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Bank Sectoral Concentration and Risk: Evidence from a Worldwide Sample of Banks

We propose a novel, stock-return based, technique to measure three aspects of banks' sectoral concentration that feature prominently in episodes of bank risk: specialization (capturing high exposures), differentiation (capturing deviation from peer banks), and financial sector exposure (capturing direct connectedness) and show external validity for these measures. We find that both individual and systemic bank risk decrease with specialization. Differentiation is particularly and positively related to individual bank risk, whereas direct connectedness of banks is particularly and positively related to systemic bank risk. These findings inform the theoretical and policy debate on the relationship between sectoral concentration and banks' stability.

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According to von Westernhagen et al. (2004), nine of the 13 major individual and systemic banking crises of the twentieth century were caused by credit concentration of banks. Theoretical models trying to rationalize this are typically built around one or more of the following aspects: (i) specialized versus diversified asset portfolios, (ii) differentiated versus nondifferentiated asset portfolios (vis-à-vis peer banks), and (iii) counterparty risk within the financial system.[1] However, theory has not given a clear answer to how these different aspects relate to bank stability. Furthermore, trying to underpin this anecdotal evidence with solid empirical relationships, let alone testing the theoretical models, has proven difficult because we lack appropriate data on banks' asset concentration—especially in a uniform way across banks and countries. Such exercise is further complicated by the fact that concentration can arise on both the asset and liability side, or even off-balance sheet.

This paper fills this gap by constructing comprehensive, stock-return based measures of concentration that overcome several shortcomings of existing measures. We develop measures of specialization (are banks' exposures diversified or not?), differentiation (are banks' exposures different from peer banks?), and financial sector exposure (how directly connected is a bank with the financial sector?), using a uniform setup for banks from different countries and provide external validity for these new measures. We then include these three dimensions of bank concentration in models explaining individual bank risk and systemic bank risk and test competing theories on the relationship between concentration and stability.

New concentration measures. In the first part of the paper, we develop a new methodology to identify banks' strategic choices with respect to concentration in *sectoral* exposures. We apply this methodology to estimate the sectoral concentration of 1,716 banks across 34 countries over the period 2002–12. The underlying assumption of this methodology is that one can identify a bank's sectoral concentration choices from the covariation between its stock returns and the returns on sectoral indices, and thus relies on market participants' information on bank choices. Earnings calls transcripts, for instance, indicate that analysts do have information about sectoral exposures. During earnings calls, analysts ask questions in terms of actual exposure to and performance across economic sectors but also in terms of hedging instruments used to hedge against sectoral concentration. We provide several examples from earnings calls transcripts in Section 1.1. We use an extended factor model and relate banks' stock returns to the returns on nine global sectoral indices, a financial sector index, and a set of common factors.[2] This allows us to see whether a bank's exposures are

1. See Diamond (1984) and Boyd and Prescott (1986) for seminal work on the benefits of diversification or Winton (1999) for theoretical and Acharya, Hasan, and Saunders (2006) for empirical work on the benefits of specialization. See, for example, Acharya and Yorulmazer (2007, 2008), Wagner (2010), Allen, Babus, and Carletti (2012), Greenwood, Landier, and Thesmar (2015), or Cai et al. (2018) for work on differentiation. See, for example, Allen and Gale (2000), Freixas, Parigi, and Rochet (2000), Gorton and Metrick (2012), or Allen and Carletti (2013) for work on counterparty risk.

2. These are the returns on the global market index, the local market index, a real estate investment trust, and the global small-minus-big, high-minus-low, and momentum factor.

well diversified (meaning that its returns are only exposed to the set of common factors) or whether a bank is also significantly exposed to certain sectors (meaning that its returns exhibit significant exposures to sectoral indices over and above the other factors in the model).[3]

We then define bank *sectoral specialization* as the percentage variation of the bank's stock returns that is incrementally explained by the sector-specific indices over and above the variation explained by the other factors. Next, we define bank *sectoral differentiation* as the Euclidean distance between a bank's estimated sectoral exposures and the average sectoral exposures of all other banks in the same country and year. Finally, we define a bank's *financial sector exposure* as the estimated sensitivity of its stock returns to the returns on the financial sector index.

To shed more light on the informational content of our measures, we hand-collect *actual* sectoral lending exposures from the notes to the annual statements for a small subsample covering the largest banks in our sample. We then show external validity for our newly created measures of sectoral specialization, differentiation, and financial sector exposure by documenting statistically and economically significant correlations with their accounting-based counterparts.

Strengths and limitations. Our approach has a number of advantages compared to other data or methods used in the literature. First, our identified exposures relate to the lending exposures of banks, but capture more. They also take into account banks' securities holdings and derivative positions through which banks might hedge excessive sectoral lending exposures (or, alternatively, create such positions when there is no sectoral lending exposure). Furthermore, they also account for sectoral exposures at the liability side of banks' balance sheets (e.g., sectoral concentration in corporate deposits). This is important given the increasing complexity of banks and their increasing focus on nonlending activities (Demirguc-Kunt and Huizinga 2010). A second advantage is that our approach allows to cover a significantly wider range of banks and countries than in previous studies, which either relied on credit register data for single country studies (e.g., De Jonghe et al. 2020) or relied on syndicated loan exposures of large, international (mainly U.S.-based) banks (e.g., Cai et al. 2018). On average, the banks in our sample cover nearly 70% of all banking assets in their respective countries, which increases the external validity of the results and relevance for policymakers. A third advantage is that this methodology can be applied to identify a wide range of strategic bank choices that are usually either only available to insiders or not available in a homogeneous way (through, for instance, earnings calls). Our methodology can be used to construct time-varying indicators of a bank's exposure to certain sectors (as in this paper), but it is quite general and could also be implemented to determine a bank's exposure to certain geographical areas,

3. This approach is similar to returns-based analysis used to deconstruct mutual fund returns in exposures to investment strategies or asset classes. This offers an indirect identification of exposures that are otherwise difficult to observe, like sectoral exposures, which cannot be easily deducted from financial statements or annual reports. Researchers have used this to identify mutual fund exposures to large vs. small stocks or value vs. growth stocks (see, e.g., Sharpe (1992) and Brown and Goetzmann (1997)).

certain types of companies (Small and Medium-sized Enterprises (SMEs) or large corporates), sovereign bond exposures (Acharya and Steffen 2015), or commodity prices (Agarwal, Duttagupta, and Presbitero 2020).

We also acknowledge some limitations of our approach. First of all, our approach is stock market-driven and hence depends on the information provided and processed by stock market participants. Furthermore, inferring information on sectoral concentration from banks' stock prices also hinges upon faith in weak form efficiency of the efficient market hypothesis. Second, our approach depends on modeling assumptions. While we will show that our measures are robust to many alterations, we only explore linear relationships. Third, by looking at the impact of sectoral concentration on market-based (systemic) risk measures, we document stylized facts for medium-sized and large banks, as small banks are usually not publicly traded.

Individual and systemic bank risk. In the second part of the paper, we relate our three new measures to individual bank risk, proxied by the banks' distance to default, and to systemic bank risk, proxied by the banks' marginal expected shortfall, and subject our findings to a battery of robustness tests. Importantly, we find four relationships that exhibit a consistent sign and significance over time and across countries and robustness checks.

First and second, bank specialization is negatively related to individual bank risk and to systemic bank risk. This result is in line with, respectively, Acharya, Hasan, and Saunders (2006) and De Jonghe (2010); and is supportive of theories advocating benefits of specialization. These benefits are generally related to more effective screening, better monitoring, and less severe adverse selection problems (Winton 1999, Marquez 2002). Third, differentiation from peer banks is positively associated with individual bank risk. While this relationship has not been explored extensively by theory, our results are consistent with Acharya and Yorulmazer (2008) who argued that differentiation may imply higher funding costs for banks, which—all else equal—imply lower margins and higher risk. Fourth, financial sector exposure is positively associated with systemic bank risk. This is in line with the findings of Gorton and Metrick (2012) and underpins the relevance of theoretical models on financial contagion developed by Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000).

As these four relationships[4] are extremely robust across methods, specifications, time, and countries, we believe that these aspects of sectoral concentration should get the most prominent role in theoretical models (insofar as they have not yet, see discussion in Section 2.5) as well as the most prominent attention of policymakers.

Related literature. Our paper contributes to several strands of the literature. Since Flannery and James (1984), there has been a long history of inferring banks' interest rate and credit risk exposures from stock market data. Subsequently, other exposures have been examined (see Schuermann and Stiroh (2006) and Baele et al. (2015) for an

4. Two others of the six examined relationships are less robust. Specifically, the relationship between differentiation and systemic bank risk is positive but entirely driven by the crisis years and is, in the cross section, significant for only very few countries. Second, the relationship between financial sector exposure and individual bank risk varies over time, both in significance and in sign.

overview). We contribute to this literature by using stock market data to infer banks' strategic choices on sectoral concentration. We are aware of only two papers that innovate in a similar way. Acharya and Steffen (2015) obtain market-based indicators of banks' exposures to sovereign stress by relating banks' stock returns to yields on German government debt and Greece, Italy, Ireland, Portugal and Spain (GIIPS) countries' debt. Agarwal, Duttagupta, and Presbitero (2020) construct time-varying bank-specific commodity exposures by regressing bank stock returns on marketwide returns and a commodity price index. Our paper, however, is the first to use this methodology to infer banks' sectoral exposures and show that such gauges match in a reasonable manner with more traditional measures of sectoral concentration, while offering distinct advantages.

Second, we contribute to the literature on lending concentration and its implications for bank performance and stability, most of which has provided evidence for return-increasing and risk-reducing effects of sectoral lending concentration. Empirical evidence by Acharya, Hasan, and Saunders (2006) for Italy and by Hayden, Porath, and Westernhagen (2007) and Jahn, Memmel, and Pfingsten (2016) for Germany documents that specialization in certain industries is accompanied by lower loan loss rates. Boeve, Duellmann, and Pfingsten (2010) find that German cooperative and saving banks exert more and better monitoring if they are specialized rather than diversified. Empirical evidence from Brazil, by Tabak, Fazio, and Cajueiro (2011), also hints to the fact that loan portfolio concentration seems to improve the performance of banks in both return and risk of default. In addition, these authors also document that the loan portfolios of Brazilian banks are more concentrated compared to, for example, Germany, Italy, and the United States. While the existing literature focuses either on single countries or syndicated lending (Cai et al. 2018), our paper is the first cross-country study on the relationship between sectoral specialization and bank risk. Unlike previous papers in this literature, our methodology allows us to take a broader view on sectoral exposure beyond lending and in a cross-county setting, allowing for a broader inference.[5] Specifically, we are the first to test theoretical hypotheses on banks' sectoral concentration using market-based data for a broad sample of banks and countries.

1. NEW MEASURES OF SECTORAL CONCENTRATION

Our goal is to construct proxies for three aspects of banks' sectoral concentration, namely, banks' sectoral specialization, banks' sectoral differentiation, and banks' financial sector exposure, using a common framework that is widely applicable. We take an innovative, data-driven approach to measure these three components of sectoral concentration.

5. A contemporaneous paper by Giannetti and Saidi (2019) considers the relationship between sectoral lending concentration and banks' liquidity support for industries in distress. The authors use syndicated lending data, but similar to our work, they find evidence for a stability-enhancing role of sectoral concentration.

