rolling windows. With the 16-quarter rolling window denoted by t to $t + 15$, the estimates are denoted as $\hat{\beta}^T_{i;[t,t+15]}$, SL$_{i;[t,t+15]}$ and IR$_{i;[t,t+15]}$. The regressions are estimated using bank characteristics in the quarter directly preceding the estimation window. These bank characteristics are denoted by $X_{i;t-1}$. Hence we estimate the coefficients in the following models from panel data:

$$\log \hat{\beta}^T_{i;[t,t+15]} = \alpha_{1t} + X_{i;t-1}\theta + \upsilon_{it}, \tag{12a}$$

$$\log \text{SL}_{i;[t,t+15]} = \alpha_{2t} + X_{i;t-1}\delta + \xi_{it}, \tag{12b}$$

$$\log \text{IR}_{i;[t,t+15]} = \alpha_{3t} + X_{i;t-1}\gamma + \nu_{it}, \tag{12c}$$

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. The time fixed effects capture variation in macroeconomic state variables as well as other sources of common variation in systemic risk over time. Moreover, we do not include bank fixed effects in our baseline model. The reason is that, in particular, the systemic linkage is relatively persistent over time (the Supporting Information Appendix provides some evidence that systemic

[15] We show in the Supporting Information Appendix that Equation 10 in Lemma 1 also holds true in a much more general setting. This more general setting encompasses, for example, a segmented linear model such that the linear model in Equation 1 holds true for $R_s < -\text{VaR}_s(\bar{p})$, and the relationship equals $R_i = \beta_i^{NT} R_s + \varepsilon_i$ for some coefficient $\beta_i^{NT} \geq 0$ (where the superscript NT indicates that it could be different from β_i^T) if $R_s \geq -\text{VaR}_s(\bar{p})$.

linkage is a significant predictor of $\hat{\beta}_i^T$ with a lag of 12 years). Owing to this persistency, fixed effects will absorb most of the variation in the systemic linkage in our data. Therefore, we exclude bank fixed effects for our purpose, which is in line with the empirical strategy of De Jonghe (2010), who investigated the relationship between bank characteristics and tail dependence. However, the robustness checks in the Supporting Information Appendix do consider bank fixed effects. Finally, to deal with the serial correlation in the error terms over time and the cross-sectional correlation in the error terms at the same point in time, we estimate standard errors that are clustered on both the bank and time level.

Estimating the coefficients $\hat{\delta}$ and $\hat{\gamma}$ reveals how the interrelationships between bank characteristics and $\hat{\beta}^T_{i;[t,t+15]}$ can be attributed to the interrelationships between bank characteristics and the two subcomponents of systemic risk. The dependent variable in the model in Equation 12a equals the sum of those in Equations 12b and 12c. Hence, theoretically, it holds true that $\theta = \gamma + \delta$. This relationship also holds true empirically—that is, $\hat{\theta} = \hat{\gamma} + \hat{\delta}$—because we estimate the models in Equations 12a–12c equation by equation using least squares panel regressions. Therefore, we can also assess how the interrelationships between bank characteristics and the two dimensions of systemic risk contribute quantitatively to the relationship between bank characteristics and the level of systemic risk.[16]

3.2 | 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 BHCs from 1992 to 2011. At the end of each quarter, we use 4 years of historical daily equity returns to estimate the three dependent variables, the $\hat{\beta}^T_{i;[t,t+15]}$ and its two subcomponents. To guarantee the quality of the data and the liquidity of the stocks on the equity market, the selected banks have total assets of at least USD 500 million and nonzero 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.[17]

Across all banks and all periods, we observe an average $\hat{\beta}^T_{i;[t,t+15]}$ of 0.97 in our sample. In an extreme market downturn, the average loss in bank equity returns is thus comparable with the loss in the financial index. The coefficient $\hat{\beta}^T_{i;[t,t+15]}$ ranges from 0.14 to 3.58, demonstrating large differences in the sensitivity of banks' capital losses to large shocks in the financial system. The $\mathrm{SL}_{i;[t,t+15]}$, which measures the strength of the link between the bank and the system in the event of widespread financial distress, ranges from 0.19 to 0.92. The variation illustrates the role that systemic linkage plays in the variation of $\beta^T_{i;[t,t+15]}$. The other component, $\mathrm{IR}_{i;[t,t+15]}$, compares banks' risk to that of the system and ranges from 0.51 to 7.72. Again, differences in this component demonstrate the role of the risk level in the variation of $\beta^T_{i;[t,t+15]}$.

Figure 2a illustrates the relationship between bank tail risk and banks' systemic risk. Although this relationship 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 2b shows that the relationship 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 variables for bank business models are constructed from the FR Y-9C reports that are made publicly available by the Federal Reserve in line with the definitions of Baele et al. (2014).[18] More specifically, at the end of each quarter we calculate the following indicators categorized into four groups. (i) Main characteristics of bank business models: the size of banks measured by the logarithm of total assets, the CAMEL ratios, and the growth rate of total assets.[19] (ii) Indicators of banks'

[16]We thank an anonymous referee for pointing out that it could be possible to estimate the model in Equation 12c using a quantile regression, since the cross-sectional variation in the $\mathrm{IR}_{i;[t,t+15]}$ component is entirely associated with that of the VaR of each bank. We do not follow this approach, because it would in general no longer hold true that $\hat{\theta} = \hat{\gamma} + \hat{\delta}$ if $\hat{\gamma}$ is estimated with a quantile regression, which would complicate the attribution analysis.

