Bank sectoral concentration and (systemic) risk: Evidence from a worldwide sample of banks[*]

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Abstract

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Keywords: bank concentration, sectoral specialization, differentiation, bank risk, systemic stability, factor model

JEL classification: G01, G21, G28, L5

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1 Introduction

Concentration of bank assets is one of the most important factors contributing to systemic banking risk. According to a 2004 Basel committee study, credit concentration of banks caused 9 of the 13 major banking crises around the world in the twentieth century (Westernhagen et al., 2004). It is fair to say that bank asset concentration also contributed significantly to the two major banking crises that the twenty-first century has witnessed so far: the simultaneous overexposure of several banks to the U.S. mortgage market initiated the global financial crisis '07-'08 (Brunnermeier, 2009), and the overexposure of several banks to sovereign debt of distressed European countries severely deepened the European debt crisis of '11-'12 (Acharya et al., 2014).

While evidence of an important link between bank asset concentration and bank performance and stability becomes more indisputable with every new banking crisis, the academic literature offers almost no guidance on the strength or even the sign of this relationship. Theory has provided contrasting predictions on the relationship between specialization and bank performance (Diamond, 1984; Winton, 1999) and there exist almost no empirical studies on the performance and stability implications of bank specialization and differentiation, especially in a cross-country setup, as the empirical literature has been hampered by the lack of appropriate data on bank asset concentration. This paper tries to take a first -but important- step to fill this gap by constructing comprehensive gauges of sectoral specialization and relating them to bank performance and (systemic) risk.

In the first part of the paper, we develop a new methodology that allows researchers to identify banks' strategic choices with respect to banks' asset concentration, and apply this methodology to a sample of 1,716 banks across 34 countries over the period 2002-2012. The methodology itself is borrowed from the mutual fund literature (returns-based style analysis) where it is used to deconstruct mutual fund returns in exposures to investment strategies or asset classes, e.g. with respect to large versus small stocks or value versus growth stocks (see e.g. Sharpe (1992), Brown and Goetzmann (1997) and ter Horst et al. (2004)). The underlying assumption when applying this methodology is that one can identify a firm's strategic choices (in this case a bank's sectoral concentration choices) from the covariation between its stock returns and the returns on selected portfolios of interest. One thus relies on market participants' information on bank choices (which might be contained in data and information shared, e.g., in earning calls). We use an extended factor model and relate bank stock returns to the returns on 9 global sectoral portfolios and a set of common factors, which include the returns on a global market index, a domestic market index, a financial sector index, a real estate index, and global Fama-French factors. We test whether a bank's assets are well diversified (meaning that its returns are only exposed to the set of common factors) or whether a bank is specialized (meaning that its returns exhibit significant exposures to certain sector-specific portfolios over and above the set of common factors in the model). More specifically, we define bank *sectoral specialization* as the percentage variation of the bank's stock returns that is incrementally explained by the sector-specific portfolios over and above the variation explained by the set of common factors. We next 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. Lastly, we define a bank's *financial sector exposure* as the estimated factor loading of its stock returns on the returns on the financial sector index.

This approach has a number of advantages compared to other data or methods used in the literature. First, this methodology can be applied to identify a wide range of strategic bank choices that otherwise often require information available only to market analysts in the form of, e.g., earning calls.[1] The methodology can be used to construct time-varying indicators of the concentration of banks' assets in certain sectors (as in this paper), but it could also be implemented to determine banks' concentration in, for instance, certain geographical areas, certain types of companies (small businesses or large corporates), sovereign bond exposures (Acharya and Steffen, 2015), or commodity prices (Agarwal et al., 2017). A second important advantage is that it allows to cover a significantly wider range of banks and countries than in the previous literature. Data on sectoral exposures are not directly available from (commercial) databases for a cross-country sample of banks. Authors of studies on lending concentration have either used confidential data gathered by the central bank's credit register for single country studies (e.g. De Jonghe et al. (2016)) or relied on syndicated loan exposures (e.g. Cai et al., 2013). In Cai et al. (2013), the sample is limited to the subset of very large, international financial institutions (mainly US-based). Moreover, the exposures are then limited to syndicated loans, which may not be representative for the overall portfolio of commercial and industrial loans. On average, the banks in our sample cover nearly

[1] Sectoral exposures are not included in financial statements and there are only limited data in the annual reports. However, earning calls transcripts indicate that analysts do have information about these exposures. During earning calls, analysts ask sectoral exposure related questions both in terms of actual exposure to and performance across economic sectors as in terms of hedging instruments used to hedge against sectoral concentration. In the Internet appendix, we provide several examples of references to sectoral concentration in earning calls transcripts.

70% of the total banking assets in their country, which increases the generalizability of the results and the relevance for policy makers. A third advantage worth emphasizing is that the identified sectoral exposures are not necessarily identical to the concentration of a banks' loan portfolio in specific sectors. Although we would expect our concentration measures to be related to the banks' lending concentration (and we show this), they are broader measures of sectoral concentration by also taking into account banks' non-lending exposures (such as securities holdings and derivative positions) through which banks might hedge excessive sectoral lending exposures (or perhaps create such positions when there is no sectoral lending exposure). This is important given the increasing focus of banks on non-lending business (Demirguc-Kunt and Huizinga, 2010).

To shed more light on the content of our three sectoral concentration measures, we hand-collect a small database on the actual sectoral lending exposures for a subsample of the largest banks, which we derive from the notes to their annual statements.[2] Using this small subsample, we show that our new measures of sectoral specialization and differentiation have both statistically and economically significant correlations with the account-based measures of sectoral specialization and differentiation, respectively. We also show that our measure of financial sector exposure correlates strongly with the accounting based lending share to the financial sector. Furthermore, we document important variation in these correlations across banks depending on their relative use of derivatives (as captured in the size of off-balance sheet items relative to total assets) and depending on the transparency of their financial statements. It thus seems that the banks' strategic concentration choices that are being picked by our methodology do relate meaningfully to the observed concentration in their loan portfolios.

In the second part of the paper, we relate these measures of bank sectoral concentration to the volatility of banks' stock returns, their franchise value and their exposure to systemic risk (marginal expected shortfall). We use a hybrid regression model (Mundlak, 1978; Wooldridge, 2010) that allows us to distinguish between the within-bank and the between-bank effects in these relationships. Following Baltagi and Griffin (1984), we interpret the within-bank results as gauges for short-term relationships and the between-bank results capture the long-term relationships.[3] As mentioned above, it is theoretically not clear in which direction the relationship between asset concentration

[2] We limit this analysis to listed banks with total assets in excess of US$ 10 billion as these are more likely to publish a detailed report on their website, and find useful information for 221 banks over the period 2007-2011.

[3] We postpone the detailed exposition, explanation and motivation for the hybrid model to Section 3.2

and bank performance and risk will go. On the one hand, the traditional portfolio theory view posits that diversification largely eliminates the impact of idiosyncratic shocks on banks' loan portfolio (Diamond, 1984; Boyd and Prescott, 1986) so that more specialized banks should be less stable and -at least in the long-run- perform worse. On the other hand, (sectoral) specialization can also result in lower information frictions between banks and borrowers. Moreover, a credible threat of better monitoring skills might also prevent risk-shifting by borrowers, as in Stiglitz and Weiss (1981). Therefore, the superior expertise of focused banks may not only result in lower default risk among their borrowers, it may also enable them to detect a deterioration of the borrower's business earlier, allowing them to mitigate risk in a timely manner by requesting additional collateral, for example, (Winton, 1999), leading ultimately to higher (risk-adjusted) returns.

Our results show that more specialized banks have lower volatility in their stock returns and lower exposure to systemic risk. These relationships hold in the short- and long-run, though the long-run (between bank) relationships are of substantially higher economic order than the short-run (within bank) relationships. Specifically, we find that in the long-run a one standard deviation increase in sectoral specialization reduces total bank risk by 0.25 standard deviation and reduces exposure to systemic risk by 0.35 standard deviation. Higher exposure (specialization) to the financial sector, on the other hand, increases total bank risk (by about 0.06 standard deviation for a one standard deviation increase in financial sector exposure) and particularly increases systemic risk exposure (by about 0.39 standard deviation for a one standard deviation increase in financial sector exposure). We find some evidence that non-financial sectoral specialization increases banks' franchise value, but very modestly and significantly only in the short-run, while financial sector exposure increases banks' franchise value in the long-run (by about 0.1 standard deviation for a one standard deviation increase in financial sector exposure). Our results suggest that markets regard specialized banks as less risky (both on the individual bank and systemic level), while specialization in (and thus higher exposure to) the financial sector increases individual bank risk and exposure to systemic risk, but also their franchise values.

Sectoral concentration, however, matters also in comparison with other banks in the system, as the degree to which banks specialize in the same sectors might affect their performance and stability. In countries where the scope for lending diversification is limited, banks' sectoral portfolios will likely be more similar to each other. However, even in countries where the scope for lending diversification is large, we have seen an increasingly homogeneous banking system over the past decades (driven only partly through increasing consolidation) (De Nicolo and Kwast, 2002). Banks may have ex-ante incentives to herd (Acharya and Yorulmazer, 2007, 2008), which can potentially be very costly for society as it implies that similar institutions will be more likely to face problems at the same time (Wagner, 2010).

Seemingly contrary to these theories, we find that sectoral differentiation is associated with higher stock volatility, lower franchise values, and higher ex-post exposure to systemic risk in both the short- and long-run, with long-run (between bank) effects again of larger economic size. Specifically, a one standard deviation increase in sectoral differentiation increases total bank risk by 0.83 standard deviation and exposure to systemic risk by 0.07 standard deviation, while it reduces franchise values by 0.13 standard deviation. These findings suggest that investors incorporate a bail-out subsidy for banks which are more similar to their peers as their stock price drops significantly less during systemic events, making it indeed optimal for banks (from their perspective) to ex-ante differentiate less. Moreover, it seems that banks that are more similar to their peers have particularly lower volatility in their stock returns and particularly lower exposure to systemic risk during '08-'09. Finally, more differentiated banks are being valued lower by the market.

We subject our findings to a battery of robustness tests, including (i) alternative dependent variables (CoVaR and accounting-based risk and performance measures), (ii) an error-in-variables specification, (iii) analyzing the impact of a potential omitted variable bias, (iv) concentration measures based on local rather than global factors, (v) narrower definitions of the sample (excluding mergers, excluding countries where banks in the sample cover less than 70% of the total banking assets), and (vi) sample splits (US versus non-US sample, pre- versus post-crisis period).

There are important policy implications of these findings. Policy makers and regulators have clearly taken actions in the new Basel III regulation according to the available academic insights, as reflected by the increased capital requirements and the limitations that have been put on the use of 'unstable' interbank funding. Lacking empirical guidance on the importance of sectoral concentration, however, policy makers 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 macro-prudential regulation. Our findings also shed doubts on the framework underlying the Basel regulatory capital requirements.

If sectoral exposures vary significantly across banks and their performance and stability depend on sectoral exposure (both on the bank-level and relative to the system), then this would have to be taken into account in risk modeling. 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. Finally, our findings 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 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 (see Baele et al. (2015) for an overview). We contribute to this literature by using stock market data to infer banks' strategic choices on sectoral concentration (borrowing the returns-based style analysis methodology from the mutual fund literature). 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 GIIPS countries' debt. Agarwal et al. (2017) construct time-varying bank-specific commodity exposures by regressing bank stock returns on market-wide returns and a commodity price index. Our paper, however, is the first to use this methodology to infer banks' sectoral exposures.

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. Using German data, Duellmann and Masschelein (2007) find that economic capital increases from 7.8% in the case of the most diversified benchmark portfolio to 11.7% for a portfolio concentrated in one sector. Empirical evidence by Acharya et al. (2006) for Italy and by Hayden et al. (2007) and Jahn et al. (2016) for Germany documents that specialization in certain industries is accompanied by lower loan loss rates. Boeve et al. (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 et al. (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 e.g. Germany, Italy and the U.S.[4] While the existing

[4] Combining loan-level and export data, Paravisini et al. (2014) show specialization of Peruvian banks in lending to exporters to specific countries, also arguing for advantages of banks in specialization, in this case geographically.

literature focuses either on single countries or syndicated lending (Cai et al., 2013), our paper is the first cross-country study on the relationship between sectoral specialization and bank performance and risk.[5] Unlike previous papers in this literature, our methodology allows us to take a broader view on sectoral exposure beyond lending and beyond one country to cross-county comparison, allowing for a broader inference.[6]

Finally, we contribute to the literature on bank herding and systemic risk (Acharya and Yorulmazer, 2007, 2008; Wagner, 2010). Our paper is the first to incorporate a measure of banks' sectoral differentiation and provides consistent evidence with one of the main assumptions of these models, namely that it is ex-post optimal for banks to ex-ante herd their sectoral exposures.