1.1 Methodology and Construction of the Measures

A bank's stock price is influenced by exposures to systematic as well as idiosyncratic risk. In line with the Arbitrage Pricing Theory model, we assume that multiple systematic risk factors can be related to a bank's stock return. In general, researchers have focussed on a limited set of factors of which the main one is a marketwide index (either global or domestic). However, if a bank's portfolio is more exposed to a certain sector than that sector's share in the economy, then the bank's stock return should not only react to economywide shocks, but also to sector-specific shocks. Likewise, if a bank is strongly connected to other financial institutions, then its stock return would also be affected by financial sector shocks. This leads us to define the following return generating process, r_d^i, for each bank i on day d:

$$r_d^i = \alpha_i + \sum_{sector=1}^{S} \beta_i^{sector} r_d^{sector} + \beta_i^{finance} r_d^{finance} + \sum_{factor=1}^{F} \beta_i^{factor} r_d^{factor} + \epsilon_d^i, \quad (1)$$

where $r_d^{finance}$ represents the daily returns to a global financial sector index, r_d^{factor} represents a systematic risk factor capturing overall economic conditions[6], and r_d^{sector} represents the daily returns to a global sectoral index. $S = 9$, so we use nine different sectoral indices, corresponding with the ICB level two-sector decomposition: oil and gas, basic materials, industrials, consumer goods, healthcare, consumer services, telecommunications, utilities, and technology. The nine β_i^{sector} (sector $= 1, \ldots S$) capture how bank i's stock return comoves with the returns on each sectoral index.

Raw sector-specific returns, r_d^{sector}, by themselves are not fully informative about pure sector-specific shocks, because sector dynamics are also affected by changes in the business cycle and financial conditions. Moreover, sectors differ in their sensitivities to the business cycle (see, e.g., Petersen and Strongin 1996, Braun and Larrain 2005) as well as in their dependence on external financing (see, e.g., Rajan and Zingales 1998), which we conjecture to be reflected in the sectoral returns. We thus decompose the nine sectoral returns into three sources of variation. They are: fluctuations due to aggregate economic conditions, fluctuations due to financial sector conditions, and idiosyncratic sector-specific conditions. Likewise, we also conjecture that the returns on the global financial sector can be decomposed into systematic variation due to global economic conditions as well as financial sector-specific conditions. These assumptions lead to the following decomposition for the sectoral returns (equation (2)) and financial sector returns (equation (3)):

$$r_d^{sector} = \alpha_{sector} + \beta_{sector}^{market} r_d^{market} + \beta_{sector}^{finance} r_d^{finance} + \epsilon_d^{sector}, \quad (2)$$

$$r_d^{finance} = \alpha_{finance} + \beta_{finance}^{market} r_d^{market} + \epsilon_d^{finance}, \quad (3)$$

6. We include several systematic risk factors, see later, of which the main one is a global and a domestic marketwide index.

where β_{sector}^{market} captures a sector's exposure to economywide fluctuations, $\beta_{sector}^{finance}$ captures a sector's exposure to global financial conditions, and ϵ_d^{sector} represents sector-specific shocks. Likewise, $\beta_{finance}^{market}$ captures the financial sector's exposure to economywide fluctuations, whereas $\epsilon_d^{finance}$ corresponds to idiosyncratic financial sector shocks. Focusing on ϵ_d^{sector} thus isolates the component of sector returns orthogonal to economywide and financial sector fluctuations, while focusing on $\epsilon_d^{finance}$ isolates the component of financial sector returns orthogonal to economywide fluctuations.

Using daily returns for each year t in our sample, we derive estimates of ϵ_d^{sector} and $\epsilon_d^{finance}$ by running year-by-year OLS regressions of equation (2) for each of the nine sectors, and of equation (3). We thus orthogonalize the global sectoral returns with respect to the global market return and global financial sector return to obtain nine $\hat{\epsilon}_d^{sector}$ series. Likewise, we orthogonalize the global financial sector return with respect to the global market return to obtain $\hat{\epsilon}_d^{finance}$. Using these residuals, we arrive at the following specification from which we will obtain our three measures:

$$r_d^i = \tilde{\alpha}_i + \sum_{sector=1}^{S} \tilde{\beta}_i^{sector} \hat{\epsilon}_d^{sector} + \tilde{\beta}_i^{finance} \hat{\epsilon}_d^{fin} + \sum_{factor=1}^{F} \tilde{\beta}_i^{factor} r_d^{factor} + \epsilon_d^i. \quad (1')$$

Equation (1′) differs from (1) by using the orthogonalized returns $\hat{\epsilon}_d^{sector}$ and $\hat{\epsilon}_d^{finance}$ rather than the raw returns r_d^{sector} and $r_d^{finance}$.[7] The orthogonalization not only delivers the idiosyncratic shocks, but also reduces the collinearity present in equation (1). Importantly, this orthogonalization is innocuous in the context of our study. Giliberto (1985) documents that such orthogonalization procedure does not affect the estimated coefficients on the sectoral returns,[8] and will thus not affect our measures of specialization and differentiation (see below for their construction).

We estimate model (1′) separately for each bank-year combination using daily returns. As such, we identify exposures to specific sectors ($\hat{\tilde{\beta}}^{sector}$ for sector $= 1, \ldots, S$) and the financial sector ($\hat{\tilde{\beta}}^{finance}$) for each bank i in each year t. The included systematic risk factors (r_d^{factor}) that might affect bank stock returns are the returns on a global and local market index, the returns on the global small-minus-big, high-minus-low, and momentum factors,[9] as well as returns on a real estate investment trust (since real estate loans are a large, but heterogeneous fraction of bank assets). The choice

7. In fact, we will standardize $\hat{\epsilon}_d^{sector}$ and $\hat{\epsilon}_d^{finance}$ as this facilitates comparing the exposures to different industries identified in equation (1′). The estimated $\hat{\tilde{\beta}}_i^{sector}$ and $\hat{\tilde{\beta}}_i^{finance}$ then immediately reflect both the exposure to as well as the riskiness (i.e., volatility) of the sectoral shocks.

8. Giliberto (1985) provides a proof that orthogonalization results in unbiased estimators of the orthogonalized variables, but may result in biased estimators of the others. This may imply that the exposures to our systematic risk factors (β_i^{factor}) are biased, but these are not of interest nor of importance for our study.

9. For detailed information on the construction of the factors, we refer the reader to Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_3developed.html

of these additional factors is supported by evidence from Baele et al. (2015) who use Bayesian Model Averaging techniques to document which factors are important for which type of banks at which point in time. The residual, ϵ_d^i, captures the idiosyncratic or bank-specific news component.

We would like to note three important things. First, the validity of our approach rests on the assumption that market participants are aware of actual exposures to and performance across economic sectors. During earnings calls, bank managers provide such information to analysts. To give a flavor, we provide two such examples from earnings calls transcripts here, but more examples as well as the hyperlinked documents can be found in the Internet Appendix (A1). For example, in the earnings conference call of 2005Q2 of the Bank of Montreal Financial Group, the head of corporate risk management, Bob McGlashan, says: "*On slide 9, you'll see the allocation of our credit protection portfolio by industry. We are active in the use of single name credit default swaps to mitigate risk related to specific credit exposures and indexed credit default swaps to mitigate sectoral risk concentrations.*" Subsequently, the COO, Yvan Bourdeau elaborates:"*Moving to slide 10, our CDS or trading book is predominantly in a loan protection position. As illustrated on the slide, our industry exposure is well diversified with significant concentration of risk in only 3 particular industries.*" During earning calls, analysts also inquire specifically about banks' sectoral exposures. For example, a Bank of America Merrill Lynch analyst raised the following question during the 2015Q2 earnings call of ING: "*And my second question is on your loan growth and industry lending. Can you please give us more detail on what sectors are working well and how you manage still to grow, although oil and gas is not doing well? I know that you are diversified but if you can explain us what other factors are.*"

Second, we do not impose constraints on the coefficients of model ($1'$) and hence allow that a bank has a negative exposure to a specific industry. A negative exposure could be due to a short position. It could also be due to (institutional) investors who, when a sector is hit by a positive shock, rebalance their portfolio out of a bank that is relatively less exposed to that sector, and into a bank that is relatively more exposed.

Third, even though loans individually mainly have downside risk and limited upside potential for a bank, we do expect specialized banks to react equally to negative and positive sectoral shocks. Within a sector, we assume there is a distribution of firm quality and firm performance. One can interpret a positive shock to the sectoral index as implying a right shift of this distribution, and vice versa for a negative shock. A positive shock is then likely to have several effects on the banks' loan portfolio. First, this creates lending opportunities for the bank to firms that the bank previously considered of too low quality, meaning that the bank can expand its activities and generate more revenues and profits. Second, the quality of the bank's lending portfolio has improved, as the average default probability of the banks' borrowers declines, meaning that the bank will need to book fewer provisions for losses and hence generate more profits on its incumbent borrowers. Third, if the positive shock also signals better investment opportunities for the firms in this sector, it is likely that the demand for loans of the incumbent borrowers will increase compared to before the shock, implying new lending opportunities to these borrowers, meaning more revenues and profits.

Likewise, in case of a negative shock, we would not only expect an increase in the probability of default of the existing borrowers, but also a reduced demand for loans by the incumbent borrowers as well as more firms that will become "unbankable" (i.e., will not see their credit being rolled over or might experience a termination of existing credit lines because of covenant violations). As such, we expect banks' returns to be correlated with both positive and negative sectoral shocks.

1.2 The Sectoral Concentration Measures

Using the extended market model (1′), we compute time-varying bank-specific measures of sectoral specialization, sectoral differentiation, and financial sector exposure. First, sectoral *specialization* is defined as the contribution of the nine sectoral shocks to the R^2 in model (1′). To measure this contribution to R^2, we also estimate an auxiliary equation (model (4)), which is the same as model (1′), except for dropping $\sum_{sector=1}^{S} \tilde{\beta}_i^{sector} \hat{\epsilon}_d^{sector}$.

$$r_d^i = \tilde{\alpha}_i + \tilde{\beta}_i^{finance} \hat{\epsilon}_d^{finance} + \sum_{factor=1}^{F} \tilde{\beta}_i^{factor} r_d^{factor} + \epsilon_d^i. \tag{4}$$

We then subtract the R^2 of model (4) from the R^2 of model (1′) to end up with the following bank-time varying sectoral specialization measure for each bank i in year t:

$$\text{Specialization}_{i,t} = R_{i,t}^2(\text{model } (1')) - R_{i,t}^2(\text{model } (4)). \tag{5}$$

Hence, bank sectoral *specialization* captures the percentage variation of the bank's stock return that is incrementally explained by the orthogonalized sector-specific return series over and above the variation explained by the other factors. A larger value indicates a higher exposure to sector-specific shocks that is not created by economy-wide or financial events.[10]

Second, we compute a measure of sectoral differentiation of banks within a country in a given year. For each bank i and year t, we compute the Euclidean distance between

10. Bank sectoral specialization thus points to a violation of the assumptions underlying the asymptotic single risk factor (ASRF) model. The ASRF model assumes that the loss rate for a well-diversified portfolio depends only on a (single) systematic risk factor and not on idiosyncratic or sectoral risk factors. The ASRF model was at the core of the Basel II regulatory capital requirements, which was in place during our sample period, but was already disputed during the design and implementation.

a bank's estimated sectoral exposures and the country-year average (excluding bank *i*) of the sectoral exposures. The Euclidean distance is computed as follows:

$$\text{Differentiation}_{i,t} = \sqrt{\sum_{sector=1}^{S} \left(\hat{\tilde{\beta}}_{i,t}^{sector} - \sum_{k \neq i}^{I_c} w_{k,c,t} * \hat{\tilde{\beta}}_{k,c,t}^{sector} \right)^2}, \tag{6}$$

where I_c is the number of other banks in country c and $w_{k,c,t}$ is the market share (in total assets) of bank k in country c in year t, excluding bank i.[11] Sectoral *differentiation* will be larger when the bank's sectoral exposures deviate more from the weighted average exposure of all other banks in the country.[12] The lower the value, the more a bank is indirectly connected with other banks in its country as it then shares the same sectoral exposures (leading to correlated exposures). Cai et al. (2018) use a similar measure to measure bank differentiation based on syndicated loan exposures.

