DISCUSSION PAPER SERIES

DP12009

BANK SECTORAL CONCENTRATION AND (SYSTEMIC) RISK: EVIDENCE FROM A WORLDWIDE SAMPLE OF BANKS

Thorsten Beck, Olivier De Jonghe and Klaas Mulier

FINANCIAL ECONOMICS

ISSN 0265-8003

BANK SECTORAL CONCENTRATION AND (SYSTEMIC) RISK: EVIDENCE FROM A WORLDWIDE SAMPLE OF BANKS

Thorsten Beck, Olivier De Jonghe and Klaas Mulier

Discussion Paper DP12009
Published 28 April 2017
Submitted 28 April 2017

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

BANK SECTORAL CONCENTRATION AND (SYSTEMIC) RISK: EVIDENCE FROM A WORLDWIDE SAMPLE OF BANKS

Abstract

We propose a new stock return-based methodology to measure three dimensions of banks' sectoral concentration (specialization, differentiation, fi nancial sector exposure). Using these measures for a broad cross-section of banks and countries between 2002 and 2012, we estimate both the short- and long-run relationship between banks' secttoral concentration and banks' performance and stability. We find that bank volatility and systemic risk exposure decrease with banks' sectoral specialization and increase with banks' sectoral differentiation and financial sector exposure. These effects are significantly stronger in the long-run. Moreover, there exists important time and cross- country variation, with effects generally stronger during systemic stress periods.

JEL Classification: G01, G21, G28, L5

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

Thorsten Beck - thorsten.beck.1@city.ac.uk
Cass Business School, City University and CEPR

Olivier De Jonghe - o.dejonghe@uvt.nl
Tilburg University and National Bank of Belgium

Klaas Mulier - klaas.mulier@ugent.be
Ghent University and National Bank of Belgium

Acknowledgements
The authors would like to thank Lamont Black, Fabio Castiglionesi, Jos e Liberti, Martin Melecky, Geoffrey Miller, Phong Ngo, Alex Popov, Glenn Schepens, Jason Sturgess, Wolf Wagner and seminar participants at the European Central Bank, FEBS conference in Surrey, the NYU-Law "2014 Law & Banking/Finance Conference", the Sydney Banking and Financial Stability Conference, the Norges Bank, the NY Fed, dePaul University, University of Glasgow, National University of Singapore, Nanyang Business School, Singapore Management University, CESifo-Munich, Australian National University, University of Melbourne, Massey University, Cardiff Business School, University of Edinburgh Business School, Universita Cattolica de Milano, Frankfurt School of Finance and Management, and Essex Business School for interesting discussions and helpful comments. This paper started as a background paper for the World Development Report 2014 entitled Risk and Opportunity: Managing Risk for Development. This paper and its findings do not necessarily reflect the opinions of the World Bank, their Executive Directors or the countries they represent. The views expressed are solely those of the authors and do not necessarily represent the views of the National Bank of Belgium.

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

Thorsten Beck† Olivier De Jonghe‡ Klaas Mulier§

April 27, 2017

Abstract

We propose a new stock return-based methodology to measure three dimensions of banks' sectoral concentration (specialization, differentiation, financial sector exposure). Using these measures for a broad cross-section of banks and countries between 2002 and 2012, we estimate both the short- and long-run relationship between banks' sectoral concentration and banks' performance and stability. We find that bank volatility and systemic risk exposure decrease with banks' sectoral specialization and increase with banks' sectoral differentiation and financial sector exposure. These effects are significantly stronger in the long-run. Moreover, there exists important time and cross-country variation, with effects generally stronger during systemic stress periods.

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

JEL classification: G01, G21, G28, L5

*The authors would like to thank Lamont Black, Fabio Castiglionesi, José Liberti, Martin Melecky, Geoffrey Miller, Phong Ngo, Alex Popov, Glenn Schepens, Jason Sturgess, Wolf Wagner and seminar participants at the European Central Bank, FEBS conference in Surrey, the NYU-Law "2014 Law & Banking/Finance Conference", the Sydney Banking and Financial Stability Conference, the Norges Bank, the NY Fed, dePaul University, University of Glasgow, National University of Singapore, Nanyang Business School, Singapore Management University, CESifo-Munich, Australian National University, University of Melbourne, Massey University, Cardiff Business School, University of Edinburgh Business School, Universita Cattolica de Milano, Frankfurt School of Finance and Management, and Essex Business School for interesting discussions and helpful comments. This paper started as a background paper for the World Development Report 2014 entitled Risk and Opportunity: Managing Risk for Development. This paper and its findings do not necessarily reflect the opinions of the World Bank, their Executive Directors or the countries they represent. The views expressed are solely those of the authors and do not necessarily represent the views of the National Bank of Belgium.

†Cass Business School, City, University of London, CEPR, e-mail: Thorsten.Beck.1@city.ac.uk

‡Corresponding author, CentER, European Banking Center, Tilburg University, National Bank of Belgium, e-mail: o.dejonghe@uvt.nl

§Ghent University, National Bank of Belgium, e-mail: klaas.mulier@ugent.be

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).

The evidence of an important link between bank specialization and differentiation, on the one hand, and bank performance and stability, on the other hand, becomes more indisputable with every new banking crisis. Surprisingly, the academic literature offers almost no guidance for policy makers and regulators 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[1], as the empirical literature has been hampered by the lack of appropriate data on bank specialization and differentiation.

This paper tries to take a first -but important- step to fill this gap. We develop a new methodology that allows researchers to identify banks' strategic choices with respect to banks' concentration (along several dimensions), and apply this methodology to identify the *sectoral* concentration of 1,587 banks across 24 countries over the period 2002-2012. For these 1,587 banks, we develop time-varying indicators of three aspects of sectoral concentration, namely sectoral specialization, sectoral differentiation, and financial sector exposure. We validate our new measures of sectoral concentration by showing statistically and economically significant correlations with accounting-based measures of sectoral concentration for a subsample of 188 banks between 2007-2011 for which we

[1] 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. Acharya et al. (2006) or De Jonghe et al. (2016)) or relied on syndicated loan exposures (e.g. Cai et al. (2013)). In the latter case, the sample is limited to the subset of very large, internationally active financial institutions. Moreover, the exposures are then limited to the syndicated loans, which may not be representative for the overall portfolio of commercial and industrial loans, let alone for non-lending exposures.

find information on sectoral concentration in the notes to financial statements. Subsequently, we investigate the relationship between the return-based indicators of sectoral concentration and bank performance and stability. More specifically, we gauge the relationship between banks' sectoral specialization, banks' sectoral differentiation, and banks' financial sector exposure on the one hand, and banks' stock return volatility (risk indicator), banks' market-to-book value (performance indicator), and banks' Marginal Expected Shortfall (exposure to systemic risk indicator, Acharya et al. (2017)) on the other hand. 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, which we interpret as gauges for short-term and long-term relationships (Baltagi and Griffin, 1984). Finally, we explore whether there is significant variation in these relationships over time and across countries.

In the first part of the paper, we develop and validate this new approach to identify banks' strategic choices with respect to bank asset concentration. The methodology itself is borrowed from the mutual fund literature (returns-based style analysis) and is there 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 very important advantage of this new methodology is that it allows researchers to identify a wide range of strategic bank choices in multi-country settings that otherwise often require disperse information available only to market analysts.[2] The methodology allows to identify the concentration of banks' assets in certain sectors (as in our case), but can also be implemented in different setups to determine exposure to, e.g., certain geographical areas, certain types of companies (small business or large corporates), sovereign bond exposures (Acharya and Steffen, 2015), or commodity prices ((Agarwal et al., 2017). Critically, it takes a more comprehensive view than balance sheet-based indicators, as it allows taking into account banks' derivative positions, either hedging balance sheet positions

[2] While sectoral exposures are not included in financial statements and there are only limited data in the annual reports, 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 Appendix 1, we provide several examples of references to sectoral concentration in earning calls transcripts.

or creating such positions.

We use an extended factor model and relate bank stock returns to returns on 9 sectoral global 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 banks are well diversified (meaning that their returns are only exposed to the set of common factors) or whether banks are specialized (meaning that their 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.[3] Lastly, we define banks' *financial sector exposure* as the estimated factor loading of their stock returns on the returns on the financial sector index.

We compare our three sectoral concentration measures with a small hand-collected database on the actual sectoral lending exposures for a subsample of the largest banks, which we derive from the notes to their annual statements.[4] 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 important variation in this relationship 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. Finally, we also show that our measure of financial sector exposure correlates strongly with the accounting based lending share to the financial

[3] 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. Secondly, 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.