[17]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.

[18]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).

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

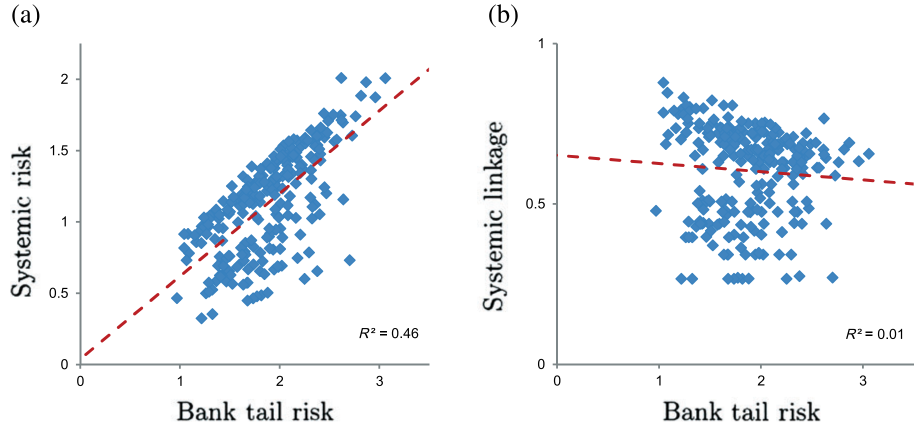

FIGURE 2 Bank tail risk and systemic risk. The figure shows the relationship between bank tail risk and, respectively, systemic risk (left panel) and systemic linkage (right panel) in 2007:Q4. Bank systemic risk is measured as β_i^T. Bank tail risk and bank systemic linkage are measured as IR_i and SL_i; for definitions, see Equation 5 [Colour figure can be viewed at wileyonlinelibrary.com]

income sources (as a ratio to total income): shares of noninterest income, fiduciary activities income, service charges on deposit accounts, trading revenue and other noninterest income. (iii) Indicators of banks' loan decompositions: 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 for the loans-to-total-assets ratio, these indicators are calculated as shares of total loans. (iv) An indicator of banks' funding structures: the deposit funding gap, defined as the difference between the loans-to-total-assets ratio and the deposits-to-total-assets ratio.

For each BHC 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.[20] We regress the systemic risk measure and its subcomponents on the characteristics of bank business models in the quarter preceding the 4-year estimation window.[21] The estimation windows for the left-hand-side variables range from 1992:Q3–1996:Q2 to 2008:Q1–2011:Q4. In addition, we exclude all observations corresponding to a zero estimate of $\hat{\beta}^T_{i;[t,t+15]}$, because our regression models require taking logarithms of the estimated $\beta^T_{i;[t,t+15]}$.[22] We end up with 13,498 bank-quarter observations.

The descriptive statistics (available in the Supporting Information Appendix) look similar to those of 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 the level of total assets, we take the logarithmic transformation in thousands of USD. Following Baele et al. (2014, appendix A), we first regress the logarithm of total assets on the other regressors, and then use the residuals as our right-hand-side variable for bank size. The rationale is that banks' choices regarding their business models directly impact their size. The estimated coefficients for all other characteristics of bank business models measure, as a consequence of this procedure, not only their direct effect on the dependent variables but also their indirect effect through bank size (as if bank size were not included as a regressor). The procedure does not affect the estimated coefficient for bank size.

4 | EMPIRICAL RESULTS

In the baseline specification we estimate the relationships in Equations 12a–12c for the CAMEL ratios, bank size, asset growth, noninterest income share, loans to assets, and deposits to assets. Table 1 presents the baseline results. Table 2 reports estimates using a further decomposition into different sources of noninterest income. Table 3 shows the results while controlling for conventional risk measures.

[20]Available at http://www.ny.frb.org/research/banking_research/datasets.html.
[21]In the Supporting Information Appendix we provide results when regressing the estimated $\beta^T_{i;[t,t+15]}$s on bank characteristics averaged over the 16 quarterly observations within the 4-year estimation window as well as on bank characteristics in the two quarters before the estimation window.
[22]In the Supporting Information Appendix we verify the impact of excluding observations corresponding to zero $\beta^T_{i;[t,t+15]}$ estimates.

TABLE 1 Baseline results on systemic risk

Variables	(1) $\log \hat{\beta}^T_{i;[t,t+15]}$	(2) $\log \mathrm{SL}_{i;[t,t+15]}$	(3) $\log \mathrm{IR}_{i;[t,t+15]}$
Bank size ($\mathrm{reslnTA}_{t-1}$)	0.072***	0.121***	-0.049***
	(0.013)	(0.007)	(0.011)
Tangible equity ratio$_{t-1}$	-0.029***	-0.028***	-0.001
	(0.005)	(0.003)	(0.004)
Nonperforming-loans ratio$_{t-1}$	3.223***	-0.211	3.434***
	(0.905)	(0.746)	(0.721)
Cost-to-income ratio$_{t-1}$	-0.631***	-0.742***	0.111
	(0.126)	(0.069)	(0.107)
Return on equity$_{t-1}$	-0.462**	-0.055	-0.408**
	(0.197)	(0.113)	(0.185)
Liquid assets$_{t-1}$	-0.054	0.114	-0.168
	(0.185)	(0.151)	(0.179)
Deposit funding gap$_{t-1}$	0.190*	0.242***	-0.052
	(0.103)	(0.068)	(0.093)
Loans to total assets$_{t-1}$	-0.091	-0.197**	0.106
	(0.103)	(0.082)	(0.085)
Noninterest income share$_{t-1}$	0.585***	0.668***	-0.084
	(0.084)	(0.055)	(0.075)
Growth in total assets$_{t-1}$	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