2 New measures of sectoral concentration

Our independent variables of interest are proxies for three aspect of banks' sectoral concentration: banks' sectoral specialization and differentiation, as well as their financial sector exposure. We take an innovative, data-driven approach to measure these three components of sectoral concentration. In particular, we estimate return-based indicators of sectoral factor exposures, of which we describe the methodology in detail below in subsection 2.2. We show that these return-based indicators of specialization, differentiation and financial sector exposure relate meaningfully to actual sectoral *lending* portfolio concentration, differentiation and financial sector exposure (subsection 2.3). For that purpose, we construct a much smaller, hand-collected database of the sectoral lending exposures reported by the largest banks in the notes to their financial statements. But first, we describe the data sources and sample composition in subsection 2.1.

2.1 Data sources and sample composition

We combine data from several sources. We obtain information on banks' balance sheets and income statements from Bankscope, which is a database compiled by Fitch/Bureau Van Dijck that contains

[5] Other studies have focussed on banks' diversification in interest and non-interest business, see De Jonghe (2010), Demirguc-Kunt and Huizinga (2010) and Stiroh and Rumble (2006), among others.

[6] A contemporaneous paper by Giannetti and Saidi (2017) considers the relationship between sectoral lending concentration and banks' liquidity support for industries in distress. Unlike our paper, the authors use syndicated lending data; similar to our work, they find evidence for a stability-enhancing role of sectoral concentration.

information on banks around the globe, based on publicly available data sources. Bankscope contains information for listed and privately held banks. While Bankscope does not contain stock market information on a daily basis, it does contain information on the ticker as well as the ISIN number of (de)listed banks' equity, which enables matching Bankscope with Datastream. From Datastream, we retrieve information on a bank's stock price as well as its market capitalization. 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 $2002-2011$.[7] We include commercial banks, bank holding companies, as well as saving banks and cooperatives.[8] Information on the countries included in the sample, the share of the banking system that we cover as well as the number of bank-year observations by country is reported in Table 1 while the definitions and sources of all variables are reported in Table 2.

Insert Tables 1 and 2 around here

2.2 Measuring banks' sectoral specialization/differentiation using a factor model

2.2.1 Constructing the measures

A bank's stock price is influenced by exposures to systematic risk as well as idiosyncratic news. If a bank's activities are well-diversified, then its stock return should mainly co-move with returns on a broad market-wide index (either capturing the global or domestic market). On the other hand, if a bank's portfolio is (over)exposed to certain sectors, then the bank's stock return should not only react to economy-wide shocks, but also to sector-specific news. Using an extended market model, we gauge the degree to which banks are well diversified or additionally exhibit significant exposures to certain sector-specific portfolios. In addition to returns on the global and local market as well as

[7] As we will discuss in more detail below, we impose restrictions on having at least five banks in each year in a country to compute differentiation measures that are meaningful.

[8] In general, savings and cooperative banks have a different business model and ownership structure compared to commercial banks and BHCs. Note, however, that they have to be listed to be included in the analysis. Saving and cooperative banks that are listed 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.

sectoral returns, we include three additional factors, in line with the factor model literature (returns on the global small-minus-big (SMB), high-minus-low (HML) and momentum (MOM) factors).[9] Finally, as a large, but heterogeneous fraction of bank assets are real estate loans, we also control for the sensitivity of bank stock returns to returns on a real estate investment trust (REIT).

Hence, using daily return data, we estimate the following equation for each bank by year:

$$r_t^i = \alpha + \sum_{s=1}^{S} \beta^s r_t^s + \beta^{fin} r_t^{fin} + \beta^{GM} r_t^{GM} + \beta^{DM} r_t^{DM} + \delta_1 r_t^{REIT} + \delta_2 r_t^{SMB} + \delta_3 r_t^{HML} + \delta_4 r_t^{MOM} + \epsilon_t^i \quad (1)$$

Specifically, we regress a bank's daily stock return (r_t^i) on the return to S (=9) different non-financial, global sectoral indices (r_t^s) and the global financial sector index (r_t^{fin}) as well as on the returns on a global market index (r_t^{GM}), a domestic market index (r_t^{DM}) and four factors (r_t^{REIT}, r_t^{SMB}, r_t^{HML}, r_t^{MOM}). The sectoral indices are based on the Industry Classification Benchmark (ICB). More specifically, we use the level 2 decomposition, which divides the total market into nine non-financial sectors (oil and gas, basic materials, industrials, consumer goods, healthcare, consumer services, telecommunications, utilities, technology) and financials. As we are interested in exposures to sector-specific news (and not the movement in sectoral indices due to economy-wide or financial sector news), we first orthogonalize each of the r_t^s series with respect to market-wide returns and the financial sector returns.[10] Doing so, we clean the sectoral returns from market-wide news as well as their dependence on financial sector (shocks). Subsequently, we standardize the orthogonalized exposures, which facilitates comparing the exposures to different industries. The estimated β^s coefficients then reflect both the exposure to as well as the riskiness (volatility) of the sectoral shocks. The residual, ϵ_t^i, captures the idiosyncratic or bank-specific news component.

We estimate Equation (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. The resulting panel dataset of estimated exposures consists of $11,702$ bank-year observations, covering $1,716$ banks from 34 countries over a ten year period starting in 2002.[11] We do not impose constraints

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

[10] The returns on the financial sector index are also orthogonal with respect to the market.

[11] In principle, this method could be applied to any listed bank of which its stock is frequently traded. Our sample is restricted to a smaller set of countries for two reasons. First, Datastream does not provide local market indices for all countries. Second, we only include countries that have at least five listed banks in each sample year in order to construct meaningful and reliable proxies for differentiation from the rest of

on the coefficients and hence allow that a bank has a negative exposure to, and hence is short in, a specific industry. A negative exposure could be due to a genuine short position, e.g. if one sector is responsible for a large amount of term deposits and certificates of deposits. But it could also be due to portfolio rebalancing of (institutional) investors in bank common stock that rebalance out of a bank that is underexposed to a sector to a bank that is overexposed to a sector, whenever that sector is hit by a shock. Information on the estimated exposures (nine sectors and the financial sector) is reported in Table 3. Panel A of Table 3 reports for each estimated factor loading the mean and standard deviation across $11,702$ observations, as well as the 5^{th}, 50^{th}, and 95^{th} percentile of the panel of estimated factor loadings. As illustrated in Panel A, the average exposure is close to zero for all but one sector (i.e. the financial sector). This indicates that the stock market believes that banks are, on average, not exposed to shocks to these sectors.[12] Unsurprisingly, the exposure to the financial sector is larger than to other sectors and positive. 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.

Insert Table 3 around here

Based on the estimated results of Equation (1), we compute two time-varying bank-specific measures capturing the intensity of (non-financial) sectoral specialization and (non-financial) sectoral differentiation. More specifically, for each bank and for each year, we calculate the following measures. First, we compute the contribution of the non-financial sectoral factors to the R-squared of the return-generating model. To that end, we first estimate (again for each bank and year) the following auxiliary equation, which is the same as Equation (1), *except for* dropping the nine sectoral factors.

$$r_t^i = \alpha + \beta^{fin} r_t^{fin} + \beta^{GM} r_t^{GM} + \beta^{DM} r_t^{DM} + \delta_1 r_t^{REIT} + \delta_2 r_t^{SMB} + \delta_3 r_t^{HML} + \delta_4 r_t^{MOM} + \epsilon_t^i \quad (2)$$

the banks in the country (see below).

[12] It is important to note that there is an asymmetry in the interpretation of significant and insignificant factor loadings. While significant factor loadings can be interpreted as implying (over)exposure to a specific sector, finding a zero (or non-significant) exposure on average can be due to three different reasons. First, banks are opaque and stock market participants are not able to make an accurate assessment (hence imprecise and insignificant estimates). Second, banks are transparent (to stock market investors) but do not have an imbalanced portfolio (precise, but zero, estimates). Third, banks may specialize in certain sectors, but could use derivative contracts to hedge these (over)exposures (precise zero estimates, but different from sectoral composition).

We then subtract the R^2 of Equation (2) from the R^2 of Equation (1) to end up with the following bank-time varying sectoral specialization measure:

$$\text{Specialization}_{i,t} = R^2_{i,t}(\text{Eq.(1)}) - R^2_{i,t}(\text{Eq.(2)}) \tag{3}$$

Hence, bank sectoral specialization captures the percentage variation of the bank's stock return that is incrementally explained by the sector-specific portfolios over and above the variation explained by the set of common factors. A larger value indicates a larger exposure to sector-specific news for bank i in year t that is not created by economy-wide or financial events.

Second, we compute a measure of sectoral lending differentiation by banks within a country in a given year. For each bank, we compute the Euclidean distance between a bank's estimated sectoral exposures and the country-year-average (excluding that bank) of the sectoral exposures. The Euclidean distance is computed as follows:

$$\text{Differentiation}_{i,t} = \sqrt{\sum_{s=1}^{S} \left(\beta^s_{i,t} - \sum_{k \neq i}^{I_c} w_{k,c,t} * \beta^s_{k,c,t} \right)^2} \tag{4}$$

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, excluding bank i. The measure, labelled 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.[13] A similar measure has also been used by Cai et al. (2013) to measure bank differentiation based on syndicated loan exposures.

Finally, we also look at a bank's exposure to financials. The higher $\hat{\beta}^{fin}$ from Equation (1) is, the more a bank's stock return co-moves with general financial sector news. We use this as a proxy for (over)exposure to the financial sector, due to for instance interconnectedness or non-sectoral

[13] 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 versus globally. Unfortunately, data on banks' foreign exposures is not available. However, we believe that the choice of the domestic market as the relevant one can be justified with two arguments. First of all, we include in the factor model both the returns on a global and a domestic portfolio, hence already partly filtering out the impact of heterogeneity in global versus domestic reach. Second, there is substantial evidence in favor of a home bias by both retail and institutional investors (French and Poterba (1991) and Coval and Moskowitz (1999)). Hence, we can assume that even if banks operate globally, investors are mainly going to compare them with their domestic peers.

herding, and label this variable *financials factor loading*.

2.2.2 Descriptive statistics of the measures

We report summary statistics on the specialization and differentiation measures in panel B of Table 3, whereas the sensitivity of a bank's stock return to financial sector news is reported in the last line of panel A. We find that the average bank has an increase in R-squared of 3.35 percentage points when the non-financial sectoral indices are included on top of the global market index, domestic market index, financial sector index and the four factors.[14] The average bank's differentiation from the country-average is 1.57. More importantly, both measures exhibit substantial variation, which will enable us to assess how these measures are related with our proxies for bank performance and stability. Specifically, specialization ranges from 0.98 (p5) to 7.25 (p95) and sectoral differentiation ranges from 0.3 (p5) to 4.44 (p95). The estimated sensitivity of the bank's return to the financial sector's return (i.e. the financials factor loading) is 0.07 for the average bank-year, and ranges from -0.35 (p5) to 0.58 (p95).

Insert Figure 1 around here

Figure 1 shows the variation of specialization, differentiation and financial sector exposure over our sample period. Specifically, we graph the mean and interquartile range ($25^{th}$and 75^{th} percentile) for each year of the three indicators. Specialization, as measured by return-based data, somewhat decreased in the years leading up to the Global Financial Crisis before it increased until 2008 and a new decrease set in. Differentiation varied little until 2008, when the mean and 75^{th} percentiles suddenly more than doubled before falling back after 2010. Finally, financial sector exposure was relatively stable until 2007, when a gap opened up between the 75^{th} percentile more than doubling and the 25^{th} percentile moving deep into negative territory. This gap somewhat closed in the latter years of our sample period.

Insert Figure 2 around here

[14]The average R-squared in the 11,702 regressions across banks and over time using model (1) is 27 percent. Hence, adding the nine sectoral factors leads to an average increase of more than 14% in the explained variation of bank stock returns.

In Figure 2, we provide some more distributional properties of the specialization and differentiation measures depending on how many of the 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-a-vis the case of zero significant exposures, does not depend much on how many exposures are significantly different from zero. Differentiation (how different your sectoral exposures are with respect to the average bank in your country) on the other hand does increase monotonically with the number of significant sectoral factor exposures.

Both findings are as expected and provide additional support for our metrics. 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 (either positive or negative), the more dimensions in which the bank differentiates itself from their peers. The former finding on specialization requires more explanation. Banks having exactly one significant sectoral factor loading are definitely specialized compared with banks having no significant sectoral factor loading. However, banks with more than one significant factor can still be considered specialized, for several reasons. First of all, specializing in one sector implies relative under-exposure to at least one other sector, but possibly many. That is, resources to focus on a specific sector can come at the expense of completely ignoring another sector or marginally under-investing in all remaining sectors. Depending on the case, this type of specialization could results in two (one positive and one negative) or many (one positive and many, small, negative) significant factor loadings. It then depends on the noise in the data whether or not small underexposures (in economic terms) will be statistically significant or not. Second, multiple significant factors might still imply specialization 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. The mean (median) of the absolute value of the 36 pairwise correlations between the 9 sectoral factors is 0.18 (0.16). Only ten pairwise correlations (in absolute value) exceed 0.25. Yet, these correlations could be indicative of the fact that shocks to one industry spill over to another. 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 orthogonalize these sectoral factors (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 would affect the number of significant factors, but not the contribution to R-squared (which is not affected by the correlation structure of the sectoral factors). Moreover, it does not affect the measure of differentiation, as the correlation structure of the sectoral factors is the same for all banks in the country.