[4] 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 188 banks over the period 2007-2011.

sector. Even though our estimates of sectoral exposures do not necessarily measure concentration of banks' sectoral loan portfolios (as our estimated exposures might also reflect non-lending exposures through securities' holdings or the use of derivatives), banks' strategic concentration choices that are being picked by our methodology do seem to 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). Theory has provided important opposing hypotheses on the relationship between concentration and bank performance and risk. 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 (for example, by requesting additional collateral) (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 0.2 standard deviation and reduces exposure to systemic risk by 0.32 standard deviation. Higher exposure (specialization) to the financial sector, on the other hand, increases total bank risk (by about 0.07 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 both (non-financial) sectoral specialization and financial sector exposure increase banks' franchise value, but very modestly. Our results suggest that markets regard specialized banks as less risky (both on the idiosyncratic and systemic risk level), while specialization in (and thus higher exposure to) the financial sector increases individual bank

risk and exposure to systemic risk.

Sectoral concentration, however, does not only matter on the individual bank-level, but 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 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, explained only partly through increasing consolidation in the sector (De Nicolo and Kwast, 2002). This lack of diversity is potentially more costly for society as it implies that similar institutions will be more likely to face problems at the same time (Wagner, 2010). It is more, banks may even have ex-ante incentives to herd, which can lead to socially very undesirable outcomes (Acharya and Yorulmazer, 2007, 2008). Seemingly contrary to these theories, we find that sectoral differentiation is associated with higher stock volatility 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 0.67 standard deviation and exposure to systemic risk by 0.07 standard deviation. Our findings suggest that investors incorporate a bail-out assumption for banks that 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, there also seems to be a limited negative relationship of sectoral differentiation with banks' franchise value.

In the last part of the paper, we explore the time and cross-country variation of our findings. The results indicate 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 not homogeneous. We observe that the magnitude and significance of the established relationships change over time and across countries[5], and that in a few occasions even the sign of the relationship may vary. However, we also find four relationships that are robust across countries and over time (although they typically show a stronger effect in '08-'09, the relationships always have the same sign and are significant). The four robust relationships are the negative

[5] Although the lack of significance is likely caused by a lack of sufficient observations in some country level estimations.

relation between bank sectoral specialization and bank volatility, the negative relation between bank sectoral specialization and systemic risk exposure, the positive relation between bank sectoral differentiation and bank volatility, and the positive relation between exposure to the financial sector and systemic risk exposure.

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 significantly increased capital requirements and the limitations that have been put on the use of 'unstable' interbank funding. Lacking empirical guidance on the importance of specialization, however, policy makers have not changed the international rules regarding sectoral specialization and diversification under the Basel III regulation. 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. The framework underlying the Basel regulatory capital requirements has been the asymptotic single risk factor model, which assumes that the loss rate for a well diversified portfolio depends only on a (single) systematic risk factor and not on idiosyncratic or sectoral risk factors. If sectoral exposure varies significantly across banks and their performance and stability depends 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 also 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. Compared to balance sheet indicators of lending concentration our market-based indicators of sectoral exposures have the advantage that they focus on a broader concept of sectoral exposure and are forward looking.

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) 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.[6] While the existing 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.[7] 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.[8]

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.

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

[7] 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.

[8] 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.

We would like to state a few caveats and limitations before proceeding. First, our paper explores sectoral specialization and abstracts from other forms of specialization, such as name concentration or geographic concentration. Second, given the nature of our exercise, we focus on listed banks, for which we have the necessary data to compute market-based performance and risk measures. Given that these are more often than not the larger and systemically more important banks, however, it is in the interest of financial stability to focus on these banks. Third, and most importantly, our factor-model based measures of sectoral specialization and sectoral differentiation do not map completely to previous studies that used credit registries or syndicated loans. However, we see this as an advantage rather than a shortcoming, given recent developments in banks' business models. Over the past two decades, lending increasingly constitutes a smaller share of the overall business of banks and our return-based measures thus capture sectoral specialization and sectoral differentiation for the banks' overall business, including non-lending activities such as security holdings and derivatives.

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. Unfortunately, these data are not directly available from (commercial) databases for a cross-country sample of banks.[9] Therefore, 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

[9] 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 the latter case, the sample is limited to the subset of very large, internationally active financial institutions (which are mainly located in the US). Moreover, the exposures are then limited to the syndicated loans, which may not be representative for the overall portfolio of commercial and industrial loans, let alone for non-lending exposures.

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 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 $10,352$ observations, on $1,587$ banks from 24 countries over the period $2002 - 2011$.[10] We include commercial banks, bank holding companies, as well as saving banks and cooperatives.[11] Information on the countries included in the sample as well as the number of bank-year observations by country is reported in Appendix Table A1 while the definitions and sources of all variables are reported in Appendix Table A2.

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

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 (and hence violate the assumption underlying the asymptotic

[10] 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.

[11] 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.

single risk factor framework, ASRF, of the Basel Committee).[12] In addition to returns on the global and local market as well as sectoral returns, we include four additional factors, in line with the factor model literature. More specifically, we include returns on the global small-minus-big (SMB), high-minus-low (HML) and momentum (MOM) factors.[13] 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).

In particular, using daily return data, we estimate the following equation for each bank and 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.[14] 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

[12] This method is similar in spirit to returns-based style analysis, which is a statistical technique mainly used to deconstruct mutual fund returns in exposures to investment strategies or asset classes (see e.g. Sharpe (1992), Brown and Goetzmann (1997) and ter Horst et al. (2004)). These exposures are then interpreted as a measure of a fund's or portfolio manager's style (e.g. with respect to large versus small stocks or value versus growth stocks). A similar approach is used by Acharya and Steffen (2015) to infer European banks' sovereign risk exposure from asset prices. They relate banks' stock returns to yields on German government debt and yields on GIIPS countries' debt, to obtain market-based indicators of banks' exposures to sovereign risk. Likewise, Agarwal et al. (2017) regresses bank stock returns on global market returns and a commodity price index to obtain a time-varying, bank-specific commodity price exposure indicator.

[13] 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`

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

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 $10,352$ bank-year observations, covering $1,587$ banks from 24 countries over a ten year period starting in 2002.[15] We do not impose constraints on the coefficients and hence allow that a bank has a negative exposure to, and hence is short in, a specific industry.[16] Information on the estimated exposures (nine sectors and the financial sector) is reported in Table 1. Panel A of Table 1 reports for each estimated factor loading the mean and standard deviation across $10,352$ observations, as well as the 5th, 50th, and 95th 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.[17] 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 Oil &Gas, Basic Materials, Healthcare and Technology.

Insert Table 1 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

[15] 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 the banks in the country (see below).

[16] 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.

[17] 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).

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.

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

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:

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

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. We label this variable sectoral *specialization*. On the other hand, a lower value for this measure also indicates that the asymptotic single risk factor assumption is more likely to be valid for a given bank in a given year.[18] Secondly, 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:

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

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

[18] The framework underlying the Basel regulatory capital requirements has been the asymptotic single risk factor model, which assumes that the loss rate for a well diversified portfolio depends only on a (single) systematic risk factor and not on idiosyncratic or sectoral risk factors. If sectoral exposure varies significantly across banks, this assumption might not hold.

larger when the bank's sectoral exposures deviate more from the weighted average exposure of all other banks in the country.[19] 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 herding, and label this variable *financials factor loading*.

We report summary statistics on the specialization and differentiation measures in panel B of Table 1, 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 3.37 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.[20] The average bank's differentiation from the country-average is 1.61. 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 1.03 (p5) to 7.24 (p95) and sectoral differentiation ranges from 0.31 (p5) to 4.54 (p95). The estimated sensitivity of the bank's return to the financial sector's return (i.e. the financials factor loading) is 0.06 for the average bank-year, and ranges from -0.36 (p5) to 0.57 (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 75th percentile for each year of the three indicators. Specialization, as measured by return-based data, somewhat

[19]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. Secondly, 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.

[20]The average R-squared in the 10,352 regressions across banks and over time using model (1) is 27 percent. Hence, adding the nine sectoral factors leads to an increase of more than 14% in the explained variation of bank stock returns.

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 75th 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 75th percentile more than doubling and the 25th percentile moving deep into negative territory. This gap somewhat closed in the latter years of our sample period.

Finally, to test the sensitivity of our sectoral concentration measures to model specification, we also construct them based on a simpler factor model. 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 1. 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.

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. Hence, we first 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. However, it is important to emphasize that the estimates of sectoral exposures do *not necessarily* measure concentration of banks' *loan* portfolios on specific sectors, but are broader measures of sectoral exposures by banks. Given the increasing focus of banks on non-lending business (Demirguc-Kunt and Huizinga (2010)), exposures to specific sectors might reflect non-lending exposures through securities' holding or the use of derivatives. On the one hand, banks might balance the exposure in their loan book to a specific sector through hedging instruments (implying a zero factor-based exposure to this sector, as discussed above); on the other

hand, they might create exposure to a sector through the use of non-lending instruments or might even create a short position in a specific sector. The interpretation of our sectoral exposure measures and consequent specialization and differentiation measures are thus on the broader bank level rather than loan portfolio level. Below, we test for the correlation between our return-based sectoral specialization and differentiation measure with a sectoral specialization and differentiation measure based on loan portfolios, but as argued, we would not necessarily expect a perfect correlation between these measures.