Note. The definitions of the dependent variables are provided in Equations 4 and 5. The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The explanatory variables are observed in 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 $1-(1-R^2)/(1-R_D^2)$, 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. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

4.1 | Size

We find that larger banks tend to be more sensitive to severe shocks in the financial system. Table 1, Model (1) suggests that banks with twice as many total assets have a β_i^T that is, on average, about 6% ($\approx 2^{0.080} - 1$) higher. This is not the result of a positive relationship of bank size to bank tail risk. We observe a small but significant negative association with bank tail risk. The tail risk of banks with twice as many assets is, on average, approximately 2% lower; see Table 1, Model (3). Instead, it is the stronger systemic linkage that induces the higher sensitivity of large banks to severe shocks in the financial system. The results in Table 1, Model (2) support an 8% higher level of systemic linkage for banks with twice as many assets.

Our results are consistent with the view that large banks may be associated with lower risk because of better diversification (see, e.g., Demsetz and Strahan, 1997). Even though better diversified banks face lower risks individually, they can ultimately be associated with more systemic risk (see, e.g., Shaffer, 1994; Wagner, 2010). Moreover, "too-big-to-fail" institutions may enjoy (implicit) guarantees that encourage them to weight their portfolios further towards risks that are

TABLE 2 Systemic risk and sources of noninterest income

Variables	(1) $\log \hat{\beta}^T_{i;[t,t+15]}$	(2) $\log \mathbf{SL}_{i;[t,t+15]}$	(3) $\log \mathbf{IR}_{i;[t,t+15]}$
Bank size (reslnTA$_{t-1}$)	0.070***	0.120***	-0.050***
	(0.013)	(0.007)	(0.010)
Tangible equity ratio$_{t-1}$	-0.029***	-0.025***	-0.004
	(0.005)	(0.004)	(0.004)
Nonperforming-loans ratio$_{t-1}$	3.066***	0.028	3.038***
	(0.874)	(0.740)	(0.685)
Cost-to-income ratio$_{t-1}$	-0.600***	-0.694***	0.095
	(0.129)	(0.068)	(0.106)
Return on equity$_{t-1}$	-0.414**	0.052	-0.466**
	(0.198)	(0.115)	(0.182)
Liquid assets$_{t-1}$	-0.043	-0.028	-0.015
	(0.189)	(0.159)	(0.176)
Deposit funding gap$_{t-1}$	0.141	0.335***	-0.194**
	(0.110)	(0.071)	(0.090)
Loans to total assets$_{t-1}$	-0.049	-0.260***	0.211***
	(0.109)	(0.083)	(0.081)
Growth in total assets$_{t-1}$	0.244***	0.100**	0.143***
	(0.058)	(0.039)	(0.045)
Fiduciary activities income share$_{t-1}$	0.496***	0.849***	-0.353***
	(0.142)	(0.091)	(0.127)
Service charges on dep. accounts share$_{t-1}$	0.114	1.294***	-1.180***
	(0.253)	(0.191)	(0.203)
Trading revenue share$_{t-1}$	1.377***	1.583***	-0.206
	(0.456)	(0.334)	(0.381)
Other noninterest income share$_{t-1}$	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

Note. The definitions of the dependent variables are provided in Equations 4 and 5. The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The explanatory variables are observed in 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 $1-(1-R^2)/(1-R^2_D)$, where R^2 is the *R*-squared in the table and where R^2_D is the *R*-squared from a regression with only dummies for the fixed effects. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

expensive to insure privately (systematic risks) (see, e.g., Penati and Protopapadakis, 1988; Pennacchi, 2006).[23] This may explain the positive relationship that we observe for systemic risk and systemic linkage.

Our findings are in line with those in earlier studies. For example, Demsetz and Strahan (1997), Pais and Stork (2013), and Tabak et al. (2013) did not observe a positive association between size and bank risk, while a positive relationship between bank size and systemic risk has also been reported by López-Espinosa et al. (2012), Brunnermeier et al. (2012),

[23]These incentives may be weaker for very large institutions, because bailing them out may not be feasible if public finances are weak (see, e.g., Acharya et al., 2014; Demirgüç-Kunt & Huizinga, 2013).