Finally, to test the sensitivity of our sectoral concentration measures to model specification, we also construct them based on a simpler model or based on local sectoral factors. First, if we estimate a simpler model by excluding the SMB, HML, and Momentum factor as well as the REIT factor from the baseline model (and hence only include the global and local market next to the sectoral returns) we get estimated factor loadings and specialization and differentiation measures that strongly correlate with the measures reported in Table 3. More specifically, for each sectoral factor loading, the correlation between the estimate from a model with and without the additional factors varies between 87% and 90%. Comparing the financial factor loading, sectoral specialization and differentiation from a model with and without the additional factors, we find correlations of 65%, 63% and 80%, respectively. Second, specialization and differentiation are measured using banks' exposures to global sectoral portfolios. This is our preferred approach as many banks have global presence. However, there may be at least two concerns with this choice. First, local industries may have idiosyncracies due to local or regional regulation or demand. Second, the global indices are going to be tilted towards the US (and other highly developed, large countries), which may not necessarily be representative for banks in developing and/or smaller countries. Therefore, we also take another approach and add local (domestic) sectoral factors rather than global sectoral factors to a model that otherwise contains the global and domestic market portfolio as well as the SMB, the HML, the momentum and REIT factor. Unfortunately, these local sectoral indices are not available for all countries (22 rather than 34). Therefore, we take the specification with global factors as baseline, and not the reverse. From these estimations, we compute the *local* sectoral specialization and differentiation measures as well as the local financial sector exposure. First of all, we compare and correlate these local measures with the global measures. The summary statistics are fairly comparable. Local specialization (differentiation) has a mean of 3.74 (1.85), compared with 3.35 (1.57) for the global specialization (differentiation) measure. Moreover, the correlation between the local and global sectoral specialization (differentiation) is very high; i.e. 53% (58%). On the other hand, while the mean of the local financial sector loading is similar to the global financial sector loading, the correlation is very low, namely 9.7%. As robustness, we will also estimate the baseline regression setup with the local measures substituting for the global measures (see Section 3.4).

2.3 External validity for the return-based sectoral specialization and differentiation measures

While return-based models have shown their merits in various aspects of financial research, we introduce them in a novel set-up. Therefore, we also conduct some analyses to provide support for their appropriateness and usefulness in our main tests. In particular, we are going to test whether our return-based measures of sectoral specialization and sectoral differentiation are related to sectoral specialization and sectoral differentiation measures based on banks' self-reported, accounting-based sectoral exposures of their *loan* books.

2.3.1 Hand-collecting sectoral lending exposures

As discussed earlier, detailed information on banks' loan composition is hard to obtain from publicly available or commercial databases. Typically, one can find a breakdown in real estate, consumer or business loans. However, in general, there is no information on the sectoral composition of the business loan portfolio. Two exceptions are the credit registers maintained by some central banks on the one hand and syndicated loan databases on the other hand. The former is confidential, only available for few countries, and does not allow cross-country comparisons; while the latter is limited to very large loans by very large banks.

Given the absence of readily available databases, we hand-collect these data, whenever available, from the notes to banks' financial statements. Some banks, mainly large ones, provide information on their sectoral loan exposures. However, there is no uniform reporting scheme as this is voluntarily disclosed by banks. The sectoral breakdown can be very detailed, but the level of detail can vary by bank and country as there is no required financial reporting format for these exposures. To harmonize the heterogeneity in the sectoral breakdown across banks, we categorize each reported exposure in ten economic sectors based on the one-digit Standard Industrial Classification.
We build a database of sectoral exposures for the largest banks as these are more likely to publish a detailed report on their website.[15] The subsample of banks for which the reports published on

[15]Starting from the sample of listed banks for which we compute the return-based measures, we impose the

their website contain useful and detailed information on the sectoral exposures counts 221 banks across 30 countries, for the years $2007 - 2011$. Table 1 shows the number of bank-year observations for this sample.

Summary statistics on these exposures are reported in panel C of Table 3. For each sector, we report the mean, standard deviation, 5^{th}, 50^{th}, and 95^{th} percentile. There is variation in the average exposure across the ten sectors, with the lowest average for the sector "Agriculture, forestry and fishing" and the largest one for "other industries". Within each sector, there is substantial heterogeneity. The value of the 5^{th} percentile is almost always zero, whereas the exposure to other industries for the bank at the 95^{th} percentile is 51%.

Based on these hand-collected exposures, we construct two indicators of sectoral specialization and differentiation in lending by banks. 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 our account-based measures of sectoral specialization and differentiation, dropping the financial sector (as in the return-based indicators) and "other industries". We capture lending specialization by the cumulative share of the three largest sectoral exposures (*Sectoral CR3*). Sectoral differentiation (herding) is computed as the Euclidean distance between a bank's sectoral loan portfolio and the weighted average sectoral composition of the bank's domestic competitors (as in Equation 4, but replacing the estimated factors with reported shares). The more similar the exposures, the lower the value of the measure and the higher the likelihood of facing common shocks. The summary statistics of these measures (in Panel D of Table 3) indicate that there is considerable heterogeneity across banks. Specifically, the cumulative exposure of the largest three sectors varies from 32% (5th percentile) to 88% (95th percentile), with a mean of 56%. *Differentiation* (accounting) also exhibits substantial cross-sectional variation. The Euclidean distance between a bank's exposure and the country's average exposure ranges from 0.07 to 0.40 (5^{th} and 95^{th} percentile), with a mean of 0.21.

following constraints to optimize the manual data collection: (i) banks need to be active in 2013, i.e. 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 US$ 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 non-missing.

2.3.2 Return and account-based measures of specialization and differentiation

We test the correlation between the account-based and return-based indicators with the following two regression specifications:

$$\text{Specialization}_{i,t} = \beta_1 \text{Sectoral CR3}_{i,t} + \gamma X_{i,t} + \nu_c + \mu_t + \epsilon_{i,t} \quad (5)$$

$$\text{Differentation}_{i,t} = \beta_2 \text{Differentiation (accounting)}_{i,t} + \gamma X_{i,t} + \nu_c + \mu_t + \epsilon_{i,t} \quad (6)$$

where subscripts i , c, and t stand for bank, country and year. Both the factor model-based and account-based sectoral specialization and differentiation measures are included in logs so that we can interpret the coefficients as indicating relative percentage changes. We estimate both equations with a set of bank-specific control variables (captured by the vector $X_{i,t}$) and include country and year fixed effects. Standard errors are clustered at the bank level. A positive and significant β_1 in Equation (5) and β_2 in Equation (6) would indicate that our return-based indicators of specialization and differentiation could serve as proxies for banks' actual sectoral lending specialization and differentiation. It is important to stress that we focus on within-country and within-year variation, so that we control for country-level differences in accounting standards or business models as well as for cyclical variation in sectoral exposures and riskiness.

We also test for differential relationships between factor model-based and account-based sectoral specialization and differentiation measures across banks. Specifically, we test for differences driven by different degrees of disclosure standards and driven by differences in the ratio of off-balance sheet items to total assets. The more information is disclosed by banks, the more accurate stock market participants can assess banks' exposures. We thus expect a stronger relationship between the return-based and account-based measures for banks with higher disclosure standards. The construction of the disclosure index follows Nier and Baumann (2006) and is normalized between zero and one, with higher values indicating more bank disclosure of critical balance sheet and income statement items. Analogous, a higher ratio of off-balance sheet items to total assets suggests that a bank is using more off-balance sheet items for hedging purposes or to create non-lending exposure to a sector. We therefore expect a weaker relationship between return-based and account-based measures for banks with higher off-balance sheet to total assets ratios. Regression results are reported in Table 4.

Insert Table 4 around here

The results in Table 4 show a positive and strongly significant correlation between return-based and account-based sectoral specialization measures in Columns 1 and 2. The coefficient estimates suggest that a one percent change in account-based specialization is associated with a 0.41 to 0.48 percent change in return-based specialization. When we interact the account-based specialization measure with the ratio of off-balance sheet items to total assets and with the disclosure index in Column 2, we find -as expected- a negative coefficient on the former interaction (significant at the 10% level) and a statistically insignificant positive coefficient on the latter interaction. This is consistent with the hypothesis that as banks rely more on derivative instruments for hedging and creating non-lending sectoral exposures, the relationship between account- and market-based specialization measures weakens, while the relationship is somewhat stronger for banks with higher disclosure standards (although statistically not significant).[16]

Columns 3 and 4 of Table 4 shows that there is a positive and significant relationship between return-based and account-based differentiation measures. The economic size of the relationship is similar to that of the specialization measures: a one percent change in account-based differentiation is associated with a 0.4 percent change in return-based differentiation. When we interact the account-based differentiation measure with the ratio of off-balance sheet items to total assets and with the disclosure index in Column 4, we find again -as expected- a negative coefficient on the former interaction and positive coefficient on the latter interaction, and both are statistically significant.

To sum up, the regressions in Table 4 show statistically and economically meaningful correlations between return-based and account-based sectoral specialization and differentiation measures. More important, these correlations differ with the extent to which banks use derivative instruments and have transparent financial statements. These findings are in line with the earlier arguments of return-based measures capturing a broader concept of sectoral exposure and risk management tools than account-based measures.

[16]In unreported regressions, we use a Hirschmann-Herfindahl index rather than the CR3 indicator and find similar results. Results are available upon request. Banks that are more specialized, i.e. have a higher value of the sectoral HHI, have a higher market-based specialization measure. However, there is a negative and significant interaction effect with off-balance sheet items; and a positive, but insignificant, interaction effect with the disclosure proxy.

2.3.3 Return and account-based measures of financial sector exposure

We run a second test that focuses on one specific sector for which the account-based and return-based sectoral classification align, namely finance and insurance. Specifically, we regress our measure of a bank's exposure to the financial sector (*financials factor loading*) on the lending share for finance and insurance and add interactions with the ratio of off-balance sheet items to total assets and the disclosure index discussed above. As in the previous test, the two indicators of financial sector exposure are included in logs so that we can interpret the coefficient estimates as percentage changes.

$$\text{Financials factor loading}_{i,t} = \beta_1 \text{Finance and Insurance}_{i,t} + \gamma X_{i,t} + \nu_i + \mu_t + \epsilon_{i,t} \tag{7}$$

The results in Table 5 show a very close co-movement in sectoral lending shares to the financial sector and factor loadings to the financial sector. 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. This indicates that stock market participants react stronger to finance and insurance exposures if they can assess a bank's exposures more accurately and when banks hedge less against their exposures.[17]

Insert Table 5 around here

While the results in subsection 2.3.2 suggest that there is relevant and significant co-movement between our two composite indicators of bank sector concentration and their accounting based counterparts, the results in Table 5 also show strong co-movements for lending to one specific sector and its factor loading. It is important to note that this is not only the most prominent sector in terms of both lending and exposure (through various contagion channels) but possibly also easier for investors to follow.

[17]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 mapping from account-based lending share to market-based factor loading.

3 Bank sectoral concentration and (systemic) risk

The second contribution of this paper is to assess how sectoral concentration is related to bank performance and risk. To that end, we will relate the return-based measures of sectoral specialization, sectoral differentiation and financial sector exposure to three variables that respectively measure the bank's performance, risk and exposure to systemic risk. We first define our indicators of bank performance and stability (section 3.1), then describe our methodology (section 3.2) and present our results (section 3.3). Finally, we discuss several robustness tests (section 3.4).

3.1 Measures of bank performance, risk, and stability

Using stock return-based measures, we gauge several aspects of bank performance.[18] In particular, we will look at bank risk, bank valuation, and exposure to systemic risk. More specifically, we will employ the following dependent variables in our analysis. First, *volatility*, measured as the annualized standard deviation of a bank's daily stock returns over the span of a calendar year, captures a bank's total risk exposure. Second, to capture the return-risk trade-off in one metric, we employ a measure of a bank's *franchise value*, proxied by the ratio of market capitalization to the book value of common equity. Finally, we estimate a bank's systemic risk exposure using the *Marginal Expected Shortfall* (Acharya et al., 2017). We follow common practice and 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 opposite of this variable such that a higher marginal expected shortfall (in absolute value) relates to a higher exposure to systemic risk.

Insert Table 6 around here

[18]We prefer capital market data to accounting data because equity prices are forward-looking and hence better identifiers of prospective performance and risks associated with different strategic choices. In addition, accounting profits reflect short-run performance, rather than capturing long-run equilibrium behavior. Furthermore, accounting-based profit (such as return on assets or return on equity) and risk measures may be noisy measures of firm performance as a result of differences in tax treatment and (discretion over) accounting practices across countries, or different provisioning and depreciation practices. Noise and biases in the dependent variable may result in low values of goodness-of-fit tests in basically all empirical setups (Smirlock et al. (1984), Stevens (1990)). Nonetheless, we will use several accounting-based risk measures in the robustness tests.