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.[21] 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. We build a database of sectoral exposures according to the following procedure. We focus on large, listed banks[22] as these are more likely to publish a detailed report on their website. However, this is not

[21] Liu (2011) investigates herding behaviour in bank lending by US commercial banks and looks at similarities in banks' loan exposures to five categories (commercial real estate, residential real estate, consumer and industrial loans, individual loans and all remaining loans. He uses the Lakonishok et al. (1992) herding measure, which is initially developed to analyze herding by institutional investors through their buy and sell signals.

[22] Starting from the universe of banks covered by Bankscope, we impose the following constraints: (i) banks need to be active in 2013, i.e. not have failed during the recent crisis; (ii) banks need to have publicly traded equity; (iii) banks need to have total assets in excess of 10 billion US$ in 2011; (iv) we only keep commercial banks, savings banks, cooperative banks and bank holding companies; and (v) 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 for the period 2009, 2010, and 2011. This selection results in a sample of 435 banks.

the case for all selected banks. The final database therefore consists only of banks for which the reports published on their website contain useful and detailed information on the sectoral exposures (188 banks across 21 countries, for the years $2007 - 2011$).[23] 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.[24]

The data collection yields a panel of accounting-based sectoral exposures at the bank level for the years $2007 - 2011$. Summary statistics on these exposures are reported in panel C of Table 1. For each sector, we report the mean, standard deviation, 5th, 50th, and 95th 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 5th percentile is almost always zero, whereas the exposure to other industries for the bank at the 95th percentile is 55%.

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 1) indicate that there is considerable heterogeneity across banks. Specifically, the cumulative exposure of the largest three sectors varies from 32% (5th percentile) to 87% (95th percentile), with a mean of 55%. *Differentiation* (accounting) also exhibits substantial cross-sectional variation. The Euclidean distance

[23] This sample yields an unbalanced panel of 813 observations, of which 283 observations relate to 60 Japanese banks and 95 observations to 23 US banks.

[24] Personal/consumer loans, loans to central governments and interbank loans were excluded. Furthermore, the data are collected as meticulous as possible, but nevertheless subject to some researcher-specific choices. For example, if the reported information is at a coarser level than the SIC one-digit level (e.g. 'Agriculture and Mining'), we divide the reported amount over the two separate sectors (i.e. half of the exposure to 'Agriculture' and the other half to 'Mining').

between a bank's exposure and the country's average exposure ranges from 0.07 to 0.40 (5th and 95th percentile), with a mean of 0.19.

2.3.2 The link between return-based 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:

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

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

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 2.

Insert Table 2 around here

The results in Table 2 show a positive and strongly significant correlation between return-based and account-based sectoral specialization measures in Column 1. The coefficient estimates suggest that a one percent change in account-based specialization is associated with a 0.48 to 0.51 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).

Column 3 of Table 2 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 0.5 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 statistically significant negative coefficient on the former interaction and positive coefficient (significant at the 10% level) on the latter interaction.

To sum up, the regressions in Table 2 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.

2.3.3 The link between return-based 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 3 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.[25]

Insert Table 3 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, we now also show stronger 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.

[25] 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 Sectoral concentration, bank performance 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 that we just described 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.[26] 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.[27] 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

[26] 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)).

[27] We also compute the marginal expected shortfall of the banks when the global, rather than the local country-specific, banking sector experiences distress. All results in the paper reported in the paper are robust to using either the local or the global banking sector as the conditioning variable in the marginal expected shortfall measure.

a higher marginal expected shortfall (in absolute value) relates to a higher exposure to systemic risk.

Insert Table 4 around here

Summary statistics on these variables are reported in panel A of Table 4. The annualized volatility of banks' stock returns is on average 39.9%, 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 14.3% (p5) to 91.7% (p95), while the market-to-book value of equity ranges from 0.3 (p5) to 3 (p95). The average marginal expected shortfall with respect to the local banking sector is 1.9, implying that the average daily stock return of banks in our sample is almost -2% on average when the bank sector experiences stress, but ranges from +0.5% (p5) to -6.6% (p95).

3.2 Empirical set-up

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. 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 as 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 the same 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 the absence of correlation between the individual effects ν_i and the regressors) indicates that Equation (8) is misspecified. In particular, it may be suggestive of a model in which one allows for a short run and a long run relationship between the dependent variable and the regressors of interest. 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 allows for a simultaneous estimation of short run (within estimation) and long run (between estimation) effects of our independent variables of interest, *bank sector specialization*, *bank sector differentiation*, and *financial sector exposure*. Moreover, it nests Equation (8). If the long run and short run responses are similar, then Equation (9) collapses to Equation (8). 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. 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. Yet, it is important to emphasize that this model rests on the assumption that the individual effects are uncorrelated with the regressors, an assumption that we will test below.

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 not. 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).[28]

While our regression set-up allows controlling for reverse causation by lagging the explanatory variables, exploiting within-bank variation and including country- and year-fixed effects and bank-level random effects, we are careful in making causal inferences from our regression results, especially for the between effects, which might be correlated with other time-invariant and (for us) unobservable bank characteristics, such as governance or business model. To the extent that these vary across countries, they will be captured by the country fixed effects, so that only within-country time-invariant bank differences that are correlated with our measures of sectoral specialization, differentiation and financial sector exposure can provide a source of omitted variable bias.

3.3 Baseline results

The estimation results of the above-mentioned regression specifications are shown in Table 5. 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 5 around here

[28]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): $\overline{y}_i = \alpha + \beta_{1b}\ \overline{Special}_i + \beta_{2b}\ \overline{Diff}_i + \beta_{3b}\ \overline{Financials}_i + \gamma_{1b}\ \overline{X}_i + \nu_i + \overline{\mu} + \overline{\epsilon}_i$.

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 fixed effect 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.[29] 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 close to zero (-0.031, -0.005 and -0.02, 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 particular in the regressions investigating bank risk and exposure to systemic risk, but also to a lesser extent for franchise value. 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.[30] 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 more than 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 0.2 standard deviation in

[29] The between transformation in (8) uses only one observation per bank for the identification of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$, while the random effects estimation of model (9) effectively uses all observations for the identification of $\hat{\beta}_{1b}$, $\hat{\beta}_{2b}$ and $\hat{\beta}_{3b}$; and hence, banks with more observations will get a larger weight.

[30] For sake of space and brevity, we only report the coefficients on the variables of interest in Table 5. However, the full regression results can be inspected in Appendix Table A3. We do not discuss or focus on the interpretation of the signs, significance and coefficients of the control variables.

the long-run.[31] 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 0.07 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 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 0.67 standard deviation in the long-run.

Column 6 of Table 5 provides some evidence that banks have a higher market value when specializing their sectoral portfolio, though the coefficient is not significant. Differentiating their exposure from their competitors, on the other hand, decreases market value, although only significantly so in the short-turn. Also the economic magnitude of the effect is quite small. A one standard deviation increase in sectoral differentiation decreases franchise value only by about 0.03 standard deviation in the short-run. The long run coefficient has the same sign and magnitude as the short-run, but is not statistically significant. Higher exposure to the financial sector leads in the long run to a statistically higher franchise value, although the economic relevance is rather small (a one standard deviation increase in financial sector exposure is associated with a 0.07 standard deviation increase in the market-to-book value.

[31] The estimated long run (between) coefficient of sectoral specialization (which has been standardized to facilitate comparison across concentration measures) on total volatility is -4.94. A one standard deviation increase in sectoral specialization would thus reduce a bank's annualized stock return volatility by -4.94, which is 20.03% of the standard deviation of bank's annualized stock return volatility (24.66) in the sample.

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 5. 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 0.32 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 leads to 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 do not seem to have higher franchise values, 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, but at the benefit of somewhat higher returns (and thus higher franchise values) and, not surprisingly, higher systemic risk exposure. 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 idiosyncratic 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. We will come back to these alternative explanations when we take a more granular view below across different years in our decade-long sample period.

3.4 Robustness tests

We subject our main results 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 2, 5 and 8 of Table 6.

Insert Table 6 around here

Secondly, 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 sixty percent of the observations and we show the results of this robustness test in Columns 3, 6 and 9 of Table 6. Comparing the results of these sensitivity analyses with the baseline results -which are reproduced in Columns 1, 4 and 7 of Table 6 - reveals that the findings are both qualitatively and quantitatively robust.