Finally, we also look at a bank's exposure to financial institutions in a given year. The higher $\tilde{\beta}_i^{finance}$ from model (1′), the more a bank i's stock return comoves with general financial sector shocks in a given year. We use this as a proxy for (over)exposure to the financial sector, due to, for instance, direct interconnectedness, and label this variable *financial sector exposure*:[13]

$$\text{Financial sector exposure}_{i,t} = \hat{\tilde{\beta}}_{i,t}^{finance}. \tag{7}$$

We obtain information on banks' balance sheets and income statements from Bankscope, which is a database compiled by Fitch/Bureau Van Dijck that contains information on banks around the globe, based on publicly available data sources. While Bankscope contains information for listed and private banks, we exclude the latter as we develop stock return-based measures. Bankscope does not contain stock market information on a daily basis, but does contain information on the ticker and ISIN number of (de)listed banks' equity, which enables matching with Datastream. From Datastream, we retrieve information on a banks' daily stock price and market capi-

11. Alternatively, we use weights based on market capitalization but find almost correlation (98.7%) between both approaches. Our baseline regressions reported in Section 2.2 are robust to using this alternative measure of differentiation, with results available in the Internet Appendix (A5.2).

12. Like in the competition literature, one has to make an assumption about the relevant market. We opt for the domestic one, but realize that banks vary in the extent to which they operate domestically vs. globally. However, we believe that the choice for the domestic market can be justified. First, we include both the returns on a global and a domestic index in model (1′), hence partly filtering out the impact of heterogeneity in global vs. domestic outreach. Second, there is substantial evidence in favor of a home bias by both retail and institutional investors. Hence, even if banks operate globally, investors will mainly compare them with domestic peers. However, in a robustness test we show that our findings are not sensitive to excluding globally active banks.

13. The Datastream Financials index includes: banks, insurance companies, real estate, financial service (including asset managers, consumer finance, speciality finance, investment services, and mortgage finance), and equity/nonequity investment instruments. It is thus a broad index of financial service companies.

talization. The combined Bankscope–Datastream sample, cleaned for missing items on variables of interest, yields 11,702 observations on 1,716 banks from 34 countries over the period 2002–12.[14] We include commercial banks, bank holding companies, savings banks, and cooperatives.[15]

We estimate model (1′) for each bank and for each year using daily returns, such that we end up with a panel database on sectoral exposures that vary at the bank-year frequency. Information on the estimated exposures is reported in Table 1. Panel A of Table 1 reports for each estimated sectoral factor loading the mean and standard deviation, as well as the 5th, 50th, and 95th percentile. As illustrated in Panel A, the average exposure is close to zero for all sectors. This indicates that the stock market believes that banks are, on average, not exposed to shocks to these sectors. However, we also find a large variation in exposures across banks and years, ranging from below minus one in Oil&Gas, Basic Materials, Healthcare, and Technology to above plus one in the same sectors.

We report summary statistics on the measures of sectoral specialization, sectoral differentiation, and financial sector exposure in Panel B of Table 1. We find that the average bank has an increase in R^2 of 3.35 percentage points when the global sectoral shocks are included on top of the other factors. The average R^2 in the 11,702 regressions across banks and over time using model (1′) is 27%. Hence, adding the nine sectoral shocks leads to an average increase of more than 14% in the explained variation of bank stock returns. Sectoral specialization ranges from 0.98 (p5) to 7.25 (p95).

The average bank's differentiation from its country peers is 1.57. This value for our Euclidean distance measure corresponds, for instance, with a bank having six sectoral exposures being exactly similar to its peer banks' average and three sectoral exposures being approximately 0.72 standard deviations away from its peer banks' average. One way to think about this is that, assuming banks' peers in the country hold the market portfolio (i.e., the peers are jointly on average diversified), banks have six sectors in which they hold a share equivalent to the sectors' share in the economy, and hence, are not over- or underexposed and therefore not different from the average peer in their country. On top of that, banks have two sectors to which they are overexposed, and, as a consequence of directing many resources to these sectors, also have one sector to which they are underexposed, and hence differ from the average peer in their country for these three sectors. The example of deviating 0.72 standard deviations in three sectors is economically plausible given that the average

14. Information on sample characteristics is reported in the Internet Appendix (A2). Variable definitions and data sources are also reported in the Internet Appendix (A3). We restrict our sample to countries (i) for which Datastream provides local market indices and (ii) that have at least five banks in each year in order to construct meaningful and reliable proxies for differentiation from the rest of the banks in the country.

15. While savings and cooperative banks often have a different business model and ownership structure, listed savings and cooperative banks are more akin to commercial banks than to small savings and cooperative banks. Excluding these 259 (275) bank-year observations for cooperative (savings) banks does not affect the results.

TABLE 1

Return- and Accounting-Based Sectoral Exposures and Concentration Measures

Variable	Mean	sd	p5	p50	p95
Panel A. Summary statistics on sectoral factor loadings					
1 = Oil & gas (OILGS)	−0.01	1.06	−1.52	−0.01	1.51
2 = Basic materials (BMATR)	−0.01	0.82	−1.12	−0.01	1.07
3 = Industrials (INDUS)	−0.03	0.60	−0.89	−0.03	0.81
4 = Consumer goods (CNSMG)	−0.01	0.63	−0.85	−0.00	0.86
5 = Healthcare (HLTHC)	0.01	0.76	−1.09	0.00	1.16
6 = Consumer services (CNSMS)	−0.00	0.60	−0.88	−0.01	0.87
7 = Telecommunications (TELCM)	0.00	0.46	−0.67	−0.00	0.69
8 = Utilities (UTILS)	0.02	0.44	−0.60	0.02	0.67
9 = Technology (TECNO)	−0.01	0.99	−1.43	−0.01	1.36
Panel B. Return-based concentration measures					
Specialization	3.35	1.99	0.98	2.92	7.25
Differentiation	1.57	1.44	0.30	1.15	4.44
Financial sector exposure	0.07	0.31	−0.35	0.04	0.58
Panel C. Summary statistics on sectoral lending shares					
Agriculture, Forestry, and Fishing	0.02	0.04	0.00	0.00	0.11
Mining and construction	0.06	0.06	0.00	0.05	0.18
Manufacturing	0.16	0.11	0.02	0.14	0.38
Transport, communication, electric, gas and sanitary service	0.07	0.07	0.00	0.05	0.22
Wholesale trade and retail trade	0.13	0.10	0.00	0.11	0.33
Real estate	0.14	0.15	0.00	0.10	0.46
Services	0.11	0.10	0.00	0.10	0.30
Public administration	0.05	0.07	0.00	0.01	0.19
Other industries	0.17	0.18	0.00	0.12	0.51
Panel D. Accounting-based concentration measures					
Specialization (accounting)	0.56	0.17	0.32	0.55	0.88
Differentiation (accounting)	0.20	0.10	0.07	0.18	0.40
Finance and Insurance	0.09	0.10	0.00	0.05	0.31

Note: Panel A contains summary statistics on the estimated sectoral factor exposures. The panel data set of estimated sectoral exposures consists of 11,702 bank-year observations, covering 1,716 banks from 34 countries over a 10-year period starting in 2002. Based on the estimated sectoral exposures, we compute a time-varying bank-specific measure of sectoral specialization, sectoral differentiation, and financial sector exposure, for which summary statistics are reported in Panel B. We provide summary statistics on the mean and standard deviation, as well as the 5th, 50th, and 95th percentile. We also hand-collect information on sectoral exposures from the notes to the banks' financial statements. This data collection yields a panel of accounting-based sectoral *lending* exposures at the bank-year level for the years 2007–11, covering 956 observations on 221 banks from 30 countries. Based on the hand-collected accounting-based lending shares (measured as the share in total corporate lending and reported in Panel C), we compute a time-varying bank-specific measure of sectoral specialization, sectoral differentiation, and financial sector exposure, for which summary statistics are reported in Panel D. A detailed description of the construction of these return-based and accounting-based measures is provided in the text as well as in Table A2 of the online appendix.

standard deviation across estimated sectoral betas is 0.70 (see Panel A of Table 1). Sectoral differentiation ranges from 0.3 (p5) to 4.44 (p95).

The estimated sensitivity of the banks' return to the global financial sector shocks (i.e., the financial sector exposure) is 0.07 for the average bank-year, and ranges from −0.35 (p5) to 0.58 (p95). Not surprising, the exposure to the financial sector is, on average, larger than the nonfinancial sectoral exposures. The units of these exposures are returns and the average of 0.07 implies that a bank's daily return will be 0.07% higher if the global financial sector's daily return is one standard deviation larger than its daily average (as we have standardized the sectoral and financial sector shocks).

Importantly, all three measures exhibit substantial variation, enabling us to assess how these measures are related to (systemic) risk. Furthermore, we find significant pairwise correlation coefficients between specialization and differentiation (0.24) and specialization and the financial sector exposure (−0.06). The pairwise correlation

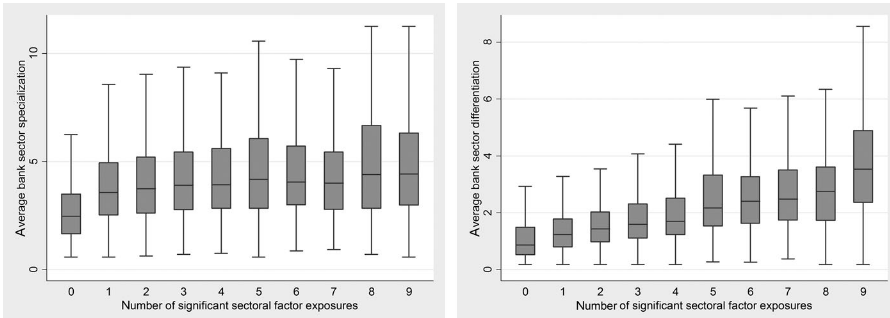

Fig 1. Specialization and Differentiation: Significant Sectoral Exposures.

NOTES: This graph consists of two subplots, one for sectoral specialization (left) and one for sectoral differentiation (right). In these graphs, we present distributional information, via a box plot, on our specialization and differentiation measure, depending on how many of the estimated sectoral factor loadings are significant at the 5% level. An input for both measures is the nine estimated sectoral factor loadings (for which summary statistics are shown in Panel A of Table 1).

between differentiation and the financial sector exposure is 0.01 and insignificant (*p*-value of 0.44). On the one hand, it is reassuring that the correlations are not large, indicating that we capture three different dimensions of sectoral concentration. On the other hand, as two of the pairwise correlation coefficients are significant, it is important to jointly analyze these aspects (e.g., in an analysis of their impact on (systemic) bank risk, see Section 2).[16]

In Figure 1, we provide some more distributional properties of sectoral specialization and differentiation depending on how many of the nine estimated sectoral factor exposures are statistically significant. In 62% of the cases, none of the factor exposures is significantly different from zero. There are 1, 2, or 3 significant exposures in 14%, 6%, and 4% of the cases, respectively. The remaining 14% is more or less equally distributed over the other bins. Our sectoral specialization measure exhibits a jump as soon as one factor is significantly different from zero. Moreover, the average increase in specialization, vis-à-vis the case of zero significant exposures, does not depend much on how many exposures are significantly different from zero. Differentiation (how different sectoral exposures are with respect to the average bank in the country) on the other hand does increase monotonically with the number of significant sectoral factor exposures.