Summary statistics on these variables are reported in panel A of Table 6. The annualized volatility of banks' stock returns is on average 39.3%, while the average franchise value equals 1.4 times the book value of the equity. Both variables also show a large variation across banks and years. The annualized volatility ranges from 14% (p5) to 89.7% (p95), while the market-to-book value of equity ranges from 0.3 (p5) to 3.1 (p95). The average marginal expected shortfall with respect to the local banking sector is 2, implying that the average daily stock return of banks in our sample is -2% on average when the bank sector experiences stress, but ranges from +0.5% (p5) to -6.7% (p95).

3.2 Empirical set-up

3.2.1 The hybrid model

A natural candidate for a regression specification that investigates whether sectoral specialization, sectoral differentiation and financial sector exposure impacts bank performance and (systemic) risk is the following model:

$$\begin{aligned} y_{it} = &\beta_1 \ Specialization_{it-1} + \beta_2 \ Differentation_{it-1} + \\ &\beta_3 \ Financials \ factor \ loading_{it-1} + \gamma \ X_{it-1} + \mu_t + \nu_i + \epsilon_{it} \end{aligned} \tag{8}$$

where y_{it} is either the annualized volatility, the market to book value, or the marginal expected shortfall of bank i in year t. The independent variables are lagged one year to mitigate concerns of reverse causality. X_{it-1} is a vector of bank characteristics to control for other factors that may affect bank performance and stability. Specifically, we include bank size (natural logarithm of total assets), revenue diversification (gross share of non-interest 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 and annual asset growth. Descriptive statistics are presented in panel B of Table 6. We winsorize all variables at the 1 and 99 percentile level to mitigate the impact of outliers. Next to the variables of interest and a set of control variables, we also include year-fixed effects μ_t. ν_i is a bank-specific effect, which can be either considered fixed or random in a panel data set-up. The standard errors are clustered at the bank level. We standardize the coefficients to make a comparison of the economic effects across the different coefficients easier.

In empirical corporate finance, fixed effects have become the default option because they yield unbiased estimates even in the presence of correlation between the individual effects ν_i and the regressors. In the absence of such correlation between ν_i and the regressors, both the fixed effects (FE) estimator and the random effects (RE) estimator will yield unbiased coefficients, but the RE estimator will be more efficient. However, when ν_i is uncorrelated with the independent variables, the two estimators need not automatically give similar point estimates. Getting different estimates of the betas using FE or RE in that case indicates that Equation (8) is misspecified. In particular, it may be suggestive of a dynamic underspecification, and, a model in which one allows for a short-run and a long-run relationship between the dependent variable and the regressors of interest might be more appropriate (Baltagi and Griffin, 1984). In our specific setup, this leads to the following specification:

$$\begin{aligned} y_{it} = {} & \beta_{1a}\ (Specialization_{it-1} - \overline{Specialization}_i) + \beta_{1b}\ \overline{Specialization}_i + \\ & \beta_{2a}\ (Differentation_{it-1} - \overline{Differentation}_i) + \beta_{2b}\ \overline{Differentation}_i + \\ & \beta_{3a}\ (Financials\ factor\ loading_{it-1} - \overline{Financials\ factor\ loading}_i) + \\ & \beta_{3b}\ \overline{Financials\ factor\ loading}_i + \gamma_{1a}\ (X_{it-1} - \overline{X}_i) + \gamma_{1b}\ \overline{X}_i + \nu_i + \mu_t + \epsilon_{it} \end{aligned} \tag{9}$$

where $\overline{Specialization}_i$, $\overline{Differentiation}_i$ and $\overline{Financials\ factor\ loading}_i$ are the bank averages over the sample period. This more general specification (9) allows for a simultaneous estimation based on the within bank variation (short-run) and between bank variation (long-run) in our independent variables of interest, *bank sector specialization*, *bank sector differentiation*, and *financial sector exposure*. Kuh (1959), Baltagi and Griffin (1984), and others have argued that the cross-sectional (between) information in panel data tends to include information on the long-run response, while the time-series (within) dimension in panel data provides information on the short-run responses. We refer the reader to (Baltagi and Griffin, 1984) for a detailed exposition and simulation analysis that shows the appropriateness of this model when the dynamic structure is unknown or the time series dimension is too short to estimate a dynamic model. Models as represented by Equation (9) are known as hybrid models (Allison, 2009), but mathematically equivalent models have been developed by Mundlak (1978) and Wooldridge (2010) and are known as correlated random-effects models. Both types of models allow for the estimation of the within estimator and the between estimator in one step.

Economically speaking, this model takes into account that long-run or persistent differences in sectoral specialization, sectoral differentiation and financial sector exposure between banks may, ceteris paribus, lead to different performance or risk profiles, while temporary changes may have other (or no) effects. In particular, $\hat{\beta}_{1a}$ 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}. Note that $\hat{\beta}_{1a}$, $\hat{\beta}_{2a}$ and $\hat{\beta}_{3a}$ will indeed be equivalent to the within estimation of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ from model (8), while $\hat{\beta}_{1b}$, $\hat{\beta}_{2b}$ and $\hat{\beta}_{3b}$ will be equivalent to the between estimation of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ from model (8).[19] Moreover, Equation (9) nests Equation (8). If the long-run and short-run responses are similar (i.e. if the coefficients obtained from a fixed effects and between effects model are similar), then Equation (9) collapses to Equation (8).

3.2.2 Endogeneity

When aspiring to guide policymakers, the ultimate goal should always be to establish causal relationships. Yet, sometimes this is hard to achieve and one needs to start from correlations. While we refrain from coining our results as strongly causal (due to the absence of an IV[20] or experiment[21] creating exogenous variation in our three independent variables of interest), we believe that our results are more than just correlations. First of all, in order to mitigate endogeneity concerns due to reverse causality, we lag the independent variables such that they are predetermined. Second, the risk profile and the choice of sectoral concentration might be jointly determined by the business model of the bank. However, we proxy for that by including a large set of control variables, next to

[19] The within transformation of model (9) is equivalent to the within transformation of model (8): $(y_{it} - \overline{y}_i) = \beta_{1a}\ (Special_{it} - \overline{Special}_i) + \beta_{2a}\ (Diff_{it} - \overline{Diff}_i) + \beta_{3a}\ (Financials_{it} - \overline{Financials}_i) + \gamma_{1a}\ (X_{it} - \overline{X}_i) + (\mu_t - \overline{\mu}) + (\epsilon_{it} - \overline{\epsilon}_i)$. Also the between transformation of model (9) is equivalent to the within transformation of model (8): $\overline{y}_i = \alpha + \beta_{1b}\ \overline{Special}_i + \beta_{2b}\ \overline{Diff}_i + \beta_{3b}\ \overline{Financials}_i + \gamma_{1b}\ \overline{X}_i + \nu_i + \overline{\mu} + \overline{\epsilon}_i$.

[20] Suitable instruments potentially need to be found for three different variables. Moreover, even if we would have three perfect instruments, our chosen methodology relying on the within and between estimators does not allow for a straightforward instrumental variable estimator.

[21] In the ideal case, one would exploit an exogenous shock, but this is difficult to do in a cross-country setup. Possible candidates would be changes in regulation, but these are usually also not exogenous as they are responses to (lending-induced) financial crises.

including country- and year-fixed effects and bank-level random effects. Furthermore, in a robustness check on a much smaller subsample, we document that controlling for ownership (which might have been an important omitted variable driving both risk choices and sectoral concentration) does not affect our results. Third, we reverse the argument of an omitted variable bias and estimate a model without bank specific control variables and do not find a large qualitative and quantitative impact on our results. This model also allows us to gauge the scope for an omitted variable bias (Altonji et al. (2005)). We find that it is unlikely that an unobserved variable, next to the rich set of control variables we already include, will have a large effect on the estimated relationships of interest. In sum, at a minimum our results document meaningful correlations. Moreover, we take some steps to alleviate endogeneity concerns and believe that a cautious causal interpretation can be attached to the results.

3.3 Baseline results

The estimation results of the above-mentioned regression specifications are shown in Table 7. We report three columns for each dependent variable. For sake of transparency, we first present the results obtained using the within and the between estimators of Equation (8). Subsequently, we report our main specification, the one-step estimation results of the hybrid specification (Equation (9)). Columns 1-3 use the annualized volatility of banks' stock return as dependent variable, columns 4-6 the market to book value of equity and columns 7-9 the systemic risk exposure, *MES*.

Insert Table 7 around here

Before discussing the economic implications of the estimated relationships, we make four statistical observations. First of all, for each dependent variable, the short-run coefficients (first three variables) are identical when using either the (bank) fixed effects estimator in specification (8) or the random effects estimator in the hybrid model (9). Second, for each dependent variable, 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 (-0.157, -0.009 and -0.005, respectively) for each dependent variable, 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 three 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, 6 and 9.[22] As can be seen in Column 3, sectoral specialization is associated with lower bank risk -as measured by the volatility of the stock price- in the short and long-run. The long-run economic effect, however, is almost ten times larger than the short-run economic effect. These results are also economically meaningful as a one standard deviation increase in sectoral specialization decreases total bank risk by about 0.25 standard deviation in the long-run.[23] 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 learning by doing. The stronger relationship in the long- than short-run might also reflect the importance of variation in risk management and business models across different banks in terms of sectoral concentration and, related, their risk performance. This importance is also reflected in the results in Column 3 concerning the financial sector exposure; short-run deviations seem to have no impact on bank risk, but in the long-run higher exposure to the financial sector is clearly related to higher bank risk, although the economic impact remains relatively modest. A one standard deviation decrease in financial sector exposure increases total bank volatility by a bit more than 0.06 standard deviation. The results in Column 3 also suggest that bank risk increases strongly with bank sectoral differentiation. The long-run impact is again significantly larger than the short-run impact. This

[22]For sake of space and brevity, we only report the coefficients on the variables of interest in Table 7. We do not discuss or focus on the interpretation of the signs, significance and coefficients of the control variables. The full regression results can, however, be inspected in Table A3 in the Internet appendix.

[23]The estimated long-run (between) coefficient of sectoral specialization (which has been standardized to facilitate comparison across concentration measures) on total volatility is -6.09. A one standard deviation increase in sectoral specialization would thus reduce a bank's annualized stock return volatility by -6.09, which is 25% of the standard deviation of bank's annualized stock return volatility (24.36) in the sample.

suggests that banks that deviate more from the industry norm in terms of sectoral exposures are considered riskier by the market. As all variables are standardized, it seems that sectoral differentiation is the most important determinant of interest in our model concerning total volatility. A one standard deviation decrease in sectoral differentiation decreases total bank volatility by about 0.83 standard deviation in the long-run.

Column 6 of Table 7 provides some evidence that banks have a higher market value when specializing their sectoral portfolio, though the coefficient is consistently significant only in the short-run. Differentiating their exposure from their competitors, on the other hand, decreases market value, both in the short- and long-turn. The economic magnitude of the effects, however, are quite small. A one standard deviation increase in sectoral differentiation decreases franchise value by about 0.13 standard deviation in the long-run, while a one standard deviation in specialization increases franchise value by only 0.01 standard deviation in the short-run. Higher exposure to the financial sector is associated with a statistically higher franchise value in the long-run, although the economic relevance is rather small (a one standard deviation increase in financial sector exposure decreases franchise value by a 0.1 standard deviation).

Finally, we gauge the relationship between sectoral specialization, differentiation, financial sector exposure and systemic risk exposure -as measured by the marginal expected shortfall- in column 9 of Table 7. 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 bank risk, the relation between sectoral specialization and systemic risk exposure also appears to be much stronger in the long-run, where the coefficient is at least ten times larger. The long-run effect is also economically meaningful. A one standard deviation increase in sectoral lending specialization leads to a 0.35 standard deviation reduction in systemic risk exposure in the long-run. We also find a positive and significant relation of sectoral differentiation with systemic risk exposure. Moreover, it seems that this impact is of similar size in both the short- and the long-run. While this findings seems at first contrary to e.g., (Acharya and Yorulmazer, 2008; Acharya, 2009; Wagner, 2010), in that more differentiated banks are more exposed to systemic risk, this can be explained with markets expecting a higher likelihood for banks being bailed-out if they fail together rather than on an idiosyncratic basis. The most important determinant of systemic risk exposure is the financial factor loading, proxying for over-exposure to the financial sector. Again, the long-run relation is much stronger than the short-run effect, but both are statistically significant at the 1 percent 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 suggests that banks that are more specialized seem to have higher franchise values in the short-run, while they face lower total bank volatility and are less exposed to systemic risk. Banks that differentiate their sectoral exposure more from that of their domestic competitors have lower franchise values, higher exposure to systemic risk, but especially higher bank risk. Banks that are overexposed to the financial sector suffer from higher stock volatility and exposure to systemic risk, but at the benefit of somewhat higher returns (and thus higher franchise values). 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.