TABLE 3 Results after controlling for normal risk measures

Variables	(1) $\log \hat{\beta}^T_{i;[t,t+15]}$	(2) $\log \mathbf{SL}_{i;[t,t+15]}$	(3) $\log \mathbf{IR}_{i;[t,t+15]}$
$\log \rho_{i;[t,t+15]}$	0.168***	0.171***	-0.003
	(0.010)	(0.010)	(0.003)
$\log(\sigma_{i;[t,t+15]}/\sigma_{i;[t,t+15]})$	0.933***	-0.035*	0.968***
	(0.020)	(0.020)	(0.013)
Bank size (reslnTA_{t-1})	0.033***	0.036***	-0.003
	(0.006)	(0.005)	(0.002)
Tangible equity ratio$_{t-1}$	-0.012***	-0.013***	0.001
	(0.002)	(0.002)	(0.001)
Nonperforming-loans ratio$_{t-1}$	-0.120	0.140	-0.260
	(0.408)	(0.400)	(0.192)
Cost-to-income ratio$_{t-1}$	-0.217***	-0.228***	0.011
	(0.047)	(0.044)	(0.019)
Return on equity$_{t-1}$	-0.134	-0.162**	0.029
	(0.083)	(0.072)	(0.035)
Liquid assets$_{t-1}$	-0.009	0.017	-0.026
	(0.094)	(0.099)	(0.033)
Deposit funding gap$_{t-1}$	0.121***	0.141***	-0.021
	(0.041)	(0.037)	(0.020)
Loans to total assets$_{t-1}$	-0.075	-0.112***	0.037*
	(0.048)	(0.041)	(0.020)
Noninterest income share$_{t-1}$	0.257***	0.263***	-0.006
	(0.038)	(0.038)	(0.016)
Growth in total assets$_{t-1}$	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

Note. The definitions of the dependent variables are provided in Equations 4 and 5. The dependent variables are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The $\rho_{i;[t,t+15]}$, $\sigma_{i;[t,t+15]}$ and $\sigma_{s;[t,t+15]}$ are the correlation between R_i and R_s, and the standard deviations of, respectively, R_i and R_s, all estimated over the same horizon as the dependent variables. All other explanatory variables are observed in 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 $1-(1-R^2)/(1-R_D^2)$, 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. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

Vallascas and Keasey (2012), and Girardi and Ergün (2013). Moreover, the positive relationship between bank size and tail dependence has also been documented by De Jonghe (2010) and Pais and Stork (2013).

4.2 | Noninterest income

We find a strong positive relationship between banks' reliance on noninterest income and their sensitivity to severe shocks in the financial system. A noninterest-income share that is 10 percentage points higher corresponds to an approximately 5.8% higher β_i^T. This 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 relationship between financial firms' reliance on noninterest income and their market betas ("systematic risk"). The observed positive relationship between noninterest income share and the sensitivity to severe financial shocks is mainly due to a stronger linkage in stress events. De Jonghe (2010) and Vallascas and Keasey (2012) documented a similar positive relationship between tail dependence and the reliance on noninterest income.

We do not observe a positive relationship between the noninterest-income share and the level of bank tail risk, although several other studies report a positive relationship between noninterest income and volatility (see, e.g., Lepetit et al., 2008; Stiroh, 2006a).[24] In Table 2 we explore a decomposition of noninterest 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 relationship between the noninterest income share and bank tail risk. In contrast, we observe no significant relationship between bank tail risk and trading revenue or bank tail risk and other noninterest income, which includes, for example, investment banking, venture capital revenues, and net-gains-on-loans sales. Nevertheless, banks with more trading revenue and other noninterest income are much more strongly related to the system in the event of financial stress. Therefore, these activities are strongly positively related to banks' systemic risk (see also Brunnermeier et al., 2012).

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 financed with deposits and characterized by relatively high loans-to-assets ratios. If traditional activities are more isolated from the risk in the financial system, then the traditionality of bank balance sheets would be associated with a lower systemic linkage, and potentially, with lower systemic risk.

First we consider the loans-to-assets ratio as a proxy of the traditionality of the bank balance sheets. From Table 1, Model (1) we observe that banks with a loans-to-assets ratio that is 10 percentage points higher are associated with a 2.0% lower level of systemic linkage. Hence banks that concentrate their business models towards traditional lending are associated with a weaker systemic linkage. However, the relationship to β_i^T is not significant, partly because of a weakly significant positive association between the loans-to-assets ratio and bank tail risk.

Whether the loan business is associated with higher systemic risk may depend on the risk profile of the loan portfolio.[25] By considering the nonperforming-loans ratio as a proxy of the general risk profile of the loan portfolio, we find that higher levels of risk in the loan portfolio is associated with higher levels of bank tail risk. This is in line with the positive association between nonperforming loans ratios and the level of volatility documented, for example, by Stiroh (2006a). The positive relationship to bank risk drives the positive association between nonperforming loans ratios and systemic risk.

In the traditional business model, lending activities are funded with deposits. The deposit funding gap is an indicator of the extent to which banks rely on other funding sources for their lending business. From Table 1, Model (1), we observe that banks with a 10-percentage-point larger deposit funding gap are associated with a 2.4% stronger systemic linkage and a 1.9% higher level of β_i^T. This is consistent with the study of López-Espinosa et al. (2012), who documented that short-term wholesale funding increased systemic risk as measured by ΔCoVaR. Similarly, Bologna (2015) documented 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 a more traditional funding profile tend to be less sensitive to severe shocks in the system because of a weaker systemic linkage.

Finally, to assess the relationship 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) documented a positive relationship between loan growth and subsequent loan-loss provisions, while López-Espinosa et al. (2013) did not find a significant relationship between loan growth and spreads on credit default swaps. Vallascas and Keasey (2012) and López-Espinosa et al. (2013) reported a positive association between loan growth and systemic risk. Our results provide some additional evidence: Banks with an asset growth rate that is 10 percentage points higher are associated with a 2.6% higher β_i^T. This is due to the relationship to bank tail risk: A 10-percentage-point higher growth rate of assets is associated with an approximately 2.1% higher level of bank tail risk.