The observed pattern for differentiation is straightforward. A bank holding the market portfolio should only load on the global or local market returns and not the sectoral factors. The more sectoral exposures that are significant (positive or negative), the more dimensions in which the bank differentiates itself from its peers. The pattern

16. The Internet Appendix (A4.1) contains information on the variation of specialization, differentiation, and financial sector exposure over our sample period.

for specialization requires more explanation. Banks having one significant sectoral coefficient are clearly specialized compared with banks having no significant sectoral coefficient. However, banks with more than one significant coefficient can still be considered specialized for several reasons. First of all, focusing on one specific sector can come at the expense of completely ignoring one other sector or marginally underinvesting in all remaining sectors.[17] Second, multiple significant coefficients might still imply specialization to only one sector because of the presence of correlation in the sectoral factor returns. These are not orthogonal to each other and do exhibit some degree of correlation.[18] As an example, think of shocks to oil and gas affecting many other sectors through increased transportation costs. The problem is that there is no clear theoretical guidance on how to position these sectoral shocks relative to each other (i.e., putting an input–output sequence to the sectors in a Cholesky sense). Moreover, this correlation is not a problem for our measures. It affects the standard errors and hence the number of significant coefficients, but not the contribution to R^2. It does not affect differentiation either, as the correlation structure of the sectoral factors is the same for all banks in a country.

1.3 Validity of the Measures

As discussed earlier, detailed information on banks' loan composition is lacking from publicly available or commercial databases. Therefore, we hand-collect these data from the notes to banks' financial statements. This is voluntarily disclosed by banks and thus lacks a uniform reporting scheme. To harmonize the used sectoral breakdown across banks, we categorize each reported exposure in 10 economic sectors based on the one-digit Standard Industrial Classification. We build our database of sectoral exposures only for the largest banks which more likely publish a detailed report, ultimately collecting data for 221 banks across 30 countries, for the years 2007–11.[19]

Summary statistics on the sectoral lending shares (measured as their share in total corporate lending) are reported in Panel C of Table 1. There is variation in the average exposure between the nine sectors, with the lowest average for the sector "Agriculture, forestry, and fishing" and the highest for "Other industries." Within each sector, there is substantial heterogeneity. The 5th percentile is almost always zero, whereas the exposure to "Real Estate" at the 95th percentile is 46%.

17. Depending on the case, this type of specialization could result in two (one positive and one negative) or many (one positive and many, small, negative) significant coefficients. It then depends on the noise in the data whether or not economically small, negative exposures will be statistically significant or not.

18. The mean (median) of the absolute value of the 36 pairwise correlations between the nine sectoral factors is 0.18 (0.16). Only 10 pairwise correlations (in absolute value) exceed 0.25.

19. Starting from our sample of banks, we impose the following constraints to optimize the manual data collection: (i) banks need to be active in 2013, that is, not have failed during the recent crisis, as we otherwise would not find a website with historical information; (ii) banks need to have total assets in excess of 10 billion U.S. in 2011; (iii) information on basic characteristics, such as: common equity, total assets, the net interest margin, loan loss provisions as well as a liquidity ratio are nonmissing.

Based on these hand-collected exposures, we construct *accounting-based* indicators of sectoral specialization, sectoral differentiation, and financial sector exposure.[20] We capture sectoral *Specialization (accounting)* by the cumulative share of the three largest sectoral lending shares. Sectoral *Differentiation (accounting)* is computed as the Euclidean distance between a bank's sectoral loan portfolio and the weighted average sectoral loan portfolio of the bank's domestic competitors (as in equation (6), but replacing the estimated factors with reported lending shares). Finally, we capture the accounting-based financial sector exposure by the lending share to the *Finance and Insurance* sector. The summary statistics of these measures are reported in Panel D of Table 1.

We then test the information content of our return-based measures by regressing each return-based measure on its accounting-based counterpart, as well as a set of bank-year level control variables and fixed effects. Both the return-based and accounting-based sectoral specialization and differentiation measures are included in logs so that we can interpret the coefficients as indicating relative percentage changes.

We also test for heterogeneity across banks driven by different degrees of disclosure standards and by differences in the ratio of off-balance sheet items to total assets. We construct a disclosure index following Nier and Baumann (2006), with higher values indicating more bank disclosure of critical balance sheet and income statement items. We take the disclosure index as a proxy for the quality of the information in the notes to the annual statements and hence a proxy for the quality of the accounting-based concentration measures.[21] Therefore, we expect a stronger relationship between the return-based and accounting-based measures for banks with higher disclosure standards. A higher ratio of off-balance sheet items to total assets implies that the balance sheet measures of specialization and differentiation may incorporate less of the banks total risks or hedging. As these cannot be observed in the lending shares, we expect a weaker relationship between return-based and accounting-based measures for banks with higher off-balance sheet to total assets ratios. The disclosure index and the off-balance sheet items to total asset ratio have been standardized before interacting them with the accounting-based measures. Regression results are reported in Table 2.

The results in Table 2 show a positive and strongly significant correlation between return-based and accounting-based sectoral specialization in Columns (1) and (2). The coefficient estimates suggest that a 1% change in accounting-based specialization is associated with a 0.42–0.48% change in return-based specialization. This suggests a less than one-to-one relationship and testifies that (partial) hedging is important to

20. Given that "other industries" is hard to interpret and captures possibly very different types of sectors across banks and countries, we focus only on eight sectors when constructing the accounting-based measures.

21. We find a significantly negative correlation between the disclosure index and the fraction of lending reported in the "other category." The more transparent banks are in general, the more informative and detailed they report their sectoral lending exposures.

TABLE 2

Relating Accounting-Based to Return-Based Measures: Specialization and Differentiation

Variables	(1) $\text{Specialization}_{it}$	(2) $\text{Specialization}_{it}$	(3) $\text{Differentiation}_{it}$	(4) $\text{Differentiation}_{it}$
Specialization $(\text{accounting})_{it}$	0.42***	0.48***		
	(0.14)	(0.14)		
Differentiation $(\text{accounting})_{it}$			0.43*	0.43**
			(0.24)	(0.21)
Specialization $(\text{accounting})_{it}$ x OBS_{it}		−0.26*		
		(0.14)		
Differentiation $(\text{accounting})_{it}$ x OBS_{it}				−0.50**
				(0.20)
Specialization $(\text{accounting})_{it}$ x DISC_{it}		0.03		
		(0.11)		
Differentiation $(\text{accounting})_{it}$ x DISC_{it}				0.25*
				(0.15)
Of-Balance Sheet Size to Total Assets $(\text{OBS})_{it}$		0.06		0.07
		(0.07)		(0.05)
Disclosure $(\text{DISC})_{it}$		−0.02		−0.04
		(0.05)		(0.03)
Bank Size_{it}	−0.20	−0.13	−0.31	−0.26
	(0.28)	(0.27)	(0.28)	(0.27)
Bank Size x Revenue $\text{Diversification}_{it}$	0.99	0.66	0.66	0.38
	(1.41)	(1.39)	(1.30)	(1.28)
Revenue $\text{Diversification}_{it}$	−0.16	−0.16	0.49***	0.47***
	(0.15)	(0.14)	(0.15)	(0.15)
Bank Capital_{it}	−0.02	0.05	−1.55***	−1.35**
	(0.54)	(0.54)	(0.56)	(0.57)
Funding $\text{Diversification}_{it}$	−0.24	−0.29*	−0.35**	−0.36**
	(0.16)	(0.16)	(0.15)	(0.14)
Loans Share_{it}	0.12	0.15	0.30**	0.31**
	(0.16)	(0.17)	(0.14)	(0.13)
$\text{Profitability}_{it}$	−0.25	−0.19	−0.54***	−0.52***
	(0.15)	(0.15)	(0.16)	(0.15)
Asset Growth_{it}	0.06	0.03	0.12	0.11
	(0.10)	(0.09)	(0.10)	(0.10)
Credit Risk_{it}	−0.02	−0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	956	956	956	956
R^2	0.31	0.32	0.25	0.26
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: This table provides information on the relationship between the hand-collected accounting-based sectoral lending specialization and differentiation and the return-based sectoral lending specialization and differentiation. We take the log of all specialization and differentiation measures, such that we estimate a log–log specification and the coefficients can be interpreted as the percentage impact on the return-based variable of a 1% change in the accounting-based variable. We estimate both equations with and without interacting the accounting based measures with a proxy for the bank's hedging efforts (of-balance sheet size to total assets (OBS)) and a proxy for the accounting transparency of banks in a country (disclosure index (DISC)). OBS and DISC have been standardized before the interaction. We further include country and year fixed effects and cluster standard errors at the bank level. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

take into account in order to identify the true (credit) exposures of a bank.[22] Columns

22. We also explore whether the market-based measures of specialization can be compared across countries or time periods. First of all, we take the two countries for which we have most bank-year observations in the accounting-based sample (Japan and the United States) and split the sample into two periods ($\leq$ 2009 and $>$ 2009). The results show that the estimated coefficients (0.73 and 0.54) are not statistically different from each other, and not statistically different from the full sample coefficient (0.42). Second, we also bootstrap our full sample estimation, drawing 200 times a random sample out of the full sample; the

(3) and (4) of Table 2 show that there is also a positive and significant relationship between return-based and accounting-based differentiation. The economic size of the relationship is similar to that of the specialization measures. When we interact the accounting-based measures with the ratio of off-balance sheet items to total assets and with the disclosure index in Columns (2) and (4), we find—as expected—a negative coefficient on the former interaction and a positive coefficient on the latter interaction (although statistically insignificant in Column (2)).

The results in Table 3 show a very close comovement in sectoral lending shares to the financial sector and factor loadings to the financial sector.[23] The coefficients enter positively and significantly across the four columns. The interaction terms with off-balance sheet exposures enter negatively and significantly, while the interaction terms with the disclosure index enter positively and significantly.

Importantly, the weaker link between the accounting-based and return-based measures for less transparent financial statements is due to more imprecise accounting reporting. In fact, we do not find that our return-based measures are more imprecise for less transparent banks. That is, we obtain similar graphs when replicating Figure 1 for banks above and below the median value of disclosure. These graphs are available in the Appendix (A4.2).

2. BANK SECTORAL CONCENTRATION AND RISK

The second goal of this paper is to carefully analyze how these newly developed measures of various dimensions of banks' sectoral concentration are related to bank risk taking and systemic stability. First of all, banks' default risk is proxied by Merton's *Distance to Default (DtD)*. The DtD measures the difference between the asset value of the bank and the face value of its debt, scaled by the standard deviation of the bank's asset value (see Merton (1974) and Campbell, Hilscher, and Szilagyi (2008)). Second, we estimate a bank's systemic risk exposure using the *Marginal Expected Shortfall* (Acharya et al. 2017). We compute the marginal expected shortfall for each bank-year observation by looking at the average daily stock return of banks on days where the country's local banking sector index (excluding the bank itself) experiences one of its 5% lowest returns in that year. Doing so, the marginal expected shortfall of bank i in year t corresponds to bank i's expected equity loss per dollar in year t conditional on the local banking sector experiencing severe stress. We take the

correction proposed by the bootstrap increases the standard error by only 0.01 (from 0.15 to 0.16). Furthermore, using the bootstrap, we find that the 95% confidence interval in which the estimated coefficient is likely to be, is between 0.16 and 0.80 and thus coefficients for the United States and Japan are well within these bounds.

23. While we would have liked to run a similar test for other sectoral lending shares and factor loadings, for none of the other sectors is there a clear sectoral mapping from the accounting-based lending share to a return-based factor loading.