These findings are consistent with theories focusing on the benefits of sectoral specialization for reducing standalone bank risk and systemic risk (e.g., Winton (1999)) but not with theories that focus on the benefits of portfolio diversification (e.g., Diamond (1984)). It is important to note that the benefits of sectoral specialization come primarily through risk reduction rather than being value increasing, i.e., markets perceive more specialized banks as less risky, including during systemic shocks. While our results are not consistent with theories focusing on the risks of similarity of banks in their exposure profile (Acharya and Yorulmazer, 2008; Acharya, 2009; Wagner, 2010), this might rather reflect underlying market expectations of bail-outs if there are too many banks to fail. Alternatively, the more adverse market reaction to more differentiated banks (especially during systemic shocks) might be due to higher information asymmetries of investors vis-a-vis banks that look more different from their peers.

3.4 Robustness and extensions

We subject our findings to a battery of robustness tests and explore some channels through which specialization and differentiation might affect performance and (systemic) risk. We structure our additional tests in four sections. First, we perform several analyses that involve changing the dependent variable (CoVaR and accounting-based risk and performance measures). Second, we perform several robustness checks that are related to our independent variables. In the third and fourth subsection, we investigate the sensitivity of our findings with respect to our sample composition and sample splits.

3.4.1 On the dependent variables

In Table 8, we report results for the baseline specification using alternative dependent variables. First of all, we use an alternative indicator of systemic risk, namely the CoVaR (Adrian and Brunnermeier, 2016), 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. Put differently, it captures the sensitivity of the other institutions in the financial system to the failure of one specific institution. While the Marginal Expected Shortfall is easier to compute (it requires less data) and perhaps captures more a bank's *exposure* to systemic risk, the CoVaR has the advantage that it provides an indication of the individual bank's *contribution* to systemic risk. The results hence provide insights into an interesting and useful second dimension of systemic risk. The results in column 1 of Table 8 confirm our earlier findings of a negative relationship between specialization and systemic risk. Also the positive relation of financial sector exposure and exposure to systemic risk is confirmed. Interestingly, we find contrasting results on differentiation (in particular 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. 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 (hence the positive effect on MES). On the other hand, if that bank fails, its impact on the entire banking system will be larger (hence negative effect on CoVaR) as fire sales by the failing bank affect the value of asset holdings held by the other banks in the system.

Insert Table 8 around here

Second, 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 non-performing loans to total loans ratio). These test do not only serve to show the robustness of our results with respect to our dependent variables, but they may also provide insights into the channels by which the general findings take place. Using accounting-based indicators has the disadvantage that they are more backward-looking than market-based performance indicators. However, they have the advantage of avoiding that our findings are driven by any mechanical relation (due to the inclusion of market-based indicators on both sides of the regression specification). The results in column 2 show that only differentiation is significantly (and negatively) associated with the Z-score, suggesting that banks that differentiate more are closer to insolvency, consistent with the previous findings documenting a positive relation with total volatility and MES. In this specification, we do not find support for the risk-reducing effect that specialization has. The results in columns 3 and 4, in contrast, do provide further evidence that specialized banks are significantly less risky by being better capitalized and by having lower credit risk. As can be seen, we also find that differentiated banks are riskier as they appear to be less capitalized and have a higher credit risk. It thus seems that the stability-enhancing effect of specialization comes through higher loan quality, leading banks to have fewer write-offs, helping them to retain more earnings and preserve higher capital buffers. Finally, the results in column 3 also show that banks with a higher financial sector loading have lower (higher) capital buffers in the long (short)-run.

In addition, we use an alternative set-up to test our hypotheses, focusing on the buy-and-hold returns of banks during the Global Financial Crisis, following the methodology by Beltratti and Stulz (2012). Specifically, they regress the buy-and-hold stock return over the crisis period from July 2007 to December 2008 on an array of bank and country characteristics. Using their empirical set-up, we gauge whether banks with higher pre-crisis specialization, differentiation and financial sector exposure provided different returns for investors than banks with lower pre-crisis specialization, differentiation and financial sector exposure. This setup serves as a robustness check for the systemic risk results. The results in Internet Appendix Table A1 show that more sectoral differentiation and more exposure to the financial sector are associated with lower buy-and-hold returns during the crisis (which is in line with the MES results). In terms of economic effects, a one standard deviation increase in differentiation (financial sector exposure) leads to a 4.6% (4.4%) lower stock return over the 18 month period from July 2007 to December 2008. These results are confirmed controlling for other bank characteristics, and extending the period for calculating the buy-and-hold returns to March or June 2009. We again find that specialization leads to higher returns (lower MES) by entering positively, but significantly only once we extend the sample period to March or June 2009. A one standard deviation increase in specialization increases the buy-and-hold return by about 2%. In summary, using buy-and-hold returns as dependent variable confirms our baseline findings that more differentiated banks and banks more exposed to the financial sector are valued less during a systemic risk event, while more specialized banks are valued more.

3.4.2 On the independent variables

We run several robustness checks focusing on the independent variables of interest. First of all, we re-run our model with an error-in-variables specification, allowing for various degrees of mismeasurement, to take into account that two of our three main variables of interest (sectoral differentiation and financial sector exposure) are based on the estimated coefficients of factor model (1), and might therefore be imprecisely measured. The results are included in Table 9, which shows that the all findings are very robust to such potential mismeasurement. In unreported results, we also use the error-in-variables estimator of Erickson et al. (2014) that uses higher order moments to identify the coefficients. This estimator can only be applied to estimate the within relationship, however, but results again hold both quantitatively and qualitatively.

Insert Table 9 around here

As a second robustness analysis on the independent variables, we re-estimate the baseline setup (i.e., replicate Table 7) but substitute the three current concentration measures (based on a factor model with global sectoral factors) with concentration measures based on a factor model with local sectoral factors (see the last paragraph of Subsection 2.2). In addition, we also estimate a specification where we add the global financial sector exposure to the model with the three local measures.[24] The results of these specifications are reported in Table 10. Using the local sectoral factors, which results in a slightly smaller sample of observations from 22 countries (rather than 34), does not affect our main conclusions on the relationships between specialization and differentiation on the one hand and bank performance and (systemic) risk on the other hand. What is different though is that the exposure to the local financial sector seems to be insignifican. Adding the exposure to the global financial sector to the specification show that banks' risk and performance is related to how their stock price co-moves with global rather than local financial news.

Third, ownership structure has been shown to affect bank risk-taking. More cash-flow rights by a large owner are associated with more risk (Laeven and Levine, 2009). Unfortunately, ownership

[24] We refrain from including all local and global measures jointly because of the high correlation between local and global specialization (as well as differentiation).

data is not publicly available for such a large sample. Therefore, we use data of Laeven and Levine (2009) from 2001 to examine whether ownership structure could be an omitted variable that drives both the choice of sectoral concentration and bank risk-taking. 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 are biased (while the bank fixed effects absorb the impact of time-invariant ownership in the within estimator). Using the between estimator, we find that excluding proxies for ownership (either cash flow or control rights) does not affect the point estimates of our variables of interest (see Internet Appendix Table A2) relative to a model that controls for ownership. Moreover, also in this much smaller sample we find by and large the same effects quantitatively and qualitatively for our variables of interest in the specifications for total volatility and MES. In unreported specifications, we also add dummies that indicate the type of majority owner (i.e. state, family, financial institution, non-financial institution, other). In the absence of more detailed ownership data for each bank-year combination in our sample, we believe that these results on a limited subsample mitigate concerns that our results suffer from an omitted variable bias related to bank ownership.

Finally, to shed further light on the scope for an omitted variable bias, we follow the procedure of Altonji et al. (2005) and Bellows and Miguel (2009). Specifically, we measure the stability of the coefficients by calculating the ratio between the value in the regression including controls (numerator) and the difference between this value and the one derived from a regression without control variables (denominator). This ratio shows how strong the covariance between the unobserved factors explaining bank performance and risk need to be, relative to the covariance between observable factors and bank performance and risk, to explain away the effect of specialization, differentiation and financial sector exposure. Unreported results for a specification with and without control variables (see Internet Appendix Table A3) allow us to compute these ratios to test directly for an omitted variable bias. Focusing on the long-run coefficients, we find that in the case of total volatility and systemic risk exposure, these ratios are at least 8, suggesting that the covariance between unobserved factors and bank performance and risk needs to be more than eight times as high as the covariance of the included control variables with bank performance and risk, which seems quite unlikely. The only regression where this ratio is only around one is that of the financial sector exposure in the franchise value regression. Computing this ratio for the short-run coefficients provides similarly high ratios.

3.4.3 On the sample composition

Next, we subject our main sample to several sensitivity tests. First, as we follow banks in a decade where the sector was marked by consolidation, we try to control for mergers and acquisitions or large divestitures by excluding observations with year-on-year asset growth below -10% or asset growth above 20%. This excludes about twenty percent of the data and we show the results of this exercise in Columns 1, 4 and 7 of Table 11.

Insert Table 11 around here

Second, we currently require banks to be present at least for 5 years in the sample and for countries to have at least 5 banks in each year in the sample to ensure a reasonable between and within estimate. We now further restrict the sample criteria and require banks to be present in each year and make our data set balanced. This drops about half of the observations and we show the results of this robustness test in Columns 2, 5 and 8 of Table 11. Comparing the results of these sensitivity analyses with the baseline results reveals that the findings are both qualitatively and quantitatively robust.

Third, the accuracy of the measure of differentiation crucially depends on how much of the total reference market (which is the country) is covered by the banks in the sample and whether or not the banks covered in the sample are different from the banks not covered. If a large part of domestic banking assets is not covered by our sample (because, for instance, many banks in the country are not listed or because of our sample selection criteria) and these banks have substantially different sectoral concentration patterns, then the measure of sectoral differentiation will be biased. Obviously, whether or not they have different sectoral exposures cannot be verified, but we do have information on the sample coverage. As can be seen in Table 1, there is some variation in the share of each country's banking system that we cover. We therefore run a robustness check on the main specification by excluding all countries where the share of banking assets covered is less than 70% of the total domestic assets. The results of these tests are reported in columns 3, 6 and 9 of Table 11. When looking at (systemic) risk, we can confirm all findings even for this smaller sample. Crucially, the effect for differentiation, the measure most affected by the coverage, remains statistically and economically significant. Additionally, in Table A4 in the Internet Appendix, we also analyze the impact for countries for which the share is smaller (larger) than 50%. In both subsamples, we confirm the findings of sectoral specialization, differentiation and financial exposure on total volatility and systemic risk. Hence, we are confident that our findings for total volatility and differentiation do not seem to be driven by varying coverage of the different banking markets. As with many other robustness checks, the results using franchise value as dependent variable are less robust.

3.4.4 Sample splits

As our sample period includes the global financial crisis, there might be significant differences in the relationship between sectoral specialization, sectoral differentiation, and financial sector exposure and bank performance and stability over the sample period. In Table 12, we report results for a sample split between two sub-sample periods, specifically, for 2003 to 2007 and 2008 to 2012. The table consists of three panels, one for each dependent variable, and in each panel the first two columns correspond with the subsamples 2003-2007 add 2008-2012, respectively.

Insert Table 12 around here

Regarding the long-run relationships (between effects), we find that most of our previous findings are consistent across the two sub-sample periods. The long-run relationship between specialization, differentiation, and financial sector loading, on the one hand, and volatility and systemic risk exposure, on the other hand, are consistent across the two sub-periods, with one exception. The positive relationship between the financial sector loading and total volatility is predominantly a 2008-2012 result. Quantitatively speaking, the estimated coefficients on the long-run relationships (in the volatility and systemic risk exposure regressions) are smaller in absolute value in the first half of the sample period. The short-run relationships between differentiation and the three performance variables are driven by the post-crisis period, whereas the coefficients enter insignificantly pre-2008. In the case of short-run specialization, none of the coefficients enter significantly across the two sub-samples, even though they are significant over the full sample period in the risk regressions. From an econometric point of view, it is not necessarily surprising nor inconsistent that the sample split yields less robust findings for the short-run than long-run relationships, as the former is based on the within variation of the variables, which are now estimated over a much shorter period.

The banks in our sample are headquartered in 34 different countries, yet more than 50% of the sample are US banks. Hence, testing whether our main findings hold for the sample of US and non-U.S. banks separately is a critical robustness test. The results in Table 12 show the results for the sub-sample of banks in the U.S. and outside the U.S in the last two columns of each panel. The results show that the findings for the overall sample are largely consistent within the sub-sample of U.S. banks and non-U.S. banks. Specifically, we confirm our findings for volatility and for systemic risk exposure for the US and non-U.S. sample, both for the short-run and long-run relationships, except for one significant contrasting finding. The insignificant short-run relationship between the financial factor loading and total volatility is due to a negative and significant relationship for US banks and a positive and significant relationship for non-US banks. We also find no significant long-run relationship between the financial factor loading and total volatility in the U.S. sample. In the case of franchise value we find positive (negative) and significant long-run relationships with financial sector exposure (differentiation) in the U.S., but not in the non-U.S. sample. Yet, the short-run impact on franchise value is stronger in the non-US sample.