[24]A difference is that our risk measure focuses explicitly on downward tail risk, which may be different from those based on the entire distribution, such as volatility.
[25]The Supporting Information Appendix presents results based on the sectoral decomposition of the loan portfolio.

4.4 | Capital buffers

Bank capital acts 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, Rochet (1992) showed that the interrelationship between bank capital and bank risks could be ambiguous if the risk weights used in capital regulation were not proportional to the actual market risks. Moreover, more equity funding may enable banks to take on more tail risk (see Perotti et al., 2011). Consequently, the empirical interrelationship between bank capital and systemic risk may be ambiguous.

Our results suggest that banks with higher capital ratios are associated with a significantly lower level of systemic risk. A tangible equity ratio that is 1 percentage point higher is associated with an approximately 2.9% lower β_i^T. This is the result of banks with high capital ratios being associated with a weaker systemic linkage. Moreover, banks with a better ability to replenish capital buffers from retained earnings, because of higher profitability, are considered by investors to bear less tail risk. The estimation results show that a 1-percentage-point higher return on equity is associated with a 0.4% lower level of bank risk and, consequently, a 0.4% lower level of β_i^T. In other words, both actual capital buffers and profitability are negatively related to systemic risk. However, the interrelationships with the two dimensions differ. Banks with higher actual capital buffers have lower β_i^Ts as a result of a weaker systemic linkage, while banks with the ability to build new capital buffers have lower β_i^Ts as a result of a lower level of bank tail risk.

Our findings on the negative relationship between capital buffers and systemic risk are consistent with the general pattern in the empirical literature (see, e.g., Brunnermeier et al., 2012; Vallascas and Keasey, 2012), and weak evidence in the studies of López-Espinosa et al. (2012) and Girardi and Ergün (2013). The negative relationship to systemic linkage is consistent with the findings of De Jonghe (2010) and Vallascas and Keasey (2012) on co-exceedances and tail dependence, respectively. Although Stiroh (2006a, 2006b) reported a lower level of volatility for banks with higher capital ratios, Ellul and Yerramilli (2013) observed a positive relationship between bank capital and tail risk. We observe an insignificant negative relationship between bank capital and bank tail risks. Moreover, the negative relationship between bank profitability and tail risk is also supported by the findings of Ellul and Yerramilli. The negative relationship between bank profit and systemic risk is also consistent with the positive relationship between competition (and hence lower profits) and systemic risk as documented by Anginer et al. (2014).

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) showed that, under the assumption of multivariate normality, the systemic risk of a bank depended on its standard deviation and its correlation with the system. Moreover, Nijskens and Wagner (2011) attributed 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 interrelationships and risks may change in the event 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 both large negative shocks and moderate shocks. For example, assume that the linear relationship $R_i = \beta_i R_s + \epsilon$ 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 on all observations 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 $\hat{\beta}_i$ at the log level arises as $\log \hat{\beta}_i = \log \hat{\rho}_i + \log(\hat{\sigma}_i / \hat{\sigma}_s)$, where $\hat{\rho}_i$ and $\hat{\sigma}_i / \hat{\sigma}_s$ are estimated from all observations. Note that $\hat{\beta}_i$ may be subject to less estimation uncertainty than $\hat{\beta}_i^T$, since $\hat{\beta}_i$ is estimated using all observations in the estimation window, whereas the EVT approach to estimating $\hat{\beta}_i^T$ only uses a subset of the observations.

When adding $\log \hat{\rho}_i$ and $\log(\hat{\sigma}_i / \hat{\sigma}_s)$ as additional explanatory variables in our models, the coefficients for bank characteristics can be interpreted as measuring that portion of their effect on the dependent variables that is not measured through their effect on $\log \hat{\rho}_i$ and $\log(\hat{\sigma}_i / \hat{\sigma}_s)$ (i.e., the effect while keeping $\hat{\rho}_i$ and $\hat{\sigma}_i / \hat{\sigma}_s$ constant). Therefore, if the estimation based on extremes provides no new information on the sensitivity of banks to large adverse shocks in the financial system, (e.g., because $\beta_i^T = \beta_i$), then 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 insignificant the coefficients of the bank characteristics. By contrast, we should expect coefficients for the bank characteristics to remain significant if part of their effect on $\log \beta_i^T$ cannot be measured through their effect on $\log \hat{\rho}_i$ and $\log(\hat{\sigma}_i/\hat{\sigma}_s)$.

Table 3 shows the estimation results after adding the conventional risk measures to our baseline specification. 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 suggests 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 relationship with conventional risk measures—follows from their coefficients in Table 3, Models (2) and (3). Most of the coefficients of bank characteristics in the model with bank tail risk as the dependent variable become insignificant. These bank characteristics thus provide little additional information on the level of bank tail risk beyond 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 interrelationship 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 noninterest income have a stronger link to the system in financial distress than their correlations would suggest.

The relationship 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 3, Model (1) shows that many coefficients remain significant in the model for β_i^T. With the aforementioned results for the subcomponents, the main reason is the systemic linkage dimension. This suggests that conventional analysis does not capture the relationship with β_i^T well because of a different dependence structure in the event 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 in this direction are quantile regressions to estimate CoVaR (Adrian & Brunnermeier, 2016), dynamic conditional correlation models to estimate SRISK (Brownlees & Engle, 2017), and extreme value approaches to estimate MES (Acharya et al., 2017, Cai et al., 2015).