Thirdly, as there might be concerns about the correlation between our main variables of interest and how it might influence the results, we separately include each of the three measures one by one in the hybrid model and exclude the other two. The correlation between the measures is actually rather low, as can be seen in Table A4. Moreover, the results in Table A5 in the appendix show that only the impact of sectoral specialization on bank return volatility loses some of its statistical significance, but other than that all the main findings are confirmed.

Fourthly, we re-run our model with an error-in-variables specification following Erickson et al. (2014). We do this 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), therefore, they might be imprecisely measured. The results are included in Appendix Table A6, which shows that the main findings quantitatively and especially qualitatively hold. Note, however, that in this errors-in-variables specification, we cannot use our preferred setup of the hybrid model.

Fifthly, 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 for a sample of 881 banks, 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. Compared to the baseline regressions, we limit our sample period to the time around the Global Financial Crisis, but the generally globally adverse conditions for the banking sector biases our test against finding significant relationships between specialization, differentiation and buy-and-hold returns, thus providing even stronger evidence if significant.

The results in Table A7 show that in line with Fahlenbrach et al. (2012), larger banks, banks with more wholesale funding, banks with more loans have significantly lower buy-and-hold returns during the crisis. Moreover, bank capital, non-interest income and faster growth also have the expected sign, but are not significant. In terms of our explanatory variables of interest, we find that more sectoral differentiation and a larger financial sector exposure are associated with lower buy-and-hold returns during the crisis. In terms of economic effects, a one standard deviation increase in differentiation (financial sector exposure) leads to a 4.3% (5%) lower stock return over the 18 month period from July 2007 to December 2008. These results are confirmed controlling for other bank characteristics (column 2), and extending the period for calculating the buy-and-hold returns to March or June 2009 (columns 3 and 4). On the other hand, specialization does not enter consistently across the four specification, although it is positive and significant at the 15% level in column 4, in line with our baseline results. 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 our baseline findings that

more specialized banks experience lower idiosyncratic and systemic volatility is not confirmed by this more focused test.

Finally, using data from 2001 on a worldwide cross-section of 268 banks, Laeven and Levine (2009) show that more cash-flow rights by a large owner are associated with more risk. As ownership data is not publicly available, we use their data to examine whether ownership structure could be an omitted variable that drives both the choice of sectoral concentration and bank risk-taking. 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 the Laeven and Levine (2009) proxies for ownership (either cash flow or control rights) do not enter the regressions significantly and more importantly that their exclusion does not affect the point estimates of our variables of interest (see Table A8). In unreported specifications, we also add dummies that indicate the type of majority owner (i.e. state, family, financial institution, non-financial institution, other). Results are unaffected and available upon request. 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.

4 Documenting heterogeneity in the established relationships

Our regression analysis has shown a statistically and economically meaningful relationship between sectoral specialization, differentiation, and bank performance and both individual and systemic bank stability. The panel dimension of our data across ten years and 24 countries allows us to test for variations in these relationships. Our sample period straddles the Global Financial Crisis and we therefore assess heterogeneity between two sub-periods and across years (section 4.1). Our sample also includes both developing and advanced countries and we therefore gauge variation in the relationships across countries (section 4.2).

4.1 Time-variation

The results discussed in the previous section and reported in Table 5 provide the average effect of sectoral specialization, sectoral differentiation and financial sector exposure on (systemic) risk and performance over a ten year time-span, including the global financial crisis. 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 7, 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 each panel consists of three columns (full sample, 2003-2007, 2008-2012).

Insert Table 7 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 two exceptions. The positive relationship between the financial sector loading and total volatility is predominantly a 2008-2012 result, while the positive relationship between differentiation and systemic risk exposure is predominantly a pre-crisis 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. Regarding the long run effects on the franchise value, we find that being more exposed to the financial sector was valuable prior to, but not during and after the Global Financial Crisis. Being differentiated from the other banks in the country was detrimental in value terms in the period 2008-2012, unlike in the pre-crisis 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 more different findings for the short run than long run relationships, as the former is based on de-meaned variables, where the mean is now estimated over a shorter period.

The 2008-2012 period in the above discussed sample split results encompasses both the global financial crisis as well as the post-crisis years. We also take a more a more granular view on the possible time variation in the established relationships between sectoral specialization, sectoral differentiation, financial sector exposure and the bank performance and stability gauges. In particular, we estimate, for each year separately, the following regression model:

$$y_i = \beta_1 \; Specialization_i + \beta_2 \; Differentation_i + \beta_3 \; Financials \; factor \; loading_i + \gamma \; X_i + \nu_c + \epsilon_i \quad (10)$$

The independent variables are one-period lagged and we include country fixed effects. The estimated coefficients of interests are reported graphically in Figure 2. The graph consists of nine bar charts corresponding to a combination of an independent variable (varies by row) and a dependent variable (varies by column). Each bar corresponds with the respective estimated beta in that given year, with dark bars being significant at the 10% level. The coefficients are standardized by the mean and standard deviation of each annual sample.

Insert Figure 2 around here

The graph confirms the negative relationship between sectoral specialization and volatility and systemic risk exposure across the years of the sample period. However, we find significant variation in the economic effect of this relationship, with the strongest effects during the crisis years 2008 and 2009, but remaining strong(er) in the post-crisis period. It was thus in particular since the peak of the financial crisis that the market perceives specialized banks to be less risky, both in individual (total volatility) and systemic terms (MES). On the other hand, most of the annual coefficients on specialization in the franchise value regressions do not enter significantly, while the two that enter significantly do so with opposite signs. Consistent with the insignificant relationship between specialization and buy-and-hold returns during the crisis, the relationship between specialization and franchise value is positive but insignificant during 2007, 2008 and 2009. Turning to sectoral differentiation, we find a consistently positive relationship with volatility across the ten years of our sample period, with the economic effect being significantly stronger after 2007, i.e., the onset of the financial crisis. The picture is more mixed for both franchise value and systemic risk exposure. In the case of the former, there are some indications of a positive effect of differentiation before the

crisis (though only the coefficients for 2005 and 2007 enter significantly), while there is a significant and negative relationship for the years 2009 to 2011, suggesting that differentiation from peers in the same country hurts bank value during the crisis years, consistent with the results of the buy-and-hold regressions. In the case of the latter, we find especially a strong positive relationship (both statistically and economically) during 2008 and 2009, and a small negative relationship during 2010 and 2011. This is consistent with our earlier interpretation that markets reward similarity during systemic stress times, as it increases the likelihood of a bail-out or puts an information premium on these banks. Finally, turning to the yearly point estimates of the financial sector factor loading, we can see that banks with a larger exposure to the financial sector where valued higher prior to the crisis, but not after, and that their exposure to systemic risk became significantly higher after 2007.

4.2 Cross-country variation

The banks in our sample are headquartered in 24 different countries, yet more than 60% 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 8 show the results for the sub-sample of banks in the U.S. and outside the U.S. The table consists again of three panels, one for each dependent variable, and each panel consists of three columns (full sample, U.S., Rest of World). 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 (two others are also different in significance levels, but not in sign). 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. In the case of franchise value we find positive and significant short run and long run relationships with specialization in the non-U.S. sample, underlining the positive impact of specialization not only on lowering volatility (as in both U.S. and non-U.S. samples) but also in terms of raising returns, resulting in a higher franchise value. We do not find any significant relationship between differentiation and franchise value for the non-U.S. sample.

Insert Table 8 around here

While the results for the U.S. and non-U.S. samples are relatively similar, there may be heterogeneity in the non-U.S. sample relationships. The sampled countries differ widely in terms of region, culture, economic development and regulation. Therefore, we now take a more granular view by re-running our models for each country separately. Specifically, for each country, we estimate the impact on total volatility, franchise value and MES of sectoral specialization, sectoral differentiation and the financial sector exposure by estimating the following model by country:

$$y_{it} = \beta_1 \; Specialization_{it-1} + \beta_2 \; Differentation_{it-1} + \beta_3 \; Financials \; factor \; loading_{it-1} + \gamma_1 X_{it-1} + \nu_i + \mu_t + \epsilon_{it} \tag{11}$$

We opt for a random effects model as this model takes a weighted average of the between and within estimation (both shown in our hybrid model). Each bar corresponds with a country in our sample, and we sort the countries from the lowest to the highest coefficient, with dark bars indicating significance at the 10% level. The coefficients are standardized by the mean and standard deviation for each country sample. We would like to point out that several countries have rather few observations (see Appendix Table A1), making it difficult to establish statistically significant relationships in these countries.