In unreported results (see Internet Appendix Section 3), we uncover sizeable differences in the relationships across countries and over years. One possible extension of our paper is to further examine the extent and sources of time and cross-country variation in the impact of sectoral concentration on bank performance and risk exhibits. While important and potentially crucial for how and when to implement a given policy related to sectoral specialization, we consider it going beyond the the scope of this paper and leave it an interesting avenue for future research.[25]

4 Conclusion

We propose a novel technique to infer banks' concentration from a factor model. We use it to identify sectoral concentration of 1,716 banks in 34 countries between 2002 and 2012, with three bank-time varying measures of sectoral concentration. With these measures in hand, we are the first to explore the impact of bank sectoral specialization, sectoral differentiation, and financial sector

[25]A parallel to the competition and stability literature can be drawn. That literature initially aimed at establishing whether the sign of the relationship is positive or negative. A robust conclusion coming from surveying many papers is that it depends on the country and time-period under examination. Only after establishing the cross-country variation in the relationship between competition and stability did researchers start to explore which regulatory factors or institutional features affect this relationship (see, e.g., Beck et al. (2013))

exposure on bank performance and (systemic) risk. The results suggests that higher specialization is associated with lower total volatility and makes banks less exposed to systemic crises. Banks that differentiate their sectoral exposure less from that of their domestic competitors have somewhat higher franchise values, but significantly lower exposure to systemic risk and lower total bank volatility. Banks that are overexposed to the financial sector have, on average, a higher stock volatility and higher systemic risk exposure, but at the benefit of higher franchise values. These effects are much stronger in the long-run than in the short-run (about tenfold). Finally, we show that the relationships between sectoral specialization, sectoral differentiation, and financial sector exposure on the one hand and bank (systemic) risk and performance on the other hand are robust to many alterations of the baseline setup.

The results in this paper contribute to the debate on how banks should be regulated in order to minimize costs related to banking stress. Diversification of loan portfolios, revenues and activities has often been advocated in policy circles as helping to reduce concentration risk and has, as such, been embedded in the core principles of banking supervision. However, our results suggest that diversification (i.e. less specialization) will, in general, increase total volatility and systemic risk exposure of banks. Allowing for more sectoral specialization could thus be desirable. Regulatory proposals regarding limits on herding (resulting either from more differentiation and/or lower exposure to the overall financial sector) may also be an interesting opportunity to explore, though it is important to note that we documented a certain variation across countries and time in these relationships. Investigating which factors determine the size and magnitude of these relationships across countries is definitely an interesting area of future research.

Finally, in this paper we take sectoral concentration as given and aim to document how it affects bank performance 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 method 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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Figure 1: Variation in specialization, differentiation and financial sector exposure

This graph provides an indication of the time variation in our main independent variables: Specialization, Differentiation and Financials factor loading. The figures provide the evolution in the mean, the first quartile (p25) and the third quartile (p75) of the distribution.

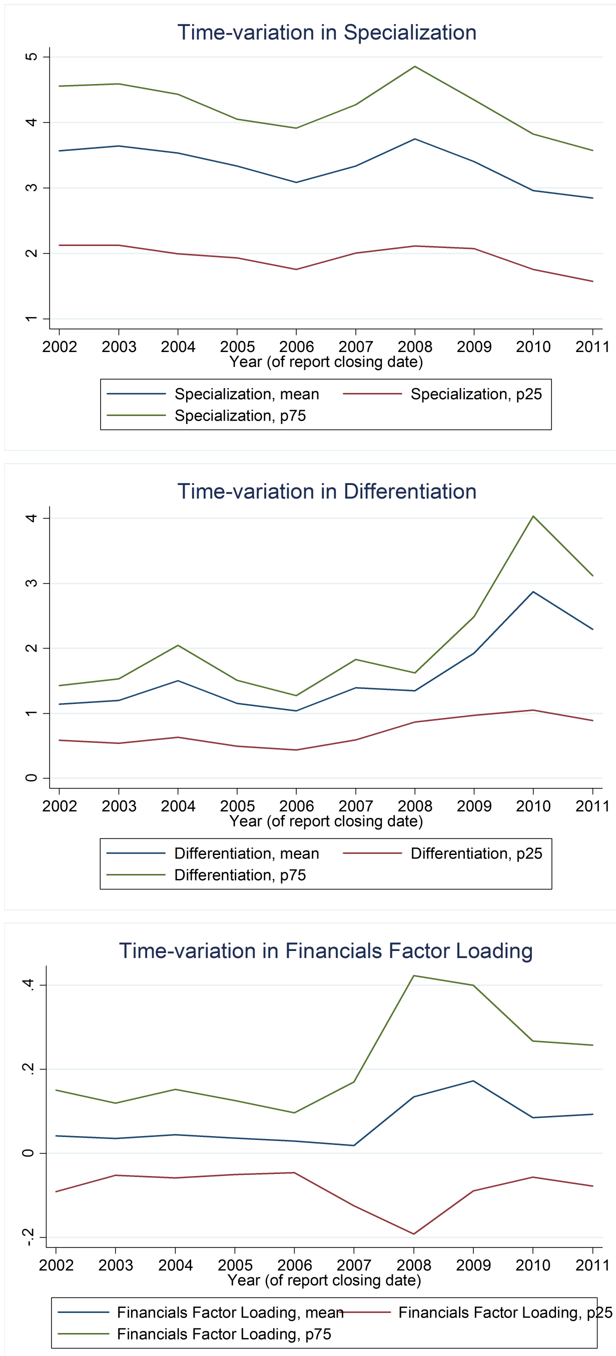

Figure 2: Specialization and differentiation: significant sectoral exposures

This graph consists of two subplots, one for the specialization indicator (upper graph) and one for the differentiation indicator (lower graph). An input for both measures are the estimated factor loadings. In these graphs, we present distributional information, via a box plot, on the specialization and differentiation measure, depending on how many of these estimated factor loadings are significant at the 5% level.

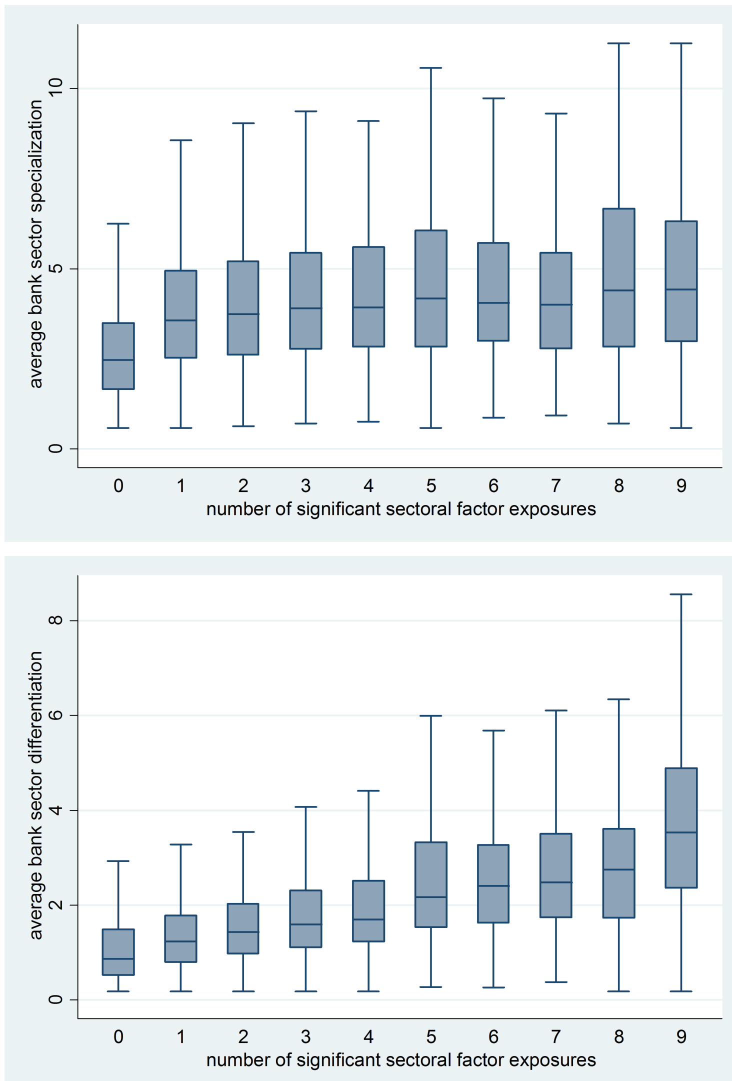

Table 1: List of countries and number of bank-year observations by country

COUNTRY	Full sample: Percentage of total domestic banking assets covered	Full sample: Bank-year observations	Accounting subsample: Bank-year observations
ARGENTINA	36	63	6
AUSTRALIA	86	64	25
AUSTRIA	33	75	8
BRAZIL	59	161	8
CANADA	86	127	
CHILE	71	69	28
DENMARK	64	353	10
FRANCE	48	268	21
GERMANY	72	127	14
GREECE	92	90	13
HONG KONG	33	98	33
INDIA	81	321	63
INDONESIA	50	103	17
ISRAEL	90	80	29
ITALY	66	230	15
JAPAN	47	938	288
MALAYSIA	64	113	
MEXICO	51	67	8
NORWAY	62	162	17
PAKISTAN	68	126	
PERU	79	65	2
PHILIPPINES	74	109	14
POLAND	79	132	43
SPAIN	88	108	15
SRI LANKA	48	59	
SWEDEN	89	51	20
SWITZERLAND	83	134	8
TAIWAN	54	229	39
THAILAND	85	119	34
TURKEY	78	112	45
U.A. EMIRATES	81	100	34
U.K.	56	92	20
U.S.A.	49	6,650	82
VENEZUELA	60	107	5

Full sample: 11,702 observations, on 1,716 banks from 34 countries, 2002-2011.
Accounting subsample: 964 observations, on 221 banks from 30 countries, 2007-2011.

Table 2: Data dictionary: Variables, Labels and Source

This table contains information on the labels and definitions of the independent variables of interest (panel A), the dependent variables (panel B) and the bank-specific control variables (panel C).

Variable Label	Variable definition	Source
Panel A: Sectoral Specialization Indicators based on Factor Loadings and Accounting data		
Specialization	Contribution to R2 of the sectoral factors	Based on Datastream
Differentiation	Euclidean distance between bank's return-based exposures and country's average exposures (excluding bank in average)	Based on Datastream
Financials factor loading	Beta on returns to financial sector	Based on Datastream
Sectoral CR3	Cumulative exposure of largest three acc. Exposures	Notes of Annual Report
Differentiation (accounting)	Euclidean distance between a bank's exposures and the country's average exposures (excluding bank in average)	Notes of Annual Report
Financial sector exposure	Lending share to finance and insurance	Notes of Annual Report
Panel B: Performance Measures		
Franchise Value	Market-to-Book value of Equity	Bankscope and Datastream
Total Volatility	Annualized Volatility of Daily Stock Return	Datastream
Systemic Risk Exposure	Marginal Expected Shortfall (5%, wrt LOCAL banking sector)	Datastream
Panel C: Bank Characteristics		
Bank Size	Natural Logarithm of Total Assets	Bankscope
Revenue Diversification	Gross Share of Non-Interest Income in Total Income	Bankscope
Bank Capital	Common Equity to Total Asset	Bankscope
Funding Diversification	Share of deposit funding in deposit and money market funding	Bankscope
Loan Share	Loans to Total Assets	Bankscope
Profitability	Return on Equity	Bankscope
Asset Growth	Annual Growth in Total Assets	Bankscope
Credit Risk	Loan Loss Provisioning to Total Assets	Bankscope

Table 3: Measuring banks' sectoral specialization and differentiation

This table contains information on sectoral factor exposures as well as sectoral specialization measures based on these factor exposures. The sectoral exposures are obtained from a regression of a bank's stock return on the returns to 10 different sectoral indices, while controlling for the returns on a broad and local market index, the returns on the HML, SMB and momentum portfolios (global) and the return on REIT. We estimate such a regression for each bank and for each year using daily returns, yielding a panel database on sectoral exposures that varies at the bank-year frequency. The panel dataset of estimated exposures consists of 11,702 bank-year observations, covering 1,716 banks from 34 countries over a ten year period starting in 2002. Panel A reports for each estimated factor loading the mean and standard deviation across 11,702 observations, as well as the fifth, fiftieth and ninety-fifth percentile of the panel of estimated factor loadings. Based on the estimated sectoral exposures, we compute two time-varying bank-specific measures of the intensity of sectoral specialization and differentiation of which summary statistics are reported in panel B. 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 exposures at the bank-year level for the years 2007-2011, covering 964 observations on 221 banks from 30 countries. Based on the hand-collected accounting-based sectoral exposures, which are reported in panel C, we compute two time-varying bank-specific measures of the intensity of sectoral specialization and differentiation of which summary statistics are reported in panel D. A detailed description of the construction of these two return-based and accounting-based measures is provided in the text as well as in Table 2.