4.6 | Exposure CoVaR

When estimating the relationship between Exposure CoVaR$_i$ and bank characteristics, we do not expect to get results similar to those for β_i^T. The reason is that, as explained in Lemma 1, the Exposure CoVaR$_i$ and β_i^T have a different relationship to the level of tail dependence, but are otherwise comparable. As a consequence, we may expect different estimation results for Exposure CoVaR when the relationship of bank characteristics to β_i^T is mainly through the systemic linkage dimension. However, we should expect similar estimation results for bank characteristics that are mainly related to β_i^T through the bank tail risk dimension.

Table 4, Models (1) and (2) show estimation results for the relationship between bank characteristics and, respectively, the level of $T(\tau_i, \xi_s)$ estimated from Equation 11 and the bank's Exposure CoVaR estimated from Equation 10. The $T(\tau_i, \xi_s)$ allows us to obtain the Exposure CoVaR$_i$ from the level of β_i^T. Hence the results in Table 4, Model (1) reveal potential differences in the coefficients of bank characteristics in the regressions with β_i^T and those with Exposure CoVaR.

The estimation results in Table 4 confirm our expectations. Bank characteristics that are mainly related to β_i^T through the systemic linkage dimension tend to have a weaker relationship to Exposure CoVaR than to β_i^T. Bank characteristics that are predominantly related to β_i^T via the systemic linkage component often have opposite signs for their relationship to $T(\tau_i, \xi_s)$. For example, larger banks and banks with higher noninterest income shares are associated with lower levels of $T(\tau_i, \xi_s)$, but with higher β_i^Ts. As a consequence, bank size and noninterest income do have a weaker relationship to Exposure CoVaR than to β_i^T; see Table 4, Model (2). In contrast, characteristics such as the nonperforming-loans ratio and asset growth, which are mainly related to β_i^T through the bank tail risk dimension (see Table 1), do have very similar relationships to Exposure CoVaR and to β_i^T.

Finally, the estimated coefficients for the Exposure CoVaR are not very sensitive to the estimation method. Table 4, Model (3) shows the relationship between bank characteristics when estimating the Exposure CoVaR based on a quantile regression, as suggested by Adrian and Brunnermeier (2016). Broadly speaking, the estimated coefficients are similar to

TABLE 4 Baseline model with exposure CoVaR

Variables	(1) $T(\hat{\tau}_{i;[t,t+15]}, \hat{\xi}_{s;[t,t+15]})$	(2) Exposure $\text{CoVaR}^{\text{EVT}}_{i;[t,t+15]}$	(3) Exposure $\text{CoVaR}^{\text{QR}}_{i;[t,t+15]}$
Bank size (reslnTA$_{t-1}$)	-0.098***	-0.026**	0.001
	(0.006)	(0.011)	(0.010)
Tangible equity ratio$_{t-1}$	0.022***	-0.007	-0.011**
	(0.003)	(0.004)	(0.004)
Nonperforming-loans ratio$_{t-1}$	0.287	3.560***	3.664***
	(0.596)	(0.702)	(0.757)
Cost-to-income ratio$_{t-1}$	0.615***	-0.019	-0.201*
	(0.057)	(0.106)	(0.105)
Return on equity$_{t-1}$	0.078	-0.389**	-0.275
	(0.092)	(0.180)	(0.183)
Liquid assets$_{t-1}$	-0.095	-0.143	-0.101
	(0.117)	(0.168)	(0.165)
Deposit funding gap$_{t-1}$	-0.199***	-0.007	-0.000
	(0.055)	(0.090)	(0.092)
Loans to total assets$_{t-1}$	0.171***	0.080	0.062
	(0.066)	(0.082)	(0.084)
Noninterest income share$_{t-1}$	-0.552***	0.034	0.155**
	(0.045)	(0.075)	(0.077)
Growth in total assets$_{t-1}$	-0.043	0.218***	0.250***
	(0.032)	(0.049)	(0.052)
Constant	0.396***	1.747***	1.652***
	(0.069)	(0.120)	(0.118)
Observations	13,498	13,498	13,498
Number of banks	510	510	510
R-squared	0.499	0.609	0.603
Partial R-squared	0.279	0.581	0.521
Time fixed effects	Yes	Yes	Yes
Clustering at bank level	Yes	Yes	Yes
Clustering at time level	Yes	Yes	Yes

Note. The dependent variables $T(\tau_i, \xi_s)$ and Exposure $\text{CoVaR}^{\text{EVT}}_i$ in Models (1) and (2) are estimated using Equations 10–11. The dependent variable in Model (3) is calculated as Exposure $\text{CoVaR}^{\text{QR}}_i = \hat{\alpha}_q + \hat{\beta}_q \times \widehat{\text{VaR}}_s(0.04)$, where $\hat{\alpha}_q$ and $\hat{\beta}_q$ are obtained from estimating the model Exposure $\text{CoVaR}^{\text{QR}}_i(0.04|R_s) = \alpha_q + \beta_q R_s + \varepsilon_q$ with a quantile regression. All dependent variables are in log levels and are calculated from 16 quarters of daily stock market returns, with a quarterly rolling window. The explanatory variables are observed in 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 $1-(1-R^2)/(1-R^2_D)$, where R^2 is the R-squared in the table and where R^2_D is the R-squared from a regression with only dummies for the fixed effects. Asterisks indicate significance at the *10%, **5%, and ***1% levels.

those in Table 4, Model (2). Nevertheless, we observe some variation in the significance of different characteristics and a slightly higher explanatory power in the model relying on the approach in Equation 10.