Insert Figures 3, 4 and 5 around here

Figure 3 shows the relationships between total volatility and sectoral specialization (top), sectoral differentiation (middle), and financials factor loading (bottom). In the case of sectoral specialization and stock volatility, we find that most coefficients are negative (and seven of them significantly so). Similarly, we find a positive relationship between sectoral differentiation and volatility for most countries, with only one country (India) having a negative *and* significant relationship. We find a more mixed picture for the financial sector loading and volatility, with both positive and negative coefficients on the country-level, although the majority of significant coefficients is positive. Figure 4 shows the relationships between specialization (top), differentiation (middle), financial sector loading (bottom) and the franchise value. Consistent with the regression analysis, there

is a wide variation in country coefficient estimates across the three explanatory variables, with positive and negative coefficients in all three cases though mostly close to zero in the case of specialization and financial sector exposure, with the majority of coefficients insignificant. Figure 5 shows the relationships between specialization/differentiation/financial sector loading and systemic risk exposure. We find that almost all country coefficients on the relationship between specialization and systemic risk exposure are negative, with half of them significant. Most of the significant country coefficients on differentiation in the regression on systemic risk exposure are positive, with the notable exception of Argentina. The majority of coefficients, however, is insignificant. Finally, most significant coefficients on the financial sector loading are positive, with the exception of Malaysia.

5 Conclusion

We propose a novel technique to infer banks' concentration from a factor model. We use it to identify sectoral concentration of 1,587 banks in 24 countries between 2002 and 2012. In a nutshell, the identification relies on the excess sensitivity of banks' daily stock returns to the returns from nine sectoral indices, over and above any sensitivity to the returns on a global market index, a domestic market index, a real estate index, a financial sector index and three factors (SMB, HML, Momentum). From this novel technique, we infer three bank-time varying measures of sectoral concentration. *Sectoral specialization* proxies for the total excess sensitivity of a bank to nine non-financial sectors, *sectoral differentiuation* proxies for how similar a bank's exposure to nine non-financial sectors is compared to the average competing bank in the same country-year, and *financials factor loading* proxies for how exposed a bank is to the financial sector.

With these measures in hand, we are the first to explore the impact of bank sectoral specialization, sectoral differentiation, and financial sector exposure on bank performance and (systemic) risk. The results suggests that banks do not benefit from higher sectoral specialization in terms of higher franchise values, while higher specialization seems to lead to 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. Markets thus reward specialization and similarity, especially during crisis times; with one possible explanation being that being specialized

(i.e., having a critical role for specific economic sectors) or being very similar to peer banks increases the likelihood of being bailed out. Banks that are overexposed to the financial sector have on average a higher stock volatility, but at the benefit of higher franchise values and, not surprisingly, higher systemic risk exposure. Interestingly, we find that these effects are much stronger in the long run than in the short run (about tenfold).

Finally, we explore the existence of time variation and cross-country variation of our findings. The results indicate 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 not homogeneous. Not only does the significance of the established relationships change over time and across countries, also the magnitude and the sign of the relationship may vary. These findings make it challenging to design or implement a one-size-fits-all regulatory approach with respect to sectoral specialization, sectoral differentiation, and financial sector exposure.

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 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. However, while these suggestions are likely to improve bank risk and systemic bank stability for most countries, it's important to keep in mind that our results also showed that a regulatory approach that fits one country does not necessarily fit another. Investigating which factors determine the size and magnitude of these relationships across countries is definitely an interesting area of future research.

References

Acharya, V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability 5*, 224–255.

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

Acharya, V., I. Hasan, and A. Saunders (2006). Should banks be diversified? Evidence from individual bank loan portfolios. *Journal of Business 79*, 1355–1412.

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

Acharya, V. V. and S. Steffen (2015). The greatest carry trade ever? understanding eurozone bank risks. *Journal of Financial Economics 115*(215-236).

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

Acharya, V. V. and T. Yorulmazer (2008). Information contagion and bank herding. *Journal of Money, Credit and Banking 40*(1), 215–231.

Agarwal, I., R. Duttagupta, and A. Presbitero (2017). Commodity prices and bank lending in low-income countries. *Unpublished manuscript*.

Allison, P. (2009). *Fixed effects regression models*. Thousand Oaks, CA: Sage.

Baele, L., V. De Bruyckere, O. De Jonghe, and R. Vander Vennet (2015). Model uncertainty and systematic risk in us banking. *Journal of Banking & Finance 53*, 49 – 66.

Baltagi, B. and J. Griffin (1984). Short and long run effects in pooled models. *International Economic Review 25(3)*, 631–645.

Beltratti, A. and R. Stulz (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics 105*(1), 1 – 17.

Boeve, R., K. Duellmann, and A. Pfingsten (2010). Do specialization benefits outweigh concentration risks in credit portfolios of german banks? *Bundesbank Discussion Paper No 10/2010*.

Boyd, J. H. and E. C. Prescott (1986). Financial intermediary-coalitions. *Journal of Economic Theory 38*(2), 211–232.

Brown, S. J. and W. N. Goetzmann (1997). Mutual fund styles. *Journal of Financial Economics 43*(3), 373–399.

Brunnermeier, M. K. (2009, March). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives 23*(1), 77–100.

Cai, J., A. Saunders, and S. Steffen (2013). Syndication, interconnectedness and systemic risk. *unpublished manuscript*.

Coval, J. D. and T. J. Moskowitz (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance 54*(6), 2045–2073.

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

De Jonghe, O., H. Dewachter, K. Mulier, S. Ongena, and G. Schepens (2016). Some borrowers are more equal than others: Bank funding shocks and credit reallocation. *http://ssrn.com/abstract=2774441*.

De Nicolo, G. and M. Kwast (2002). Systemic risk and financial consolidation: Are they related? *Journal of Banking & Finance 26(5)*, 861–880.

Demirguc-Kunt, A. and H. Huizinga (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics 98*(3), 626–650.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies 51*(3), 393–414.

Duellmann, K. and N. Masschelein (2007). A tractable model to measure sector concentration risk in credit portfolios. *Journal of Financial Services Research 32*(1-2), 55–79.

Erickson, T., C. H. Jiang, and T. Whited (2014). Minimum distance estimation of the errors-in-variables model using linear cumulant equations. *Journal of Econometrics 183*(2), 211–221.

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

Flannery, M. J. and C. M. James (1984). The effect of interest-rate changes on the common-stock returns of financial institutions. *Journal of Finance 39*(4), 1141–1153.

French, K. R. and J. M. Poterba (1991). Investor diversification and international equity markets. *American Economic Review 81*(2).

Hayden, E., D. Porath, and N. Westernhagen (2007). Does diversification improve the performance of german banks? evidence from individual bank loan portfolios. *Journal of Financial Services Research 32*(3), 123–140.

Laeven, L. and R. Levine (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics 93*(2), 259–275.

Lakonishok, J., A. Shleifer, and R. W. Vishny (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics 32*(1), 23–43.

Liu, C. (2011). Herding behavior in bank lending: Evidence from us commercial banks. *Unpublished manuscript*.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica 46(1)*, 69–85.

Nier, E. and U. Baumann (2006). Market discipline, disclosure and moral hazard in banking. *Journal of Financial Intermediation 15*(3), 332–362.

Paravisini, D., V. Rappoport, and P. Schnabl (2014). Comparative advantage and specialization in bank lending. *Working paper, London School of Economics and New York University*.

Sharpe, W. (1992). Asset allocation: Management style and performance measurement. *Journal of Portfolio Management 18*(2), 7–19.

Smirlock, M., T. Gilligan, and W. Marshall (1984). Tobin's q and the structure-performance relationship. *The American Economic Review 74*(5), 1051–1060.

Stevens, J. L. (1990). Tobin's q and the structure-performance relationship: Comment. *The American Economic Review 80*(3), 618–623.

Stiglitz, J. and A. Weiss (1981). Credit rationing in markets with imperfect information. *American Economic Review 71*, 393–410.

Stiroh, K. and A. Rumble (2006). The dark side of diversification: The case of u.s. financial holding companies. *Journal of Banking and Finance 30*(8), 2131–2161.

Tabak, B. M., D. M. Fazio, and D. O. Cajueiro (2011). The effects of loan portfolio concentration on brazilian banks' return and risk. *Journal of Banking and Finance 35*(11), 3065–3076.

ter Horst, J. R., T. E. Nijman, and F. A. de Roon (2004). Evaluating style analysis. *Journal of Empirical Finance 11*(1), 29–53.

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

Westernhagen, N., E. Harada, T. Nagata, B. Vale, J. Ayuso, J. Saurina, S. Daltung, S. Ziegler, E. Kent, J. Reidhill, and S. Peristiani (2004). Bank failures in mature economies. *Basel Committee on Banking Supervision Working Paper 13*.

Winton, A. (1999). Don't put all your eggs in one basket? Diversification and specialization in lending. *Working paper available at SSRN: http://ssrn.com/abstract=173615*.