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
10= Financials(FINAN)	0.07	0.31	-0.35	0.04	0.58
Panel B: Factor-based sectoral specialization and differentiation					
Specialization	3.35	1.99	0.98	2.92	7.25
Differentiation	1.57	1.44	0.30	1.15	4.44
Panel C: Summary Statistics on Sectoral Lending shares					
S1 ”Agriculture, Forestry and Fishing”	0.02	0.04	0.00	0.00	0.11
S2 ”Mining and Construction”	0.06	0.06	0.00	0.05	0.18
S3 ”Manufacturing”	0.16	0.11	0.02	0.14	0.38
S4 ”Transport, communication, Electric, Gas and Sanitary service”	0.07	0.07	0.00	0.05	0.22
S5 ”Wholesale trade and Retail trade 0.13	0.10	0.00	0.11	0.33	
S6 ”Finance and Insurance”	0.09	0.10	0.00	0.05	0.31
S7 ”Real estate”	0.14	0.15	0.00	0.10	0.46
S8 ”Services”	0.11	0.10	0.00	0.10	0.30
S9 ”Public administration”	0.05	0.07	0.00	0.01	0.19
S10 ”Other industries”	0.17	0.18	0.00	0.12	0.51
Panel D: Accounting-based sectoral specialization and differentiation					
Sectoral CR3 (accounting)	0.56	0.18	0.32	0.55	0.88
Differentiation (accounting)	0.21	0.11	0.07	0.18	0.40

Table 4: Relating accounting to return-based measures of sectoral concentration

This table provides information on the relationship between the hand-collected accounting-based sectoral lending specialization and differentiation measures and the return-based sectoral lending specialization and differentiation measures. More specifically, the left panel provides regression results for a regression of Specialization on Sectoral CR3 (i.e. Specialization accounting), whereas the right panel provides results for a regression of Differentiation on Differentiation (accounting). We estimate both equations with and without interacting the accounting based measures with a proxy for the bank's hedging efforts (off balance sheet size to total assets) and a proxy for the accounting transparancy of banks in a country (disclosure). 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.

VARIABLES	(1) Specialization$_{it}$	(2) Specialization$_{it}$	(3) Differentiation$_{it}$	(4) Differentiation$_{it}$
ln(Specialization accounting based)$_{it}$	0.41***	0.48***		
	(0.15)	(0.15)		
ln(Differentiation accounting based)$_{it}$			0.40*	0.40**
			(0.23)	(0.20)
ln(Specialization accounting based)$_{it}$ x OBS$_{it}$		-0.27*		
		(0.15)		
ln(Differentiation accounting based)$_{it}$ x OBS$_{it}$				-0.51***
				(0.19)
ln(Specialization accounting based)$_{it}$ x DISC$_{it}$		0.05		
		(0.12)		
ln(Differentiation accounting based)$_{it}$ x DISC$_{it}$				0.31**
				(0.14)
Off Balance Sheet Size to Total Assets (OBS)$_{it}$		0.06		0.07
		(0.08)		(0.05)
Disclosure (DISC)$_{it}$		-0.02		-0.05*
		(0.05)		(0.03)
Bank Size$_{it}$	-0.17	-0.12	-0.26	-0.22
	(0.26)	(0.25)	(0.27)	(0.27)
Revenue Diversification$_{it}$	-0.17	-0.18	0.48***	0.45***
	(0.15)	(0.14)	(0.15)	(0.15)
Bank Size$_{it}$ x Revenue Diversification$_{it}$	0.97	0.75	0.41	0.19
	(1.31)	(1.29)	(1.29)	(1.26)
Bank Capital$_{it}$	-0.10	0.05	-1.45***	-1.22**
	(0.56)	(0.54)	(0.54)	(0.53)
Funding Diversification$_{it}$	-0.26	-0.30*	-0.34**	-0.34**
	(0.17)	(0.17)	(0.14)	(0.14)
Loans Share$_{it}$	0.16	0.17	0.23*	0.22*
	(0.18)	(0.18)	(0.13)	(0.12)
Profitability$_{it}$	-0.20	-0.13	-0.49***	-0.45**
	(0.16)	(0.16)	(0.18)	(0.18)
Asset Growth$_{it}$	0.09	0.08	0.12	0.12
	(0.09)	(0.09)	(0.10)	(0.10)
Credit Risk$_{it}$	-0.01	-0.00	0.05	0.06*
	(0.04)	(0.04)	(0.03)	(0.03)
Observations	964	964	964	964
R-squared	0.31	0.32	0.25	0.26
Country Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Clustered SE	Bank	Bank	Bank	Bank

Table 5: Relating accounting to return-based measures of financial sector exposure

This table provides information on the relationship between the hand-collected accounting-based sectoral lending share to 'finance and insurance' and the estimated factor exposure to financials. More specifically, the table provides regression results for a regression of the Financials factor loading on the sectoral lending share to Finance and Insurance (S6), while controlling for a set of bank-specific control variables, as well as bank and year fixed effects. We also augment the the model by interacting the sectoral lending share to Finance and Insurance (S6) with a proxy for the bank's hedging efforts (off balance sheet size to total assets) and a proxy for the accounting transparancy of banks in a country (disclosure) or both. Standard errors are clustered at the bank level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	(1)	(2)	(3)	(4)
VARIABLES	**Financials factor loading$_{it}$**			
Finance and Insurance (=S6)$_{it}$	0.72***	1.26***	0.83***	1.27***
	(0.27)	(0.38)	(0.27)	(0.38)
Finance and Insurance (=S6)$_{it}$ x OBS$_{it}$		-0.83**		-0.70*
		(0.38)		(0.38)
Finance and Insurance (=S6)$_{it}$ x DISC$_{it}$			0.61**	0.55**
			(0.24)	(0.25)
Off Balance Sheet Size to Total Assets (OBS)$_{it}$		0.11**		0.10*
		(0.05)		(0.06)
Disclosure (DISC)$_{it}$			-0.03	-0.03
			(0.02)	(0.02)
Bank Size$_{it}$	0.18	0.14	0.14	0.11
	(0.29)	(0.29)	(0.29)	(0.29)
Revenue Diversification$_{it}$	0.05	0.04	-0.00	-0.01
	(0.28)	(0.28)	(0.27)	(0.26)
Bank Size x Revenue Diversification$_{it}$	-0.20	0.07	0.04	0.24
	(1.31)	(1.33)	(1.31)	(1.32)
Bank Capital$_{it}$	1.85	1.79	1.92	1.87
	(1.36)	(1.35)	(1.32)	(1.31)
Funding Diversification$_{it}$	-0.26	-0.30	-0.28	-0.31
	(0.23)	(0.23)	(0.23)	(0.22)
Loans Share$_{it}$	-0.25	-0.28	-0.26	-0.29
	(0.33)	(0.32)	(0.33)	(0.33)
Profitability$_{it}$	0.36	0.39*	0.37*	0.39*
	(0.23)	(0.22)	(0.22)	(0.22)
Asset Growth$_{it}$	0.11	0.13	0.13	0.14
	(0.13)	(0.13)	(0.12)	(0.13)
Credit Risk$_{it}$	0.08	0.08*	0.08	0.08
	(0.05)	(0.05)	(0.05)	(0.05)
Observations	964	964	964	964
R-squared	0.09	0.09	0.10	0.10
Number of bankid	221	221	221	221
Bank Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Clustered SE	Bank	Bank	Bank	Bank

Table 6: Summary statistics on bank performance, (systemic) risk (exposures) and bank characteristics

This table contains summary statistics on the performance measures (panel A , 2003-2012) and the bank characteristics used as control variables (panel B, 2002-2011). 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 specialization 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 fifth, fiftieth and ninety-fifth percentile) on three performance measures and eight control variables. A detailed description of the construction of these measures is provided in the text as well as in Table 2.

variable	mean	sd	p5	p50	p95
Panel A: Summary Statistics on franchise value and (systemic) risk					
Total Volatility	39.31	24.36	13.98	32.26	89.74
Franchise Value	1.42	0.94	0.28	1.26	3.08
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

Table 7: Sectoral specialization, sectoral differentiation and financial sector exposure: baseline regressions

This Table shows the impact of bank sector specialization, bank sector differentiation and financial sector exposure on (i) total volatility, (ii) banks' franchise value, and (iii) systemic risk exposure. Columns 1, 4 and 7 contain the results using the within estimator. Columns 2, 5 and 8 contain the results using the between estimator. Columns 3, 6 and 9 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 and asset growth. 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.

	Total Volatility$_{it}$			**Franchise Value**$_{it}$			**Systemic Risk exposure**$_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel	FE	BE	RE	FE	BE	RE	FE	BE	RE
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.70***		-0.70***	0.01**		0.01**	-0.06***		-0.06***
	(0.19)		(0.20)	(0.01)		(0.01)	(0.02)		(0.02)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	3.82***		3.82***	-0.05***		-0.05***	0.14***		0.14***
	(0.29)		(0.29)	(0.01)		(0.01)	(0.02)		(0.02)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.10		0.10	-0.01		-0.01	0.09***		0.09***
	(0.24)		(0.24)	(0.01)		(0.01)	(0.02)		(0.02)
$\overline{\text{Specialization}}_{i}$		-5.70***	-6.09***		0.07**	0.06		-0.60***	-0.81***
		(0.51)	(0.61)		(0.03)	(0.05)		(0.05)	(0.06)
$\overline{\text{Differentiation}}_{i}$		18.84***	20.22***		-0.13***	-0.12***		0.12**	0.16**
		(0.52)	(0.87)		(0.03)	(0.04)		(0.05)	(0.07)
$\overline{\text{Financials factor loading}}_{i}$		1.41***	1.58**		0.09***	0.09***		0.79***	0.90***
		(0.54)	(0.73)		(0.03)	(0.03)		(0.05)	(0.08)
Observations	11,702	11,702	11,702	11,702	11,702	11,702	11,702	11,702	11,702
R-squared	0.47	0.60	0.52	0.37	0.27	0.30	0.33	0.57	0.47
Number of bankid	1,716	1,716	1,716	1,716	1,716	1,716	1,716	1,716	1,716
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	No	No	Yes	No	No	Yes	No	No
Country Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Corr(Fit,ν_i)	-0.157			0.009			-0.005		
Wald test 1 (p-value)			0.00			0.04			0.00
Wald test 2 (p-value)			0.00			0.00			0.00
Wald test 3 (p-value)			0.09			0.01			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: $\overline{\overline{\text{Financials factor loading}}}_{it-1} - \overline{\text{Financials factor loading}}_{i} = 0$.

Table 8: Robustness: Alternative dependent variables

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 subsequent columns, we use accounting-based indicators of bank risk, which are respectively the Z-score (column 2), bank capital (column 3) and an accounting-based indicator of credit risk (non-performing loans to gross loans,column 6) as dependent variable. 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 and asset growth. Standard errors are clustered at the bank level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

VARIABLES	(1) CoVaR	(2) ln(Z-score)	(3) Equity to Total Assets	(4) Non Performing Loans
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.03***	0.01	0.09***	-0.14***
	(0.01)	(0.01)	(0.03)	(0.04)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	0.06***	-0.15***	-0.17***	0.49***
	(0.01)	(0.02)	(0.04)	(0.05)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.13***	0.01	0.07**	-0.04
	(0.01)	(0.01)	(0.03)	(0.04)
$\overline{\text{Specialization}}_{i}$	-0.76***	-0.03	0.34	-0.24*
	(0.13)	(0.05)	(0.23)	(0.14)
$\overline{\text{Differentiation}}_{i}$	-0.32**	-0.71***	-0.46*	1.86***
	(0.13)	(0.05)	(0.25)	(0.18)
$\overline{\text{Financials factor loading}}_{i}$	1.06***	-0.06	-1.39***	-0.09
	(0.13)	(0.05)	(0.25)	(0.16)
Observations	8,536	7,913	9,886	9,084
R squared	0.397	0.231	0.286	0.395
Number of bankid	1,530	1,510	1,592	1,525
Bank Controls	YES	YES	YES	YES
Bank Fixed Effects	NO	NO	NO	NO
Year Fixed Effects	YES	YES	YES	YES
Country Fixed Effects	YES	YES	YES	YES
Wald test 1 (p-value)	0.00	0.62	0.00	0.00
Wald test 2 (p-value)	0.00	0.00	0.00	0.00
Wald test 3 (p-value)	0.00	0.34	0.00	0.63

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: $\overline{\overline{\text{Financials factor loading}}}_{it-1} - \overline{\text{Financials factor loading}}_{i} = 0.$