5 | POLICY DISCUSSION

Over the past decade, the emphasis of banking regulation has shifted from the micro- towards the macroprudential objective. The decomposition of systemic risk provides an explanation of why the two objectives can have different implications for regulation. The decomposition also reveals the interrelationship between the two objectives. As a consequence of the shift toward the macroprudential objective, regulators have to take an additional dimension into consideration besides bank risk: the strength of the link between banks and the system in financial distress, or systemic linkage. Empirically, characteristics of bank business models have different relationships to the two dimensions of systemic risk. These differ-

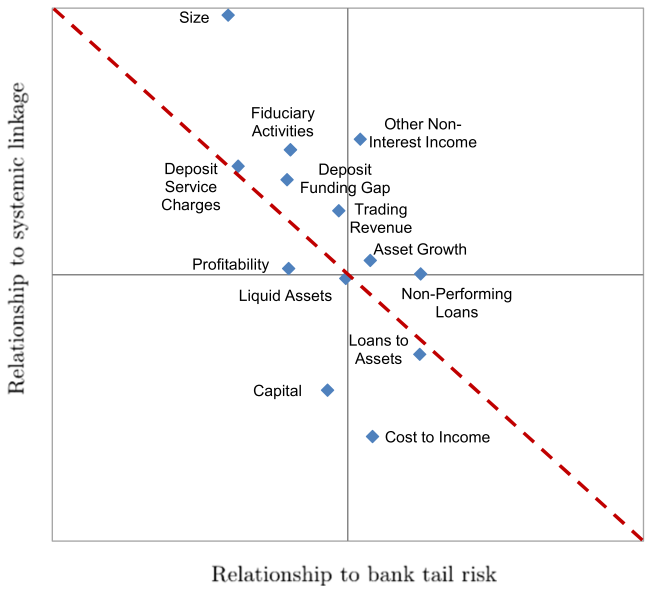

FIGURE 3 Bank characteristics and systemic risk. The figure shows the relationship between different bank characteristics and systemic risk. Dots further to the right (left) of the vertical axis in the center of the figure imply a stronger positive (negative) relationship between that particular characteristic and bank tail risk. Dots further above (below) the dashed diagonal signify a positive (negative) relationship between that particular characteristic and systemic risk. A larger distance from the diagonal signifies a stronger relationship. The figure is based on a scatter plot of the estimated coefficients in Table 2, Models (2) and (3). On the vertical and horizontal axes are the coefficients for $\log \mathrm{SL}_{i;[t,t+15]}$ in Model (2) and the coefficient for $\log \mathrm{IR}_{i;[t,t+15]}$ in Model (3), respectively. The magnitude of the coefficients is normalized by the standard deviation of the relevant variable [Colour figure can be viewed at wileyonlinelibrary.com]

ences may explain why the scope and direction of policy proposals have changed as the macroprudential objective gained traction in the regulatory debate.

The decomposition of systemic risk and our main empirical findings are illustrated in Figure 3. The figure shows a scatter plot based on the estimated coefficients in the models for systemic linkage and bank risk; see Table 2, Models (2) and (3), respectively. Each dot represents a single bank characteristic. The horizontal location of a bank characteristic depends on the standardized coefficient for bank tail risk.[26] A characteristic located far away from the vertical axis in the center of the figure indicates a strong relationship to bank tail risk. Moreover, its vertical location depends on the standardized coefficient for systemic linkage. Characteristics located far away from the horizontal axis in the center of the figure exhibit a strong relationship to systemic linkage. The dashed diagonal refers to positions in the diagram where the two relationships precisely cancel out with respect to the level of systemic risk. Characteristics located far away from the diagonal have a relatively strong relationship to systemic risk: A position in the northeastern (southwestern) half of the plane indicates a positive (negative) relationship.

Figure 3 shows which characteristics of bank business models provide an indication of banks' tail risk and systemic risk. From a purely microprudential point of view, the effective indicators are far away from the vertical axis, as those have stronger relationships to bank tail risk. From a macroprudential point of view, the relevant indicators are bank characteristics that are located far away from the diagonal, as those have stronger relationships to systemic risk.

Policy implications inspired by the micro- and macroprudential objectives for regulation may differ in scope. For example, trading revenue and other noninterest income, which includes investment banking, venture capital revenue and net gains on loans sales, are very close to the vertical axis. Those activities are hardly related to the level of bank tail risk. However, these indicators are located above and away from the diagonal. Consequently, trading revenue and other noninterest income are associated with a higher level of banks' systemic risk. This suggests that whether banks are involved in these activities is likely to be relevant from a macroprudential point of view, which is in line with the introduction of the "Volcker rule" to curb risks from proprietary trading or positions in hedge funds and private equity funds at US banks.

Policy implications based on the two objectives may also differ in direction. Although large banks are generally associated with less tail risk, bank size is located far above the diagonal, which implies that its relationship to systemic risk

[26]Due to standardization, a larger distance from 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.

has an opposite sign. This may partly explain why prudential regulation was hardly concerned with bank size before the crisis, while bank size arises as an important indicator in the context of requiring additional capital buffers at globally systemically important banks (see, e.g., BCBS, 2013). Discouraging large banks may help to enhance stability of the financial system, but may also increase risk at individual institutions by reducing diversification possibilities for each bank.