TABLE 3

RELATING ACCOUNTING-BASED TO RETURN-BASED MEASURES: FINANCIAL SECTOR EXPOSURE

Variables	(1)	(2)	(3)	(4)
	Financial sector exposure$_{it}$			
Finance and Insurance$_{it}$	0.70**	1.26***	0.81***	1.27***
	(0.27)	(0.38)	(0.27)	(0.37)
Finance and Insurance$_{it}$ x OBS$_{it}$		−0.84**		−0.72*
		(0.36)		(0.37)
Finance and Insurance$_{it}$ x DISC$_{it}$			0.56**	0.50**
			(0.22)	(0.23)
Off-Balance Sheet Size to Total Assets (OBS)$_{it}$		0.11**		0.11*
		(0.06)		(0.06)
Disclosure (DISC)$_{it}$			−0.04*	−0.04
			(0.02)	(0.02)
Bank Size$_{it}$	0.06	0.02	0.05	0.02
	(0.34)	(0.34)	(0.34)	(0.33)
Bank Size x Revenue Diversification$_{it}$	0.41	0.68	0.53	0.75
	(1.56)	(1.60)	(1.55)	(1.57)
Revenue Diversification$_{it}$	0.12	0.11	0.08	0.07
	(0.29)	(0.28)	(0.27)	(0.27)
Bank Capital$_{it}$	1.63	1.56	1.77	1.70
	(1.41)	(1.40)	(1.39)	(1.38)
Funding Diversification$_{it}$	−0.26	−0.30	−0.27	−0.30
	(0.24)	(0.23)	(0.23)	(0.23)
Loans Share$_{it}$	−0.23	−0.27	−0.27	−0.29
	(0.35)	(0.34)	(0.35)	(0.35)
Profitability$_{it}$	0.17	0.19	0.17	0.19
	(0.20)	(0.19)	(0.19)	(0.19)
Asset Growth$_{it}$	0.08	0.09	0.09	0.10
	(0.13)	(0.13)	(0.13)	(0.13)
Credit Risk$_{it}$	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	956	956	956	956
R^2	0.08	0.09	0.09	0.10
Number of banks	221	221	221	221
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

NOTE: This table provides information on the relationship between the hand-collected accounting-based sectoral lending share to "Finance and Insurance" and the estimated financial sector exposure. More specifically, the table provides regression results for a regression of the financial index factor loading on the sectoral lending share to the "Finance and Insurance" sector, while controlling for a set of bank-specific control variables, as well as bank and year fixed effects. We also augment the model by interacting the sectoral lending share to "Finance and Insurance" with a proxy for the bank's hedging efforts (of-balance sheet size to total assets (OBS)) and a proxy for the accounting transparency of banks in a country (disclosure index (DISC)) or both. OBS and DISC have been standardized before the interaction. Standard errors are clustered at the bank level. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

opposite of this variable such that a higher marginal expected shortfall (in absolute value) relates to a higher exposure to systemic risk.

The average bank's DtD is 4.98, implying that the value of a bank's assets is 4.98 standard deviations away from default. The measure also shows a large variation across banks and years, ranging from 0.86 (p5) to 12.76 (p95). This is in line with Anginer et al. (2018) who report an average of 5.3 for U.S. banks and 5.9 for non-U.S. banks. The average marginal expected shortfall is 2, implying that the average daily stock return of banks in our sample is −2% on average when the local banking sector experiences stress, but ranges from +0.5% (p5) to −6.7% (p95).

TABLE 4

Summary Statistics on (Systemic) Bank Risk and Bank Characteristics

Variable	Mean	sd	p5	p50	p95
Panel A. Summary statistics on total bank risk and systemic risk					
Distance to default	4.98	3.54	0.86	4.26	12.76
Systemic risk exposure	1.98	2.30	−0.48	1.42	6.71
Panel B. Summary statistics on bank characteristics					
Bank size	7.97	2.12	5.09	7.57	11.93
Revenue diversification	0.19	0.15	0.00	0.16	0.45
Bank capital	0.09	0.05	0.04	0.09	0.18
Funding diversification	0.89	0.15	0.56	0.94	1.00
Loan share	0.63	0.16	0.32	0.66	0.84
Asset growth	0.11	0.18	−0.07	0.07	0.44
Disclosure	0.81	0.12	0.60	0.85	1.00
Panel C. Summary statistics on alternative dependent variables					
Δ CoVaR	2.01	2.79	−1.95	1.59	7.27
Total volatility	39.31	24.36	13.98	32.26	89.74
ln(Z-score)	3.66	1.27	1.42	3.78	5.55
Nonperforming loans	3.06	3.99	0.09	1.60	10.60
Franchise value	1.42	0.94	0.28	1.26	3.08

Note: This table contains summary statistics on the main dependent variables: distance to default and systemic risk exposure (Panel A, 2003–12), the lagged bank characteristics used as control variables (Panel B, 2002–11), and the alternative dependent variables (Panel C, 2003–12). The sample consists of 11,702 observations, on 1,716 banks from 34 countries. This sample corresponds with the sample for which we can estimate the return-based sectoral concentration measures on countries that have at least five listed banks in each sample year. In each panel, we provide summary statistics (mean, standard deviation as well as the 5th, 50th, and 95th percentile). A detailed description of the construction of these measures and data sources is provided in the text, as well as in Table A2 of the online appendix.

2.1 Methodology and Specification

A natural candidate for a regression specification to investigate whether sectoral specialization, sectoral differentiation, and financial sector exposure impact (systemic) bank risk is the following:

$$\begin{aligned} y_{it} = {} & \beta_1\, Specialization_{it-1} + \beta_2\, Differentation_{it-1} \\ & + \beta_3\, Financial\ sector\ exposure_{it-1} + \gamma\, X_{it-1} + \mu_t + \nu_i + \epsilon_{it}, \end{aligned} \tag{8}$$

where y_{it} is either the DtD or the marginal expected shortfall of bank i in year t. X_{it-1} is a vector of bank characteristics to control for other factors that may affect bank stability.[24] Model (8) also includes year-fixed effects μ_t. ν_i is a bank-specific effect (random or fixed).

In empirical corporate finance, subject fixed effects have become the default option because they yield unbiased estimates in the presence of correlation between the individual effects for the subject (ν_i) and the regressors included in the model. In

24. We include bank size (natural log of total assets), revenue diversification (gross share of noninterest income in total income), bank capital (common equity to total assets), funding diversification (share of deposit funding in deposit and money market funding), loan to asset ratio, annual asset growth, and the bank disclosure index. These variables capture various dimensions of a bank's business model and are often used in other studies modeling (systemic) bank risk, see, for example: Demirguc-Kunt and Huizinga (2010) or Laeven and Levine (2009). Descriptive statistics on the control variables are presented in Panel B of Table 4.

the absence of correlation between ν_i and the regressors, both the fixed effects (FE) and the random effects (RE) estimator yield unbiased coefficients, but the RE estimator will be more efficient. However, the two estimators need not necessarily give similar point estimates in the absence of correlation between ν_i and the regressors. In that case, different point estimates indicate that equation (8) is misspecified and may be suggestive of a dynamic underspecification. Kuh (1959), Baltagi and Griffin (1984), and others have argued that the cross-sectional (between) dimension in panel data tends to include information on the long-run responses, while the time-series (within) dimension provides information on the short-run responses. If this is the case, a model which allows for a short- and long-run relationship between dependent variable and regressors might be more appropriate (Baltagi and Griffin 1984).

Such models are known as hybrid or correlated random-effects models and differ from model (8) as they require a within-subject transformation of the regressors (notation: double bars) and are augmented with the subject averages of the regressors (notation: single bar). In our setup, this leads to model (9), which allows for a simultaneous estimation based on the within-bank variation (capturing short-run effects) and between-bank variation (capturing long-run effects) of our variables of interest: bank sectoral *specialization*, *differentiation*, and *financial sector exposure*.

$$\begin{aligned} y_{it} = {} & \beta_{1a}\, \overline{\overline{Specialization}}_{it-1} + \beta_{2a}\, \overline{\overline{Differentation}}_{it-1} \\ & + \beta_{3a}\, \overline{\overline{Financial\ sector\ exposure}}_{it-1} + \gamma_{1a}\, \overline{\overline{X}}_i \\ & + \beta_{1b}\, \overline{Specialization}_i + \beta_{2b}\, \overline{Differentation}_i \\ & + \beta_{3b}\, \overline{Financial\ sector\ exposure}_i + \gamma_{1b}\, \overline{X}_i + \nu_i + \mu_t + \epsilon_{it}, \end{aligned} \tag{9}$$

where $\overline{Specialization}_i$ is the bank average of $Specialization_{it-1}$ over the sample period and $\overline{\overline{Specialization}}_{it-1} = Specialization_{it-1} - \overline{Specialization}_i$ is the within-bank transformation, and analogous for $Differentiation$ and $Financial\ sector\ exposure$. ν_i are random effects in this model.

It is important to stress that the short run, within-bank estimates in model (9) are *equivalent* to estimating model (8) with bank fixed effects. Similarly, the long run, between-bank estimates in model (9) are equivalent to estimating model (8) using the between estimator. Model (9) simply gives the researcher all the information at once when there is no correlation between ν_i and the regressors. $\hat{\beta}_{1a}$ will be the short-run impact of sectoral specialization on y_{it} and $\hat{\beta}_{1b}$ will be the long-run impact of sectoral specialization on y_{it}. Equivalently, $\hat{\beta}_{2a}$ ($\hat{\beta}_{3a}$) will be the short run and $\hat{\beta}_{2b}$ ($\hat{\beta}_{3b}$) the long-run impact of sectoral differentiation (financial sector exposure) on y_{it}.

2.2 *Baseline Results*

The results of estimating model (9) are shown in Table 5. Prior to the regression, we winsorize all variables at the 1 and 99 percentile level to mitigate the impact of outliers. We standardize the variables to make a comparison of the economic effects

TABLE 5

Baseline Regressions: The Hybrid Model

	Distance to Default$_{it}$			Systemic Risk Exposure$_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel	FE	BE	RE	FE	BE	RE
$\overline{\overline{\text{Specialization}}}_{it-1}$	0.07**		0.07**	−0.06***		−0.06***
	(0.03)		(0.03)	(0.02)		(0.02)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	−0.27***		−0.27***	0.14***		0.14***
	(0.04)		(0.04)	(0.02)		(0.02)
$\overline{\overline{\text{Financial sector exposure}}}_{it-1}$	−0.09***		−0.09***	0.09***		0.09***
	(0.02)		(0.02)	(0.02)		(0.02)
$\overline{\text{Specialization}}_{i}$		0.85***	1.02***		−0.60***	−0.80***
		(0.10)	(0.13)		(0.05)	(0.06)
$\overline{\text{Differentiation}}_{i}$		−1.93***	−2.05***		0.13**	0.17***
		(0.10)	(0.13)		(0.05)	(0.07)
$\overline{\text{Financial sector exposure}}_{i}$		−0.21*	−0.23**		0.78***	0.89***
		(0.11)	(0.10)		(0.05)	(0.08)
Observations	11,702	11,702	11,702	11,702	11,702	11,702
R^2	0.21	0.41	0.37	0.33	0.57	0.47
Number of banks	1,716	1,716	1,716	1,716	1,716	1,716
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	No	No	Yes	No	No
Country fixed effects	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Corr(Fit,ν_i)	−0.024			−0.006		
Wald test 1 (p-value)			0.00			0.00
Wald test 2 (p-value)			0.00			0.00
Wald test 3 (p-value)			0.00			0.00

H0 Wald test 1: $\overline{\overline{\text{Specialization}}}_{it-1} - \overline{\text{Specialization}}_{i} = 0$.

H0 Wald test 2: $\overline{\overline{\text{Differentiation}}}_{it-1} - \overline{\text{Differentiation}}_{i} = 0$.

H0 Wald test 3: $\overline{\overline{\text{Financial sector exposure}}}_{it-1} - \overline{\text{Financial sector exposure}}_{i} = 0$.