Wooldridge, J. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

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$_{it-1}$, Differentation$_{it-1}$ and Financials factor loading$_{it-1}$. The figures provide the evolution in the mean, the first quartile (p25) and the third quartile (p75) of the distribution.

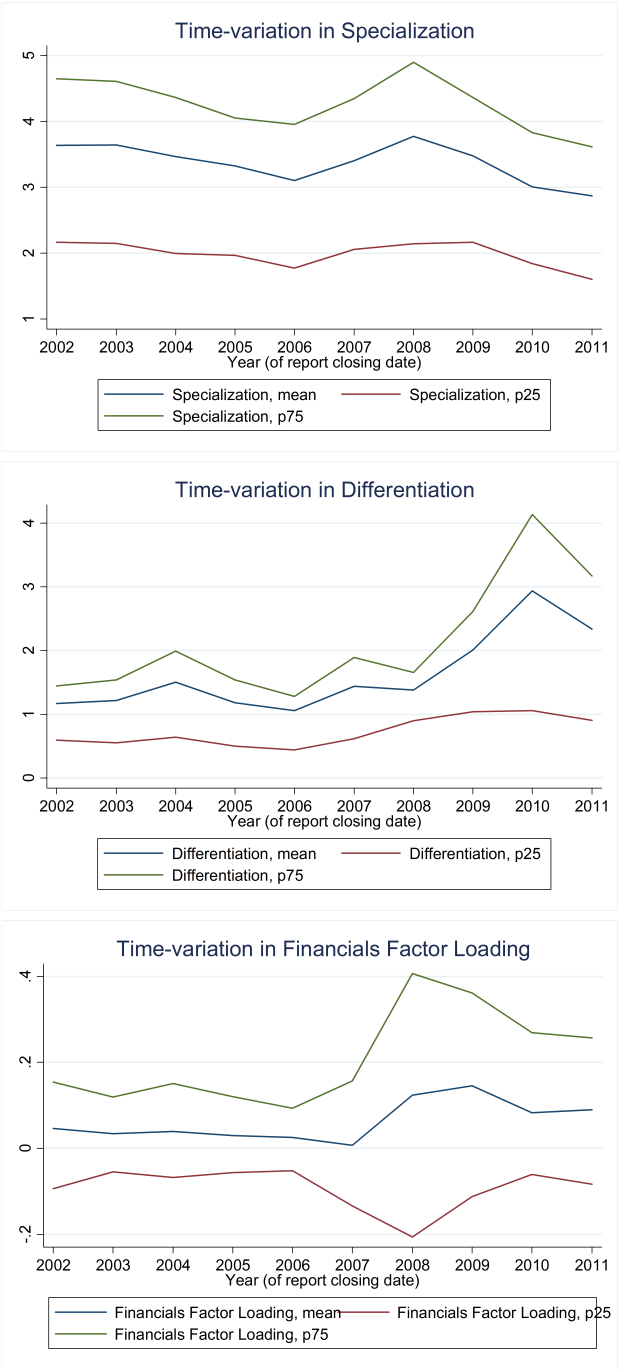


Figure 2: Time variation in relationship between bank performance and specialization, differentiation or financial sector exposure

This graph provides an indication of the year-to-year heterogeneity in the estimated relationship between three measures of bank performance, being bank risk (first column), bank franchise value (second column) and sytemic risk exposure (third column), and sectoral specialization (first row), sectoral differentiation (second row) and financial sector exposure (third row). For each year, we estimate the following random effects model with country fixed effects for each measure of bank performance: $Bank\ Performance_{it} = \alpha + \beta_1\ Specialization_{it-1} + \beta_2\ Differentation_{it-1} + \beta_3\ Financials\ factor\ loading_{it-1} + \gamma_1\ X_{it-1} + \mu_c + \epsilon_{it}$. Each bar corresponds with the respective estimated beta in that given year.

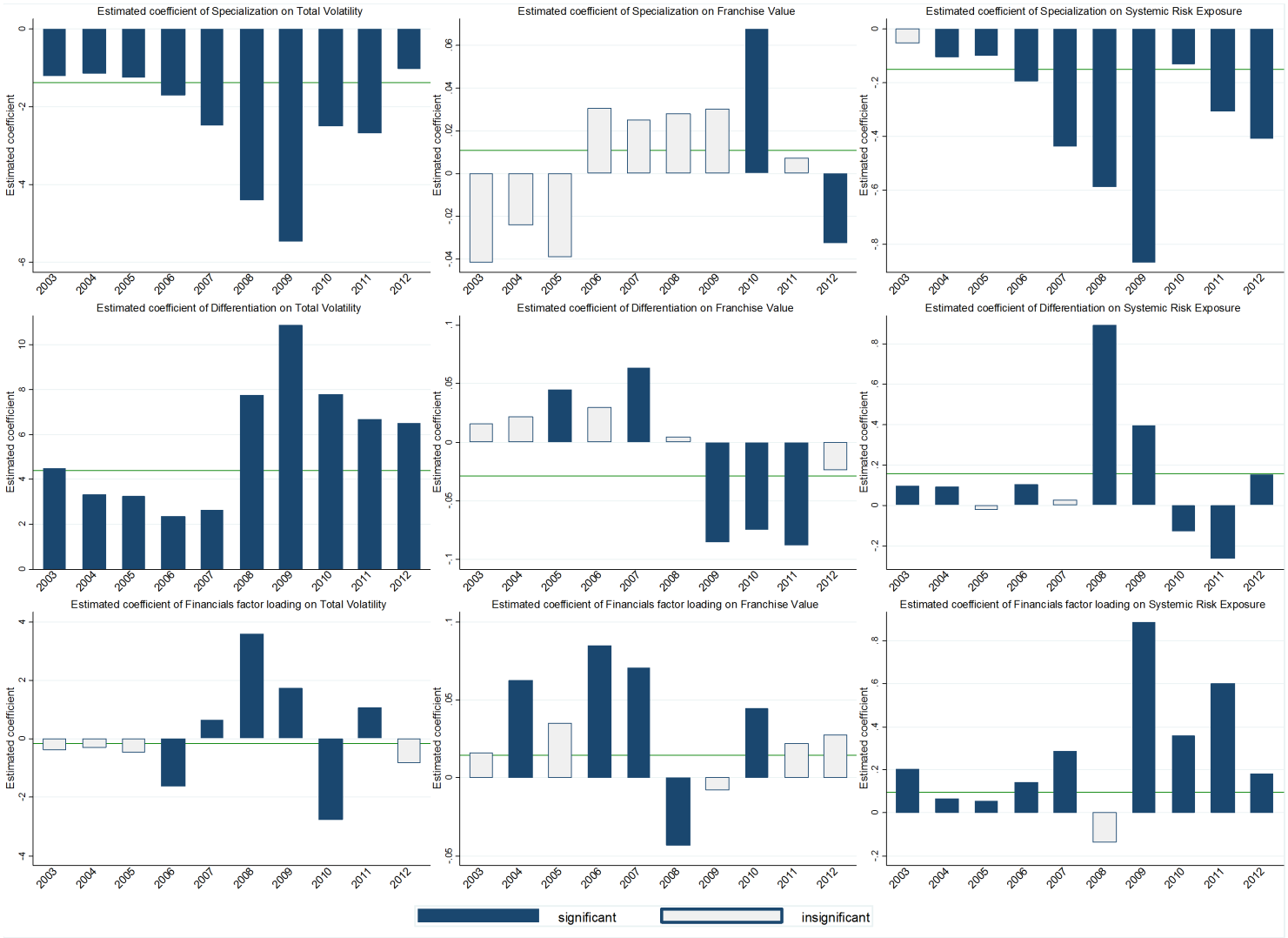


Figure 3: Country variation in relationship between total volatility and specialization, differentiation or financial sector exposure

This graph provides an indication of the between country heterogeneity in the estimated relationship between bank risk, measured as total stock return volatility, and sectoral specialization (upper graph), sectoral differentiation (middle graph) and financial sector exposure (lower graph). For each country, we estimate the following random effects model by country: $Total\ Volatility_{it} = \alpha + \beta_1\ Specialization_{it-1} + \beta_2\ Differentation_{it-1} + \beta_3\ Financials\ factor\ loading_{it-1} + \gamma_1\ X_{it-1} + \mu_t + \nu_i + \epsilon_{it}$. We opt for a random effects model as this model takes a weighted average of the between and within estimation (both shown in our hybrid model). Each bar corresponds with a country in our sample, and we sort the countries from the lowest to the highest coefficient.