6 | CONCLUSION

Our analysis shows that some characteristics of bank business models have a similar relationship to both tail risk and systemic risk. For those characteristics, micro- and macroprudential objectives may have similar implications. However, the analysis also reveals that some characteristics have different relationships to bank tail risk and systemic risk. This is a result of their relationship to systemic linkage. For these characteristics, policy implications following from the two regulatory objectives may differ in scope or direction. Identifying areas in which the micro- and macroprudential objectives have different implications is a highly relevant topic for future research.

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 how bank business models relate to risk at an individual level, but also on how they relate to systemic linkage. The balance between these two relationships determines the relationship to systemic risk. This study is a first step to empirically assess these relationships based on measures estimated from extremely adverse shocks in financial markets.

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REFERENCES

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

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

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2009). Regulating systemic risk, *Restoring Financial Stability: How to Repair a Failed System*. Hoboken, NJ: Wiley, pp. 283–304.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2013). How to calculate systemic risk surcharges, *Quantifying Systemic Risk*. Chicago, IL: University of Chicago Press, pp. 175–212.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *Review of Financial Studies*, *30*(1), 2–47.

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

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, *106*(7), 1705–1741.

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

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

BCBS (2013). Global systemically important banks: Updated assessment methodology and the higher loss absorbency requirement. (*Technical document*). Basel, Switzerland: Basel Committee on Banking Supervision.

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

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

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

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

Benoit, S., Colliard, J.-E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: A survey on systemic risk. *Review of Finance*, *21*(1), 109–152.

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559.

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

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

Borio, C. (2014). The international monetary and financial system: Its Achilles heel and what to do about it. (*BIS Working Papers, 456*). Basel, Switzerland: Basel Committee on Banking Supervision.

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

Brownlees, C., & Engle, R. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, *30*(1), 48–79.

Brunnermeier, M. K., Dong, G., & Palia, D. (2012). Banks' non-interest income and systemic risk, Princeton: Princeton University. (*Working paper*) Available at SSRN: https://ssrn.com/abstract=1786738

Cai, J.-J., Einmahl, J. H. J., Haan, L., & Zhou, C. (2015). 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.

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

Dàvila, E., & Korinek, A. (2018). Pecuniary externalities frictions. *Review of Economic Studies*, *85*(1), 352–395.

De Bandt, O., Hartmann, P., & Peydró, J. L. (2010). Systemic risk in banking: An update, *The Oxford Handbook of Banking* (pp. 633–672). Oxford, UK: Oxford University Press.

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

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

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

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

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

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

Embrechts, P., de Haan, L., & Huang, X. (2000). Modelling multivariate extremes, *Extremes and integrated risk management* (pp. 59–67). London, UK: Risk Waters Group.

Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). *Modelling extremal events for insurance and finance*, Vol. *33*. Berlin, Germany: Springer.

Fahlenbrach, R., Prilmeier, R., & Stulz, R. M. (2012). 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.

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

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

Giglio, S., Kelly, B., & Pruitt, S. (2016). Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, *119*(3), 457–471.

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

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

Hartmann, P., Straetmans, S. T. M., & de Vries, C. G. (2007). Banking system stability: A cross-Atlantic perspective, *The risks of financial institutions* (pp. 133–192). Chicago, IL: University of Chicago Press.

Hartmann, P., Straetmans, S. T. M., & Vries, C. G. (2004). Asset market linkages in crisis periods. *Review of Economics and Statistics*, *86*(1), 313–326.

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

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

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

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

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

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

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

Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *Journal of Finance*, *56*(2), 649–676.

López-Espinosa, G., Moreno, A., Rubia, A., & Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global CoVaR approach. *Journal of Banking and Finance*, *36*(12), 3150–3162.

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

Mikosch, T., & De Vries, C. G. (2013). Heavy tails of OLS. *Journal of Econometrics*, *172*(2), 205–221.

Nijskens, R., & Wagner, W. (2011). 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 and Finance*, *35*(6), 1391–1398.

Pais, A., & Stork, P. A. (2013). Bank size and systemic risk. *European Financial Management*, *19*(3), 429–451.

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

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

Pennacchi, G. (2006). Deposit insurance, bank regulation, and financial system risks. *Journal of Monetary Economics*, *53*(1), 1–30.

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

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

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

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

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

Straetmans, S. T. M., Verschoor, W. F. C., & Wolff, C. C. P. (2008). Extreme US stock market fluctuations in the wake of 9/11. *Journal of Applied Econometrics*, *23*(1), 17–42.

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

Vallascas, F., & Keasey, K. (2012). Bank resilience to systemic shocks and the stability of banking systems: Small is beautiful. *Journal of International Money and Finance*, *31*(6), 1745–1776.

Van Oordt, M. R. C., & Zhou, C. (2016). Systematic tail risk. *Journal of Financial and Quantitative Analysis*, *51*(2), 685–705.

Van Oordt, M. R. C., & Zhou, C. (2017). Estimating systematic risk under extremely adverse market conditions. *Journal of Financial Econometrics*. Advance online publication https://doi.org/10.1093/jjfinec/nbx033

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

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

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

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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