Note: This table shows the impact of bank sector specialization, bank sector differentiation, and financial sector exposure on distance to default (left panel) and systemic risk exposure (right panel). Columns (1) and (4) contain the results using the within estimator. Columns (2) and (5) contain the results using the between estimator. Columns (3) and (6) show the baseline results using the hybrid estimator. Bank controls are time-varying bank characteristics and include a measure of bank size, revenue diversification, an interaction between bank size and revenue diversification, bank capital, loan share, funding diversification, asset growth, and disclosure. Standard errors in the fixed and random effects models are clustered at the bank level. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

across the different coefficients easier. Standard errors are clustered at the bank level. For completeness, we first present the results obtained using the bank fixed effects estimator and the between estimator of model (8). Subsequently, we report our main specification: the one-step estimation results of the hybrid specification (model (9)). Columns (1)–(3) use the bank's DtD as dependent variable and Columns (4)–(6) the marginal expected shortfall.

Before discussing the economic implications of the estimated relationships, we make four statistical observations. First of all, the short-run coefficients (first three lines) are identical when using either the (bank) fixed effects estimator in specification (8) or the random effects estimator in the hybrid model (9). Second, the long-run coefficients (next three variables) are nearly identical when using either the between estimator in specification (8) or the random effects estimator in the hybrid model (9).

They are not exactly identical due to the unbalanced nature of our panel. Third, we report the correlation between the estimated bank-specific effects, $\hat{\nu}_i$, and the fitted values of the independent variables, $X\hat{\beta}_{it}$, at the bottom of the table (in the column containing the results of the fixed effects estimation). This correlation appears to be low or even close to zero for each dependent variable (-0.024 and -0.005, respectively), suggesting that the within and between estimator should yield similar results in the absence of model misspecification. Fourth, in the hybrid model we can directly test whether the short-run and long-run coefficients are significantly different from each other. We report the p-values of these tests in the last three lines of the table in the columns reporting the results of the hybrid model. The test results indicate that the equality of $\hat{\beta}_{1a}$ and $\hat{\beta}_{1b}$ is rejected as well as the equality of $\hat{\beta}_{2a}$ and $\hat{\beta}_{2b}$, and $\hat{\beta}_{3a}$ and $\hat{\beta}_{3b}$, in the regressions of all dependent variables. In sum, the absence of correlation between the individual effects and the regressors as well as the statistically significant different coefficients in the within and between estimations provide strong support for the use of a hybrid model as in equation (9).

We now turn the discussion to the economic aspect of the estimated relationships and focus only on the coefficients reported in Columns (3) and (6).[25] As can be seen in Column (3), sectoral specialization is associated with lower bank default risk (i.e., a higher DtD) in the short and long run. The long-run economic effect, however, is almost 15 times larger than the short-run economic effect. These results are also economically meaningful as a one-standard-deviation increase in sectoral specialization decreases bank default risk by about 0.29 standard deviation in the long run.[26] One possible explanation for the higher long-term economic effect is that the information benefit from specializing in lending to a certain sector, which is expected to lead to a better quality of the borrowers in the portfolio and more stable income, requires experience in specialization.[27] The stronger relationship in the long run might also reflect the importance of variation in risk management and business models across different banks in terms of sectoral specialization and, related, their risk performance. The results in Column (3) further indicate that bank default risk increases particularly with bank sectoral differentiation. The long-run impact is again significantly larger than the short-run impact. This suggests that banks that deviate more from the industry norm in terms of sectoral exposures are considered riskier by the market. A one-standard-deviation increase in sectoral differentiation decreases banks' DtD by

25. We only report variables of interest in Table 5, but report the control variables in the Internet Appendix (Table A11).

26. The estimated long-run (between) coefficient of sectoral specialization (which has been standardized) on DtD is 1.02. A one-standard-deviation increase in sectoral specialization would thus increase a bank's DtD by 1.02, which is 28.8% of the standard deviation of bank's DtD (3.54) in the sample.

27. Berger, Minnis, and Sutherland (2017) document that sectoral expertise (through lending specialization) allows banks to acquire information over time on that sector, resulting in lower information acquisition costs on new borrowers in that sector, without compromising credit quality. They show that each year of experience provides more expertise and the effects only materialize after 4.5 years of lending specialization.

about 0.58 standard deviation in the long run. Concerning the financial sector exposure, short-run deviations have a small effect on bank's default risk. In the long run, higher direct exposure to the financial sector is also related to a lower DtD, although the economic impact also remains relatively modest. A one-standard-deviation increase in financial sector exposure decreases banks' DtD by a bit more than 0.06 standard deviation.

In Column (6) of Table 5, we gauge the relationship between sectoral specialization, differentiation, financial sector exposure, and systemic risk exposure, as measured by the marginal expected shortfall. It can be seen that sectoral specialization is associated with lower systemic risk exposure in both the short run and the long run. In line with the observed relation between sectoral specialization and banks' default risk, the relation between sectoral specialization and marginal expected shortfall also appears to be much stronger in the long run, where the coefficient is at least 10 times larger. The long-run effect is also economically meaningful. A one-standard-deviation increase in sectoral specialization leads to a 0.35 standard deviation reduction in marginal expected shortfall in the long run. We further find a positive and significant relation of sectoral differentiation with marginal expected shortfall, and it seems that this impact is of similar size in both the short and the long run. The most important determinant of systemic risk is the financial sector exposure, proxying for direct connectedness to the global financial sector. Again, the long-run relation is much stronger than the short-run effect, but both are statistically significant at the 1% level. A one-standard-deviation increase in financial sector exposure is associated with a 0.39 standard deviation increase in systemic risk exposure in the long run.

All in all, the results suggest that banks that are more specialized face lower bank default risk and are less exposed to systemic risk. Banks that differentiate their sectoral exposure more from that of their domestic competitors have higher exposure to systemic risk, but especially higher bank default risk. Banks that are overexposed to the global financial sector have a slightly higher default risk but are particularly more exposed to systemic risk. These findings are qualitatively robust to using either the within or between estimator. However, as confirmed by a Wald test, the short-run (within) coefficients significantly underestimate the magnitude of the effects.

Our concentration measures provide additional and unique information on the factors driving individual and systemic bank risk. We see this when we compare adjusted R^2 of a regression where we regress banks' DtD or Systemic Risk Exposure on our bank controls but without our sectoral concentration measures to the adjusted R^2 of a regression where we additionally add our sectoral concentration measures. Furthermore, we do this once with minimal fixed effects and once with maximal fixed effects. The results of these four sets of regressions are shown in Panels A to D of Table 6. Panels A and B should be compared with each other, and Panels C and D also.

The results suggest that—in absolute terms—including our three concentration measures in the DtD regressions, improves the model fit by on average 1 percentage point for the within estimator, 14 percentage points for the between estimator, and 9.5 percentage points for the hybrid estimator. Regarding the Systemic Risk Exposure regressions, the results suggest that—in absolute terms—including our three

TABLE 6

The Information Content of Our Concentration Measures in Explaining Bank Risk

	Distance to Default$_{it}$			Systemic Risk Exposure$_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel	FE	BE	RE	FE	BE	RE
Panel A. Minimal fixed effects, no concentration measures						
R^2	0.03	0.06	0.06	0.04	0.20	0.11
Bank controls	YES	YES	YES	YES	YES	YES
Concentration measures	NO	NO	NO	NO	NO	NO
Bank fixed effects	YES	NO	NO	YES	NO	NO
Year and country fixed effects	NO	NO	NO	NO	NO	NO
Panel B. Minimal fixed effects, with concentration measures						
R^2	0.04	0.21	0.17	0.05	0.35	0.23
Bank controls	YES	YES	YES	YES	YES	YES
Concentration measures	YES	YES	YES	YES	YES	YES
Bank fixed effects	YES	NO	NO	YES	NO	NO
Year and country fixed effects	NO	NO	NO	NO	NO	NO
Panel C. Maximal fixed effects, no concentration measures						
R^2	0.20	0.28	0.29	0.33	0.46	0.37
Bank controls	YES	YES	YES	YES	YES	YES
Concentration measures	NO	NO	NO	NO	NO	NO
Bank fixed effects	YES	NO	NO	YES	NO	NO
Year and country fixed effects	YES	YES	YES	YES	YES	YES
Panel D. Maximal fixed effects, with concentration measures						
R^2	0.21	0.41	0.37	0.33	0.57	0.47
Bank controls	YES	YES	YES	YES	YES	YES
Concentration measures	YES	YES	YES	YES	YES	YES
Bank fixed effects	YES	NO	NO	YES	NO	NO
Year and country fixed effects	YES	YES	YES	YES	YES	YES

Note: This table provides insight into the information content of bank sector specialization, bank sector differentiation, and financial sector exposure vis-à-vis other bank characteristics in explaining variation in the distance to default or the systemic risk exposure. In order to assess how much additional information is provided by specialization/differentiation/financial sector exposure compared to these bank characteristics, we compare the adjusted R^2 in a regression where we regress banks' Distance to Default (or Systemic Risk Exposure) on our bank controls but without our sectoral concentration measures (Panels A and C) to the adjusted R^2 of a regression where we additionally add our sectoral concentration measures (Panels B and D). Furthermore, we do this once with minimal fixed effects (Panels A and B) and once with maximal fixed effects (Panels C and D). We cluster standard errors at the bank level. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

concentration measures to the models, improves the model fit by on average 0.5 percentage point for the within estimator, 13 percentage points for the between estimator, and 11 percentage points for the hybrid estimator. In relative terms, the inclusion of our three concentration measures to the models often improves the model fit by 25% and even doubles the model fit in some cases. This shows that sectoral concentration measures are important in understanding bank's idiosyncratic and systemic risk, and bring new information not captured by the standard bank characteristics included in banking research, especially in comparing across banks.

2.3 Causality

Even though we lack quasi-exogenous variation in our three measures of concentration, we nevertheless believe that our established relationships hint at causality due to a combination of insights.

First, to mitigate endogeneity concerns due to reverse causality, we lag the independent variables such that they are predetermined (although we do realize they are persistent). Second, we conduct a test using buy-and-hold returns during the Global Financial crisis, which is the value loss during a systemic event. Like Beltratti and Stulz (2012), we measure buy-and-hold returns over the period July 2007 to June 2009, and use precrisis values of our sectoral concentration measures. The results are shown in Table A9 in the Internet Appendix and indicate that banks more differentiated from peer banks before the crisis and banks with a larger financial sector exposure before the crisis are associated with lower buy-and-hold returns during the crisis. We also find that sectoral specialization leads to higher crisis returns. These results are in line with the marginal expected shortfall results in our baseline model (Column (6) of Table 5).

Third, we include a rich set of control variables to mitigate endogeneity concerns due to simultaneity or omitted variables. One potentially important characteristic that we could not include in our analysis but has been shown to affect bank risk taking, is ownership structure. More cash-flow rights by a large owner are associated with more risk (Laeven and Levine 2009). However, ownership may also affect choices related to sectoral concentration. Unfortunately, ownership data are not publicly available for such a large sample like ours, therefore we resort to the data of Laeven and Levine (2009), who collected such information for one particular year, namely, 2001. Matching their data with ours leads to information on 159 banks (1,071 observations), which is less than 10% of our total sample. As ownership structure is (almost) time-invariant, we are especially concerned that our long-run (between) estimates would be biased. Using the between estimator, we find that including proxies for ownership (either cash-flow rights or control rights) does not affect the point estimates of our variables of interest relative to a model that does not control for ownership. The results are shown in Table A10 in the Internet Appendix and confirm the same effects for our variables of interest, even for this much smaller sample.