Table 9: Robustness: Error in variables estimator

This Table shows the impact of bank sector specialization, bank sector differentiation and financial sector exposure on (i) total volatility, (ii) banks' franchise value, and (iii) systemic risk exposure using an error-in-variables estimator that allows for mismeasured variables and requires the econometrician to choose how reliable the mismeasured variables are. We set this reliability of the mismeasured financials factor loading and differentiation once at 80 % and once at 90 % (both for the demeaned and averaged variables). In unreported results we also use the error-in-variables estimator of Erickson et al. (2014) that uses higher order moments to identify the coefficients. This estimator can only be applied to demeaned data, but results for the demeaned data are very robust. In the models, we treat bank sector differentiation and financial sector exposure as variables that are mismeasured. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	Total Volatility$_{it}$		**Franchise Value**$_{it}$		**Systemic Risk exposure**$_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Error in variable estimator	reliability 80%	reliability 90%	reliability 80%	reliability 90%	reliability 80%	reliability 90%
$\overline{\overline{\text{Specialization}}}_{it-1}$	-1.08***	-0.88***	0.02**	0.02*	-0.08***	-0.07***
	(0.20)	(0.20)	(0.01)	(0.01)	(0.02)	(0.02)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	5.19***	4.47***	-0.07***	-0.06***	0.19***	0.16***
	(0.27)	(0.24)	(0.01)	(0.01)	(0.03)	(0.02)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.11	0.10	-0.01	-0.01	0.12***	0.11***
	(0.22)	(0.20)	(0.01)	(0.01)	(0.02)	(0.02)
$\overline{\text{Specialization}}_{i}$	-7.74***	-6.85***	0.05**	0.03*	-0.94***	-0.98***
	(0.38)	(0.38)	(0.02)	(0.02)	(0.04)	(0.04)
$\overline{\text{Differentiation}}_{i}$	27.71***	23.62***	-0.28***	-0.24***	0.35***	0.29***
	(0.46)	(0.40)	(0.02)	(0.02)	(0.05)	(0.04)
$\overline{\text{Financials factor loading}}_{i}$	3.19***	2.54***	0.07***	0.06***	1.46***	1.23***
	(0.49)	(0.42)	(0.02)	(0.02)	(0.05)	(0.04)
Observations	11,702	11,702	11,702	11,702	11,702	11,702
R-squared	0.55	0.52	0.29	0.29	0.47	0.46
Number of bankid	1,716	1,716	1,716	1,716	1,716	1,716
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	No	No
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Robustness: using local sectoral factors

This Table shows the impact of bank sector specialization, bank sector differentiation and financial sector exposure on (i) total volatility, (ii) banks' franchise value, and (iii) systemic risk exposure. Columns 1, 5 and 9 contain the results using the within estimator. Columns 2, 6 and 10 contain the results using the between estimator. Columns 3, 7 and 11 show the baseline results using the hybrid estimator. Columns 4, 8 and 12 show the results using the hybrid estimator for an extended specification. The main difference between this table and Table 5, which contains the baseline results is that the sectoral factors that enter the factor model are not global but **local** (i.e. country-specific). In columns 4, 8 and 12, we additionally add the exposure to the global financial sector in addition to the exposure to the local financial sector. 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 and asset growth. 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.

	Total Volatility$_{it}$				**Franchise Value**$_{it}$				**Systemic Risk exposure**$_{it}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel	FE	BE	RE	RE	FE	BE	RE	RE	FE	BE	RE	RE
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.91***		-0.91***	-0.91***	0.01		0.01	0.01	-0.11***		-0.11***	-0.10***
	(0.22)		(0.22)	(0.22)	(0.01)		(0.01)	(0.01)	(0.02)		(0.02)	(0.02)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	3.15***		3.17***	3.17***	-0.02**		-0.02**	-0.02**	0.07***		0.07***	0.07***
	(0.35)		(0.35)	(0.35)	(0.01)		(0.01)	(0.01)	(0.02)		(0.02)	(0.02)
$\overline{\overline{\text{Local Financials factor loading}}}_{it-1}$	-0.09		-0.09	-0.08	-0.00		-0.00	-0.00	-0.03*		-0.03*	-0.04**
	(0.25)		(0.25)	(0.25)	(0.01)		(0.01)	(0.01)	(0.02)		(0.02)	(0.02)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$				-0.06				-0.01				0.09***
				(0.24)				(0.01)				(0.02)
$\overline{\text{Specialization}}_{i}$		-5.35***	-5.78***	-5.55***		-0.02	-0.04	-0.02		-0.87***	-1.08***	-0.89***
		(0.49)	(0.53)	(0.57)		(0.03)	(0.04)	(0.05)		(0.05)	(0.06)	(0.05)
$\overline{\text{Differentiation}}_{i}$		18.84***	20.49***	20.48***		-0.13***	-0.13***	-0.14***		0.13**	0.09	0.08
		(0.59)	(0.87)	(0.87)		(0.04)	(0.05)	(0.04)		(0.06)	(0.08)	(0.08)
$\overline{\text{Local Financials factor loading}}_{i}$		0.63	1.01	0.85		0.02	-0.00	-0.02		-0.01	-0.05	-0.20**
		(0.64)	(0.87)	(0.86)		(0.04)	(0.04)	(0.04)		(0.07)	(0.08)	(0.08)
$\overline{\text{Financials factor loading}}_{i}$				1.03				0.09**				0.90***
				(0.80)				(0.04)				(0.07)
Observations	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863	9,863
R-squared	0.53	0.59			0.44	0.27			0.35	0.54		
Number of bankid	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492
Bank Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank Fixed Effects	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Corr(Fit,ν_i)	-0.227				0.002				-0.018			
Wald test 1 (p-value)			0.00	0.00			0.43	0.56			0.00	0.00
Wald test 2 (p-value)			0.00	0.00			0.00	0.00			0.00	0.01
Wald test 3 (p-value)			0.44	0.55			0.98	0.92			0.19	0.01
Wald test 4 (p-value)				0.41				0.02				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: $\overline{\overline{\text{Local Financials factor loading}}}_{it-1} - \overline{\text{Local Financials factor loading}}_{i} = 0$.

H0 Wald test 4: $\overline{\overline{\text{Financials factor loading}}}_{it-1} - \overline{\text{Financials factor loading}}_{i} = 0$.

Table 11: Robustness: sample composition

This Table shows the impact of bank sector specialization, bank sector differentiation and financial sector exposure on (i) total volatility, (ii) banks' franchise value, and (iii) systemic risk exposure. Columns 1, 4 and 7 show the baseline estimation on a subsample of the data that controls for large divestitures and mergers (by excluding observations with asset growth<-10% or asset growth>20%). Columns 2, 5 and 8 show the baseline estimation on the subsample of the data that is balanced and thus available for 10 years. Finally, in columns 3, 6 and 9, we only include banks from countries for which the share of sampled listed banks in total banking sector assets is more than 70 per cent. 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 and asset growth. Standard errors are clustered at the bank level. ***, ** and * denote $p<0.01$, $p<0.05$ and $p<0.1$ respectively.

	Total Volatility$_{it}$			**Franchise Value**$_{it}$			**Systemic Risk exposure**$_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	moderate growth	balanced panel	coverage ≥ 70pct	moderate growth	balanced panel	coverage ≥ 70pct	moderate growth	balanced panel	coverage ≥ 70pct
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.55***	-0.43*	-1.14***	0.01	0.01	0.04*	-0.06***	-0.07***	-0.15***
	(0.21)	(0.25)	(0.44)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	2.96***	3.94***	2.64***	-0.05***	-0.08***	-0.02	0.09***	0.15***	0.23***
	(0.30)	(0.37)	(0.50)	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)	(0.06)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.37	0.13	0.59	-0.01**	-0.02***	0.00	0.11***	0.14***	0.13***
	(0.27)	(0.32)	(0.56)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.05)
$\overline{\text{Specialization}}_{i}$	-5.79***	-7.55***	-6.87***	0.08	-0.19***	-0.09	-0.81***	-1.53***	-1.12***
	(0.65)	(0.81)	(1.06)	(0.05)	(0.07)	(0.13)	(0.07)	(0.11)	(0.13)
$\overline{\text{Differentiation}}_{i}$	21.09***	22.54***	15.35***	-0.13***	-0.15**	0.21	0.22***	0.59***	0.51***
	(1.05)	(1.05)	(1.37)	(0.04)	(0.07)	(0.18)	(0.08)	(0.13)	(0.15)
$\overline{\text{Financials factor loading}}_{i}$	2.04**	2.92***	5.56***	0.09**	-0.12**	0.09	0.99***	1.37***	0.84***
	(0.80)	(1.02)	(1.45)	(0.03)	(0.06)	(0.15)	(0.08)	(0.11)	(0.17)
Observations	9,052	6,360	2,068	9,052	6,360	2,068	9,052	6,360	2,068
Number of bankid	1,643	636	350	1,643	636	350	1,643	636	350
R squared	0.546	0.533	0.471	0.323	0.365	0.334	0.464	0.506	0.593
Bank Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald test 1 (p-value)	0.00	0.00	0.00	0.16	0.01	0.13	0.00	0.00	0.00
Wald test 2 (p-value)	0.00	0.00	0.00	0.00	0.00	0.39	0.00	0.00	0.00
Wald test 3 (p-value)	0.02	0.01	0.00	0.01	0.00	0.85	0.00	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: $\overline{\overline{\text{Financials factor loading}}}_{it-1} - \overline{\text{Financials factor loading}}_{i} = 0$.

Table 12: Robustness: time and country sample splits

This Table shows the impact of bank sector specialization, bank sector differentiation and financial sector exposure on (i) total volatility, (ii) banks' franchise value, and (iii) systemic risk exposure. Columns 1, 5 and 9 show the baseline estimation on the subsample from 2003 to 2007, while columns 2, 6 and 10 show the baseline estimation on the subsample from 2008 to 2012. The last two columns of each panel are for the US and non-US banks, respectively. 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 and asset growth. Standard errors are clustered at the bank level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	Total Volatility$_{it}$				**Franchise Value**$_{it}$				**Systemic Risk exposure**$_{it}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sample	pre 2008	post 2007	US	non-US	pre 2008	post 2007	US	non-US	pre 2008	post 2007	US	non-US
$\overline{\overline{\text{Specialization}}}_{it-1}$	0.15	-0.21	-1.02***	-0.97***	0.00	0.01	0.01	0.03***	-0.01	-0.00	-0.06**	-0.09***
	(0.15)	(0.30)	(0.25)	(0.24)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	-0.19	1.14***	3.09***	2.57***	0.02	-0.02***	-0.03***	-0.02*	-0.00	0.05**	0.05**	0.21***
	(0.36)	(0.32)	(0.37)	(0.40)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.03)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.22	-0.22	-0.57**	0.92**	-0.00	-0.01**	-0.00	-0.02	0.11***	-0.02	0.03	0.20***
	(0.34)	(0.25)	(0.29)	(0.37)	(0.02)	(0.00)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
$\overline{\text{Specialization}}_{i}$	-3.80***	-5.80***	-5.11***	-6.06***	-0.00	0.07	-0.03	0.16	-0.34***	-1.17***	-0.78***	-0.85***
	(0.46)	(0.92)	(0.86)	(0.69)	(0.04)	(0.05)	(0.05)	(0.10)	(0.04)	(0.10)	(0.08)	(0.08)
$\overline{\text{Differentiation}}_{i}$	10.01***	20.59***	21.61***	14.40***	0.07	-0.15***	-0.16***	-0.01	0.13**	0.33***	0.19**	0.30***
	(1.09)	(0.92)	(1.07)	(1.14)	(0.06)	(0.03)	(0.04)	(0.08)	(0.05)	(0.08)	(0.08)	(0.09)
$\overline{\text{Financials factor loading}}_{i}$	-0.44	2.48***	0.62	6.13***	0.21***	0.02	0.07**	0.15	0.43***	0.91***	0.80***	0.82***
	(1.09)	(0.81)	(0.88)	(1.04)	(0.07)	(0.02)	(0.03)	(0.09)	(0.06)	(0.09)	(0.09)	(0.10)
Observations	5,975	5,727	6,650	5,052	5,975	5,727	6,650	5,052	5,975	5,727	6,650	5,052
R squared overall	0.420	0.504	0.631	0.472	0.195	0.284	0.368	0.321	0.526	0.450	0.396	0.539
Number of bankid	1,572	1,320	1,043	673	1,572	1,320	1,043	673	1,572	1,320	1,043	673
Bank Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald test 1 (p-value)	0.00	0.00	0.00	0.00	0.99	0.12	0.51	0.01	0.00	0.00	0.00	0.00
Wald test 2 (p-value)	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.25	0.06	0.00	0.01	0.00
Wald test 3 (p-value)	0.76	0.01	0.07	0.00	0.01	0.09	0.09	0.05	0.00	0.00	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: $\overline{\overline{\text{Financials factor loading}}}_{it-1} - \overline{\text{Financials factor loading}}_{i} = 0$.