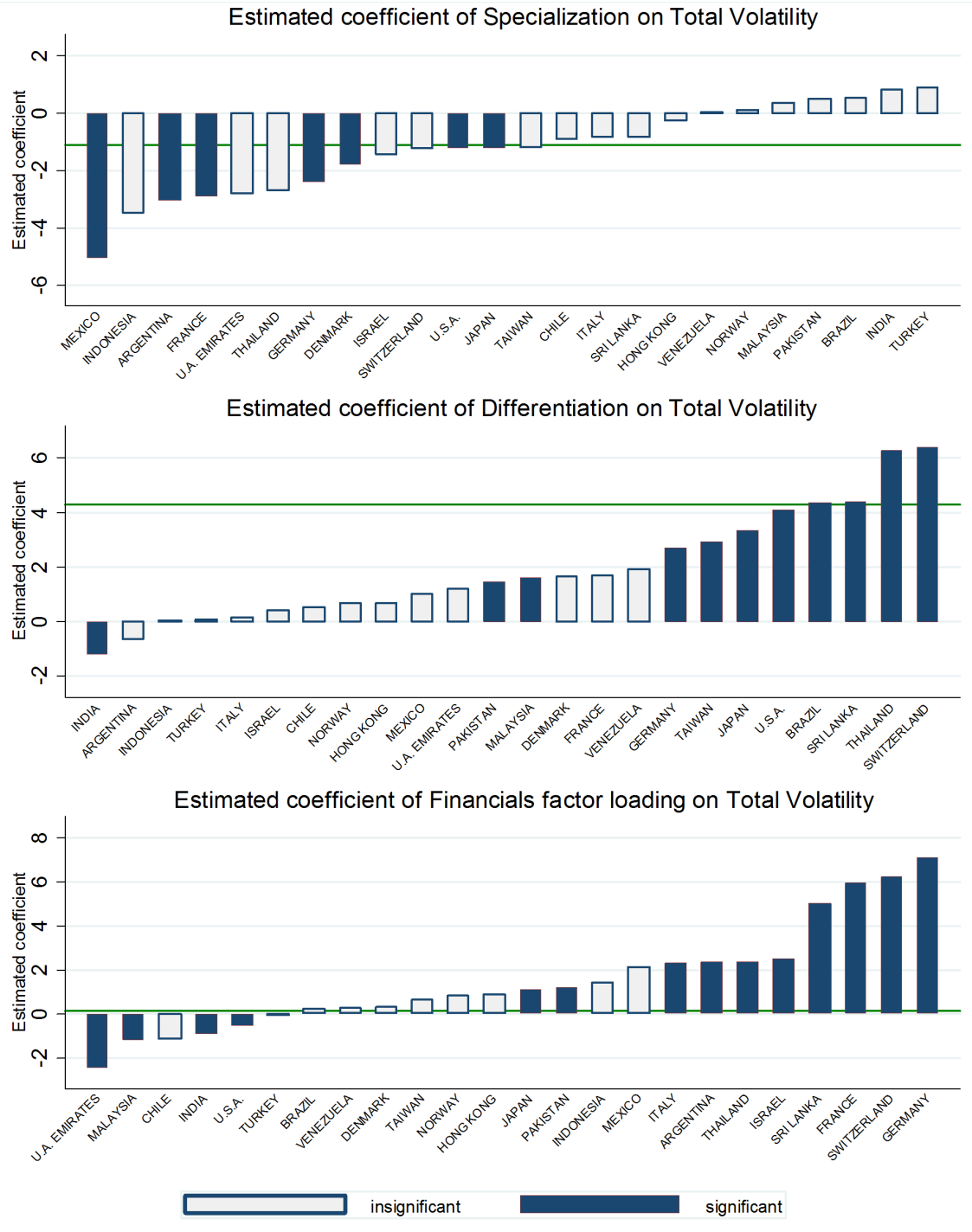


Figure 4: Country variation in relationship between franchise value and specialization, differentiation or financial sector exposure

This graph provides an indication of the between country heterogeneity in the estimated relationship between bank franchise value, measured as the market-to-book value of equity, and sectoral specialization (upper graph), sectoral differentiation (middle graph) and financial sector exposure (lower graph). For each country, we estimate the following random effects model by country: $Franchise\ Value_{it} = \alpha + \beta_1\ Specialization_{it-1} + \beta_2\ Differentation_{it-1} + \beta_3\ Financials\ factor\ loading_{it-1} + \gamma_1\ X_{it-1} + \mu_t + \nu_i + \epsilon_{it}$. We opt for a random effects model as this model takes a weighted average of the between and within estimation (both shown in our hybrid model). Each bar corresponds with a country in our sample, and we sort the countries from the lowest to the highest coefficient.

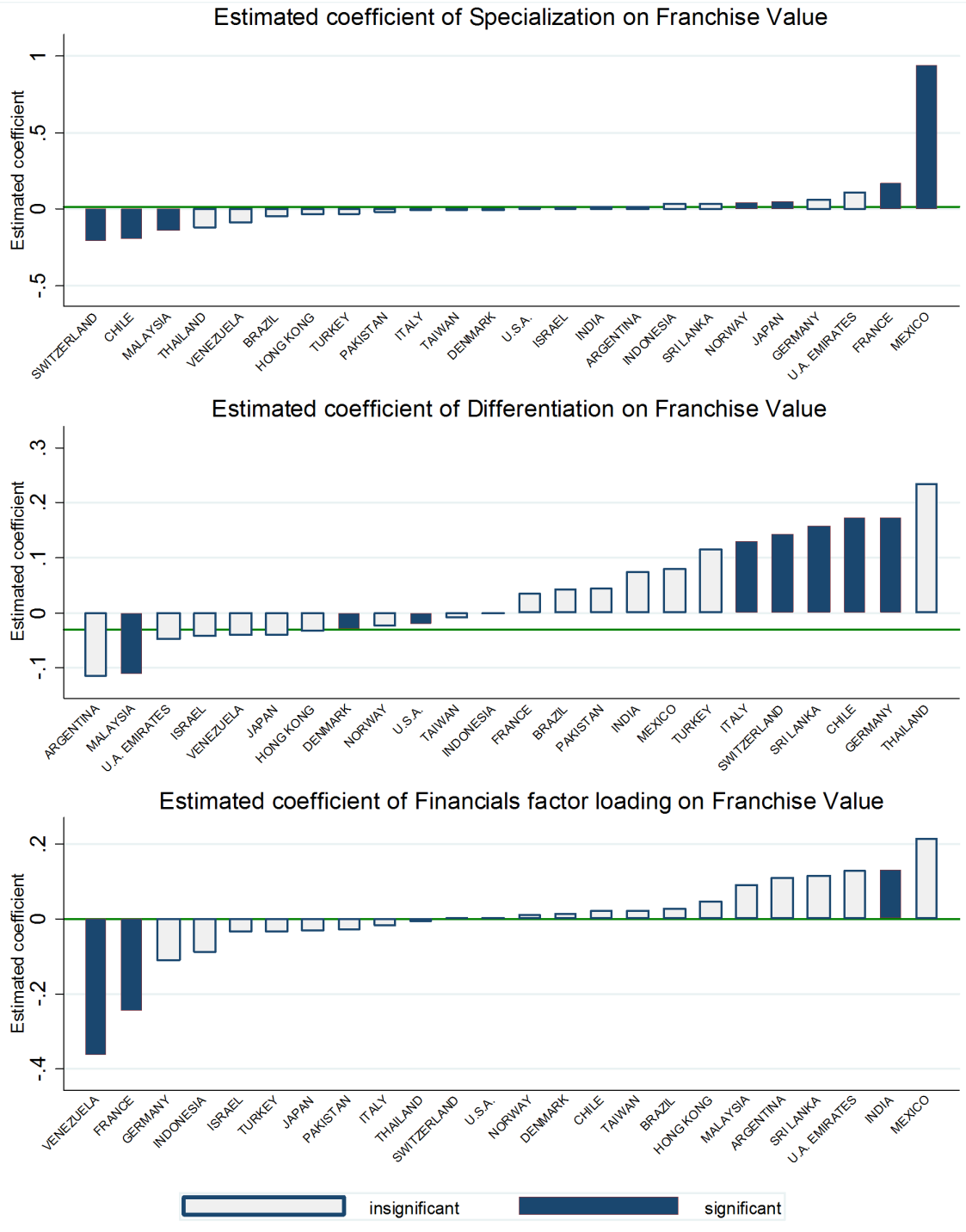


Figure 5: Country variation in relationship between systemic risk exposures and specialization, differentiation or financial sector exposure

This graph provides an indication of the between country heterogeneity in the estimated relationship between systemic risk exposures, measured as the marginal expected shortfall, and sectoral specialization (upper graph), sectoral differentiation (middle graph) and financial sector exposure (lower graph). For each country, we estimate the following random effects model by country: $Systemic\ Risk\ Exposure_{it} = \alpha + \beta_1\ Specialization_{it-1} + \beta_2\ Differentation_{it-1} + \beta_3\ Financials\ factor\ loading_{it-1} + \gamma_1\ X_{it-1} + \mu_t + \nu_i + \epsilon_{it}$. We opt for a random effects model as this model takes a weighted average of the between and within estimation (both shown in our hybrid model). Each bar corresponds with a country in our sample, and we sort the countries from the lowest to the highest coefficient.