Fourth, we try to mitigate endogeneity concerns due to omitted variables by following the procedure of Altonji, Elder, and Taber (2005) and Bellows and Miguel (2009). Their test procedure measures the stability of the coefficients by calculating the ratio between the coefficient in the regression with control variables (numerator) and the difference between this coefficient and the one derived from a regression without control variables (denominator).[28] The regression results of a specification without control variables are in the Internet Appendix (Table A11). Focusing on the long-run coefficients, we find that these ratios are at least 8, suggesting that the covariance between unobserved factors and (systemic) bank risk needs to be more than eight times as high as the covariance of the included control variables with (systemic) bank risk, which seems quite unlikely. We find similarly high ratios for the short-run

28. This ratio shows how strong the covariance between the unobserved factors explaining individual bank risk (systemic risk exposure) needs to be, relative to the covariance between observable factors and individual bank risk (systemic risk exposure), to explain away the effect of specialization, differentiation, and financial sector exposure.

coefficients. We are thus confident that it is unlikely that an unobserved, omitted variable would explain and hence bias our findings.

In sum, at a minimum our results document meaningful correlations. Moreover, having taken several steps to alleviate endogeneity concerns, we believe that a cautious causal interpretation can also be attached to the results.

2.4 Economic Channels

In Table 7, we report results that show robustness and shed light on the economic channels at work. First, we use the CoVaR (Adrian and Brunnermeier 2016) as an alternative indicator of systemic risk, defined as the change in the value at risk of the financial system conditional on an institution being under distress relative to its median state. While the Marginal Expected Shortfall captures a bank's *exposure* to systemic risk, the CoVaR provides an indication of the individual bank's *contribution* to systemic risk. The results hence provide insights into a second dimension of systemic risk. The results in Column (1) of Table 7 confirm our earlier findings of a negative relationship between specialization and systemic risk. The positive relation between financial sector exposure and systemic risk is also confirmed. Interestingly, we find contrasting results on differentiation (in the long run) suggesting that banks that are *ex ante* more similar to their peers contribute more to systemic risk. These opposite findings are not necessarily inconsistent. On the contrary, they provide insight into the economic mechanisms at play. A bank that is more similar to its peers, may be *ex post* penalized less by investors if the banking sector collapses as the likelihood of being bailed-out might be higher (positive effect on Marginal Expected Shortfall (MES)). However, if such a bank fails, its impact on the entire banking system will be larger as fire sales by the failing bank affect the value of the similar assets held by the other banks in the system (negative effect on CoVaR).

Second, as a robustness to the DtD measure, we use a bank's total stock return volatility. A higher value of volatility indicates more risk, so we expect opposite signs compared to the DtD results. We find that sectoral specialization is associated with lower total stock volatility, while sectoral differentiation is associated with higher total volatility. Higher exposure to the financial sector is related to higher stock volatility, but the effect is economically small. Hence, we find similar results for total stock volatility as for DtD.

Third, we employ three accounting-based indicators of individual bank risk: the natural logarithm of the Z-score, capitalization (equity to total assets) and credit risk (the nonperforming loans to total loans ratio). Accounting-based indicators are more backward-looking but allow confirming that our findings are not driven by any mechanical relation (due to the inclusion of market-based indicators on both sides of the regression specification). The results in columns (3)–(5) show that specialized banks are better capitalized and have lower credit risk, but not significantly higher Z-scores. *Ceteris paribus*, higher loan quality leads banks to have fewer write-offs,

TABLE 7

ECONOMIC CHANNELS

Variables	(1) Δ CoVaR	(2) Total volatility	(3) ln(Z-score)	(4) Equity to total assets	(5) Nonperforming loans	(6) Franchise value	(7) Cost of equity
$\overline{\overline{\text{Specialization}}}_{it-1}$	−0.03**	−0.83***	0.01	0.07**	−0.15***	0.01**	−0.01***
	(0.01)	(0.20)	(0.01)	(0.03)	(0.04)	(0.01)	(0.00)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	0.05***	4.15***	−0.16***	−0.19***	0.51***	−0.05***	0.03***
	(0.01)	(0.30)	(0.02)	(0.04)	(0.05)	(0.01)	(0.00)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.12***	0.07	0.01	0.06*	−0.04	−0.01	0.04***
	(0.01)	(0.25)	(0.01)	(0.03)	(0.04)	(0.01)	(0.00)
$\overline{\text{Specialization}}_{i}$	−0.57***	−6.17***	−0.02	0.35*	−0.24*	0.05	−0.21***
	(0.11)	(0.61)	(0.05)	(0.21)	(0.14)	(0.05)	(0.02)
$\overline{\text{Differentiation}}_{i}$	−0.23*	20.29***	−0.72***	−0.49**	1.85***	−0.11***	0.06***
	(0.12)	(0.87)	(0.05)	(0.22)	(0.17)	(0.04)	(0.02)
$\overline{\text{Financials factor loading}}_{i}$	0.99***	1.85***	−0.10**	−0.87***	−0.11	0.12***	0.27***
	(0.12)	(0.71)	(0.05)	(0.20)	(0.17)	(0.03)	(0.02)
Observations	9,170	11,702	7,913	10,578	9,084	11,702	11,702
R^2	0.380	0.513	0.225	0.327	0.392	0.296	0.404
Number of banks	1,638	1,716	1,510	1,702	1,525	1,716	1,716
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: This table shows the impact of bank sector specialization, bank sector differentiation, and financial sector exposure on alternative dependent variables. In Column (1), we use an alternative systemic risk indicator, being the CoVaR. This indicator captures a bank's contribution to systemic risk (see Adrian and Brunnermeier 2016). In Column (2), we proxy bank risk by the total (annualized) volatility of the banks' daily stock returns. In subsequent columns, we use alternative accounting-based indicators of bank risk, which are, respectively, the Z-score (Column (3)), bank capital (Column (4)), and an accounting-based indicator of credit risk (nonperforming loans to gross loans, Column (5)) as dependent variable. In Column (6), the dependent variable is the franchise value of a bank (measured as the market-to-book value of equity), and in the last column the dependent variable is the banks' beta^{CAPM} in a given year, proxying for the banks' cost of equity. Bank controls are time-varying bank characteristics and include a measure of bank size, revenue diversification, an interaction between bank size and revenue diversification, bank capital, loan share, funding diversification, asset growth, and disclosure. Standard errors are clustered at the bank level. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

helping them to retain more earnings and preserve higher capital buffers. Furthermore, the results in Table 7 confirm that differentiated banks are riskier as they appear to be less capitalized, have a higher credit risk, and a significantly lower Z-score suggesting that banks that differentiate more are closer to insolvency.

Fourth, Column (6) of Table 7 provides evidence that banks have a higher franchise value (market-to-book value of equity) when specializing their sectoral portfolio, though the coefficient is significant only in the short run. Differentiating their exposure from their competitors, on the other hand, decreases their franchise value, both in the short- and long run. Higher exposure to the financial sector is associated with a statistically higher franchise value in the long run. The economic magnitude of the effects, however, is quite small.

Finally, Column (7) tests whether funding costs is a channel through which sectoral specialization affects bank risk. We proxy for a bank's cost of equity with a bank's beta^{CAPM}. To get bank-year varying beta^{CAPM} estimates, we estimate yearly regressions of the CAPM model using our daily bank return data. The results show that banks that differentiate their sectoral exposure to a larger extent (from that of their domestic competitors) have a higher cost of equity, while specialized banks have a lower cost of equity and banks more exposed to the financial sector have a higher cost of equity.

In summary, it seems that the effects of specialization and differentiation work mostly through affecting risk and funding costs, rather than generating value. This is consistent with theories linking specialization to lower asymmetric information and thus agency conflicts between lenders and borrowers (Winton 1999, Marquez 2002). The findings are also consistent with Acharya and Yorulmazer (2008) who have argued that differentiation may imply higher funding costs for banks, which—all else equal—implies lower margins and higher risk.

2.5 Uncovering Stylized Relationships

We uncover four relationships that exhibit a consistent sign and significance over time and across countries and robustness checks (see the overview in Table 8 and the online appendix for more details). First, the relationship between specialization and individual bank risk is robustly negative. While not consistent with theories that focus on the benefits of portfolio diversification (e.g., Diamond 1984), this result is in line with Acharya, Hasan, and Saunders (2006) and is supportive of theories advocating the benefits of specialization such as, for instance, economies of scale or reduced information frictions, which lead to more effective screening, better monitoring skills, and less severe adverse selection problems (Winton 1999, Marquez 2002).

Second, the relationship between specialization and systemic bank risk appears robustly negative, consistent with earlier empirical research on a European sample by De Jonghe (2010). Yet, we are not aware of any research that has tried to model the relationship between specialization and systemic bank risk, holding differentiation constant. At first sight, Wagner (2010) and Ibragimov, Jaffee, and Walden (2011) model specialization/diversification choices in relation to systemic risk, however, in

TABLE 8

Robustness Checks: Summary Table

Potential concern	Robustness analysis	Appendix
Model specification could affect the concentration measures	Alternative approaches: (i) Weekly returns, (ii) Nonnegative exposures, (iii) Raw returns, (iv) Downside risk exposures, and (v) Local indices	A5.1
Differentiation measure: choice of weights is arbitrary	Market capitalization rather than market shares	A5.2
Specialization is an aggregate statistic	Alternative approaches: (i) Sector-specific specialization, (ii) Cyclical/Defensive, (Non)Tradable sectors, (iii) Positive/Negative betas, and (iv) Upside/downside specialization	A5.3
Correlation vs. causality	(i) Buy-and-hold returns, (ii) Ownership structure, and (iii) Scope for omitted variables	A5.4
Are market-based measures better than accounting-based measures?	Horse-race between the two approaches	A5.5
Measurement error in the concentration measures	Errors-in-variables estimation	A5.6
Results may be driven by U.S. banks or internationally active banks	(i) Sample splits U.S. vs. non-U.S. banks and (ii) sample splits for domestic/international banks	A5.7
Results may be driven by specific years or countries	Year-by-year, country-by-country regressions	A5.8

Note: This table provides a summary of the robustness tests conducted on the concentration measures and the estimated relationships. A detailed description of the motivation for each test and associated results can be found in the online appendix.

these models specialization/diversification ultimately impacts systemic risk through a lack of differentiation. Given that we simultaneously test for the effect of differentiation, the empirical relationship between specialization and systemic risk that we document cannot be explained by this, and thus calls for additional theoretical motivation.

Third, the relationship between differentiation from peer banks and individual bank risk appears robustly positive. This relationship has not been explored extensively by theory. Our results are consistent with Acharya and Yorulmazer (2008) who have argued that differentiation may imply higher funding costs for banks, which all else equal implies lower margins and higher risk. Deviating asset holdings vis-à-vis peer banks should thus get a more prominent role in theories of individual bank risk.

Fourth, the relationship between exposure to the financial sector and systemic risk is robustly positive and economically sizeable. This underpins the relevance of theoretical models on financial contagion developed by Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000), and is in line with the findings of Gorton and Metrick (2012).

Two relationships are less robust. The relationship between financial sector exposure and individual bank risk appears to be confined in time, has varying signs across specification, and is economically negligible. The relationship between differentiation and systemic risk appears to be confined to the global financial crisis years and varies across countries.

3. CONCLUSION

We propose a novel technique to identify three aspects of banks' sectoral concentration that are often brought up in discussions on (systemic) banking crises: banks' specialization, banks' differentiation from peer banks, and banks' financial sector exposure. Our methodology allows to infer these measures in a uniform way for listed banks and we apply it to 1,716 banks from 34 countries between 2002 and 2012. Using these newly developed measures of banks' sectoral concentration, we test several hypotheses on the relationships between concentration and individual bank risk (DtD) and systemic bank risk (marginal expected shortfall).

We find four relationships that exhibit a consistent sign and significance over time and across countries. Specialization is negatively associated with individual bank risk and systemic bank risk. Specialization results in better risk management and lower lending risk (through lower nonperforming loans). Differentiation from peer banks is positively associated with individual bank risk (lower DtD). Differentiated banks appear to be less capitalized and have a higher fraction of nonperforming loans. Finally, financial sector exposure is positively associated with systemic bank risk.

Two relationships are less robust. The relationship between financial sector exposure and individual bank risk appears to be confined in time, has varying signs, and is economically negligible. The relationship between differentiation and systemic risk appears to be confined to the global financial crisis years and varies across countries. The latter is somewhat surprising as herding (i.e., lack of differentiation from peer banks) has received a prominent role in models of systemic risk taking (Acharya and Yorulmazer 2007, Wagner 2010), while this does not seem to be fully supported in our data. Moreover, when significant, our results even point in the opposite direction: herding (in our case: less sectoral differentiation) is related to *less* systemic risk exposure. This might reflect underlying market expectations of bail-outs being incorporated in bank returns when there are "too-many-banks-to-fail" at the same time. These results have implications for theoretical models incorporating the relationship between differentiation/herding and systemic risk.

We believe that the four robust relationships between bank (sectoral) concentration and risk should get the most prominent role in theoretical models (insofar as they have not yet, see discussion in previous section) as well as the most prominent attention of policymakers. For example, the new Basel III regulations have reflected the currently available academic insights, including higher capital requirements and limitations on the use of "unstable" interbank funding. Lacking empirical guidance on the importance of (sectoral) concentration, however, policymakers have not changed the international rules regarding (sectoral) specialization and diversification under the Basel III regulatory framework. Our findings stress the importance of distinguishing between specialization on the bank level and differentiation within the banking system and thus the distinction between micro- and macroprudential regulation. As sectoral exposures vary significantly across banks and their performance and stability depends on these sectoral exposure (both on the bank level and relative to the system), this should be taken into account more prominently in risk modeling and supervision. Our results further stress that it is important to distinguish between short-term trends and longer-term bank-level factors when assessing the stability repercussions of specialization and differentiation. Our findings also underline that one size does not fit all and that the regulatory regime might have to differentiate between different types of banks, country circumstances, and across business and financial cycles.

Our approach is sufficiently flexible enabling additional applications. First, it allows identifying which sectors contribute to aggregate specialization, as well as identifying whether this is due to an over- or underexposure. Likewise, our approach allows constructing semiaggregate sectoral specialization indices (cyclical versus defensive sectors, tradable versus nontradable sectors). Such sector-specific specialization measures might be more useful for regulatory or early warning purposes than our aggregate measure of specialization as it allows assessing which banks will be hit more when a specific shock hits the economy (e.g., an oil price shock, a pandemic, …). Second, our methodology is also sufficiently flexible to adapt it to tail risk exposures (for an example, see the Appendix). Our methodology may thus also serve to answer other research questions.

Finally, in this paper we take sectoral concentration as starting point and aim to document how it affects bank risk and systemic risk. While outside the scope of this paper, we believe it is an interesting avenue for further research to explore the origins of variation in sectoral concentration. Why do banks specialize in certain sectors? Why do banks differentiate from or herd with other banks? Do regulatory variables influence the choice of sectoral concentration? Follow-up papers could adopt our methodology to measure these three dimensions of sectoral concentration and use them as dependent variables to shed light on the aforementioned questions. Such tests could provide more insight and guidance to regulators who are trying to understand what may push a bank in the direction of being specialized or not.

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LITERATURE CITED

Acharya, Viral, Iftekhar Hasan, and Anthony Saunders. (2006) “Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios.” *Journal of Business*, 79, 1355–412.

Acharya, Viral V., Lasse H. Pedersen, Thomas Philippon, and Matthew Richardson (2017) “Measuring Systemic Risk.” *Review of Financial Studies*, 30, 2–47.

Acharya, Viral V., and Sascha Steffen. (2015) “The Greatest Carry Trade Ever? Understanding Eurozone Bank Risks.” *Journal of Financial Economics*, 115, 215–36.

Acharya, Viral V., and Tanju Yorulmazer. (2007) “Too Many to Fail—An Analysis of Time-Inconsistency in Bank Closure Policies.” *Journal of Financial Intermediation*, 16, 1–31.

Acharya, Viral V., and Tanju Yorulmazer. (2008) “Information Contagion and Bank Herding.” *Journal of Money, Credit and Banking*, 40, 215–31.

Adrian, Tobias, and Markus K. Brunnermeier. (2016) “CoVaR.” *American Economic Review*, 106, 1705–41.

Agarwal, Isha, Rupa Duttagupta, and Andrea Presbitero. (2020) “Commodity Prices and Bank Lending.” *Economic Inquiry*, 58, 953–79.

Allen, Franklin, Ana Babus, and Elena Carletti. (2012) “Asset Commonality, Debt Maturity and Systemic Risk.” *Journal of Financial Economics*, 104, 519–34.

Allen, Franklin, and Elena Carletti. (2013) “What is Systemic Risk?” *Journal of Money, Credit and Banking*, 45, 121–27.

Allen, Franklin, and Douglas Gale. (2000) “Financial Contagion.” *Journal of Political Economy*, 108, 1–33.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. (2005) “Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools.” *Journal of Political Economy*, 113, 151–84.

Anginer, Deniz, Asli Demirguc-Kunt, Harry Huizinga, and Kebin Ma. (2018) “Corporate Governance of Banks and Financial Stability.” *Journal of Financial Economics*, 130, 327–46.

Baele, Lieven, Valerie De Bruyckere, Olivier De Jonghe, and Rudi Vander Vennet. (2015) “Model Uncertainty and Systematic Risk in US Banking.” *Journal of Banking and Finance*, 53, 49–66.

Baltagi, Badi, and James M. Griffin. (1984) “Short and Long Run Effects in Pooled Models.” *International Economic Review*, 25, 631–45.

Bellows, John, and Edward Miguel. (2009) “War and Local Collective Action in Sierra Leone.” *Journal of Public Economics*, 93, 1144–57.

Beltratti, Andrea, and Rene Stulz. (2012) “The Credit Crisis around the Globe: Why did Some Banks Perform Better?”*Journal of Financial Economics*, 105, 1–17.

Berger, Philip, Michael Minnis, and Andrew Sutherland. (2017) “Commercial Lending Concentration and Bank Expertise: Evidence from Borrower Financial Statements.” *Journal of Accounting and Economics*, 64, 253–277.

Boeve, Rolf, Klaus Duellmann, and Andreas Pfingsten. (2010) “Do Specialization Benefits Outweigh Concentration Risks in Credit Portfolios of German Banks?” Bundesbank Discussion Paper No 10/2010.

Boyd, John H., and Edward C Prescott. (1986) “Financial Intermediary-Coalitions.” *Journal of Economic Theory*, 38, 211–32.

Braun, Matias, and Borja Larrain. (2005) “Finance and the Business Cycle: International, Inter-Industry Evidence.” *Journal of Finance*, 60, 1097–128.

Brown, Stephen J., and William N. Goetzmann. (1997) “Mutual Fund Styles.” *Journal of Financial Economics*, 43, 373–99.

Cai, Jian, Frederik Eidam, Anthony Saunders, and Sascha Steffen. (2018) “Syndication, Interconnectedness and Systemic Risk.” *Journal of Financial Stability*, 34, 105–20.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi. (2008) "In Search of Distress Risk." *Journal of Finance*, 63, 2899–939.

De Jonghe, Olivier. (2010) "Back to the Basics in Banking? A Micro-Analysis of Banking System Stability." *Journal of Financial Intermediation*, 19, 387–417.

De Jonghe, Olivier, Hans Dewachter, Klaas Mulier, Steven Ongena, and Glenn Schepens. (2020) "Some Borrowers are More Equal than Others: Bank Funding Shocks and Credit Reallocation." *Review of Finance*, 24, 1–43.

Demirguc-Kunt, Asli, and Harry Huizinga. (2010) "Bank Activity and Funding Strategies: The Impact on Risk and Returns." *Journal of Financial Economics*, 98, 626–50.

Diamond, Douglas W. (1984) "Financial Intermediation and Delegated Monitoring." *Review of Economic Studies*, 51, 393–414.

Flannery, Marc J., and Christopher M. James. (1984) "The Effect of Interest-Rate Changes on the Common-Stock Returns of Financial Institutions." *Journal of Finance*, 39, 1141–53.

Freixas, Xavier, Bruno M. Parigi, and Jean-Charles Rochet. (2000) "Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank." *Journal of Money Credit and Banking*, 32, 611–38.

Giannetti, Mariassunta, and Farzad Saidi. (2019) "Shock Propagation and Banking Structure." *Review of Financial Studies*, 32, 2499–540.

Giliberto, Michael. (1985) "Interest-Rate Sensitivity in the Common-Stocks of Financial-Intermediaries—A Methodological Note." *Journal of Financial and Quantitative Analysis*, 20, 123–26.

Gorton, Gary, and Andrew Metrick. (2012) "Securitized Banking and the Run on Repo." *Journal of Financial Economics*, 104, 425–51.

Greenwood, Robin, Augustin Landier, and David Thesmar. (2015) "Vulnerable Banks." *Journal of Financial Economics*, 115, 471–85.

Hayden, Evelyn, Daniel Porath, and Nataljav Westernhagen. (2007) "Does Diversification Improve the Performance of German Banks?" *Journal of Financial Services Research*, 32, 123–40.

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden. (2011) "Diversification Disasters." *Journal of Financial Economics*, 99, 333–48.

Jahn, Nadya, Christoph Memmel, and Andreas Pfingsten. (2016) "Banks' Specialization versus Diversification in the Loan Portfolio." *Schmalenbach Business Review*, 17, 25–48.

Kuh, Edwin. (1959) "The Validity of Cross-Sectionally Estimated Behavior Equations in Time Series Applications." *Econometrica*, 27, 197–214.

Laeven, Luc, and Ross Levine. (2009) "Bank Governance, Regulation and Risk Taking." *Journal of Financial Economics*, 93, 259–75.

Marquez, Robert. (2002) "Competition, Adverse Selection, and Information Dispersion in the Banking Industry." *Review of Financial Studies*, 15, 901–26.

Merton, Robert. (1974) "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29, 449–70.

Nier, Erlend, and Ursel Baumann. (2006) "Market Discipline, Disclosure and Moral Hazard in Banking." *Journal of Financial Intermediation*, 15, 332–62.

Petersen, Bruce, and Steven Strongin. (1996) "Why are Some Industries More Cyclical than Others?"*Journal of Business & Economic Statistics*, 14, 189–98.

Rajan, Raghuram G., and Luigi Zingales. (1998) "Financial Dependence and Growth." *American Economic Review*, 88, 559–86.

Schuermann, Till, and Kevin J. Stiroh. (2006) "Visible and Hidden Risk Factors for Banks." FRB of New York Staff Report Nr. 252.

Sharpe, William. (1992) "Asset Allocation: Management Style and Performance Measurement." *Journal of Portfolio Management*, 18, 7–19.

Tabak, Benjamin M., Dimas M. Fazio, and Daniel O. Cajueiro. (2011) "The Effects of Loan Portfolio Concentration on Brazilian Banks' Return and Risk." *Journal of Banking and Finance*, 35, 3065–76.

Wagner, Wolf. (2010) "Diversification at Financial Institutions and Systemic Crises." *Journal of Financial Intermediation*, 19, 373–86.

von Westernhagen, Natalia, Eiji Harada, Takahiro Nagata, Bent Vale, Juan Ayuso, Jesus Saurina, Sonia Daltung, Suzanne Ziegler, Elizabeth Kent, Jack Reidhill, and Stavros Peristiani. (2004) "Bank Failures in Mature Economies." BIS WP 13.

Winton, Andrew. (1999) "Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending." Working paper available at SSRN: http://ssrn.com/abstract=173615.

SUPPORTING INFORMATION

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Figure A5: Country variation in the relationship between systemic risk exposures and specialization, differentiation or financial sector exposure

Table A17: Relating return-based concentration measures to bank characteristics

Data S1

Data S2