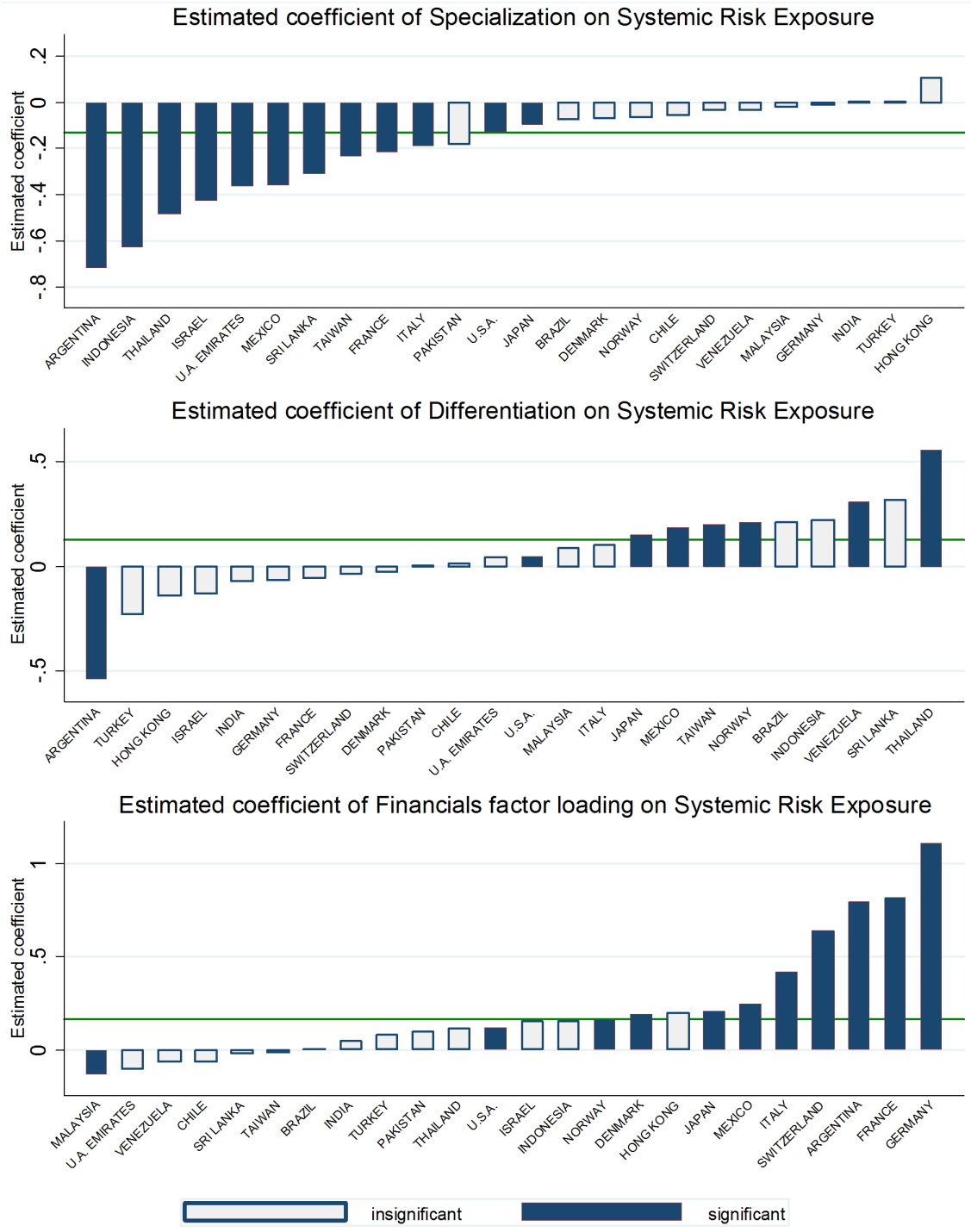


Table 1: Measuring banks' sectoral specialization and differentiation

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 10,352 bank-year observations, covering 1,587 banks from 24 countries over a ten year period starting in 2002. Panel A reports for each estimated factor loading the mean and standard deviation across 10,352 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 813 observations on 188 banks from 21 countries. Based on the hand-collected accounting-based 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 C. 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 4.

variable	mean	sd	p5	p50	p95
Panel A: Summary Statistics on Sectoral Factor Loadings					
1= Oil & gas (OILGS)	-0.01	1.08	-1.58	-0.02	1.56
2= Basic materials (BMATR)	-0.02	0.84	-1.15	-0.01	1.10
3= Industrials (INDUS)	-0.04	0.62	-0.92	-0.03	0.84
4= Consumer goods (CNSMG)	-0.01	0.64	-0.88	-0.01	0.88
5= Healthcare (HLTHC)	0.00	0.77	-1.11	-0.00	1.18
6= Consumer services (CNSMS)	-0.01	0.61	-0.90	-0.01	0.89
7= Telecommunications (TELCM)	-0.00	0.47	-0.69	-0.01	0.69
8= Utilities (UTILS)	0.02	0.45	-0.61	0.02	0.68
9= Technology (TECNO)	-0.02	1.01	-1.48	-0.02	1.38
10= Financials(FINAN)	0.06	0.31	-0.36	0.04	0.57
Panel B: Factor-based sectoral specialization and differentiation					
Specialization	3.37	1.96	1.03	2.97	7.24
Differentiation	1.61	1.47	0.31	1.17	4.54
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	0.12	0.02	0.14	0.39
S4 "Transport, communication, Electric, Gas and Sanitary service"	0.07	0.07	0.00	0.05	0.22
S5 "Wholesale trade and Retail trade"	0.12	0.10	0.00	0.11	0.33
S6 "Finance and Insurance"	0.08	0.10	0.00	0.05	0.28
S7 "Real estate"	0.14	0.15	0.00	0.09	0.48
S8 "Services"	0.11	0.10	0.00	0.10	0.30
S9 "Public administration"	0.05	0.07	0.00	0.01	0.20
S10 "Other industries"	0.19	0.18	0.00	0.15	0.55
Panel D: Accounting-based sectoral specialization and differentiation					
Sectoral CR3 (accounting)	0.55	0.17	0.32	0.53	0.87
Differentiation (accounting)	0.19	0.10	0.07	0.17	0.40

Table 2: Relating accounting to return-based measures of sectoral specialization and differentiation

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)$_{it}$	0.48***	0.51***		
	(0.14)	(0.15)		
ln(Differentiation accounting based)$_{it}$			0.50**	0.52**
			(0.25)	(0.23)
ln(Specialization accounting based)$_{it}$ x OBS$_{it}$		-0.22*		
		(0.12)		
ln(Differentiation accounting based)$_{it}$ x OBS$_{it}$				-0.46**
				(0.20)
ln(Specialization accounting based)$_{it}$ x DISC$_{it}$		0.09		
		(0.12)		
ln(Differentiation accounting based)$_{it}$ x DISC$_{it}$				0.24*
				(0.14)
Off Balance Sheet Size to Total Assets (OBS)$_{it}$		0.02		0.05
		(0.07)		(0.05)
Disclosure (DISC)$_{it}$		-0.02		-0.05
		(0.05)		(0.03)
Bank Size$_{it}$	-0.32	-0.31	-0.53	-0.50
	(0.33)	(0.32)	(0.33)	(0.34)
Revenue Diversification$_{it}$	-0.13	-0.11	0.42**	0.41***
	(0.16)	(0.15)	(0.16)	(0.15)
Bank Size$_{it}$ x Revenue Diversification$_{it}$	2.40	2.40	1.80	1.70
	(1.61)	(1.59)	(1.51)	(1.49)
Bank Capital$_{it}$	0.23	0.43	-1.68***	-1.51***
	(0.63)	(0.66)	(0.60)	(0.58)
Funding Diversification$_{it}$	0.01	-0.02	-0.48***	-0.46***
	(0.19)	(0.18)	(0.18)	(0.17)
Loans Share$_{it}$	0.04	0.04	0.20	0.19
	(0.19)	(0.20)	(0.17)	(0.15)
Profitability$_{it}$	-0.26	-0.21	-0.57***	-0.53***
	(0.19)	(0.20)	(0.18)	(0.18)
Asset Growth$_{it}$	0.02	0.02	0.08	0.06
	(0.11)	(0.11)	(0.12)	(0.12)
Credit Risk$_{it}$	-0.01	0.01	0.05	0.06*
	(0.04)	(0.04)	(0.04)	(0.04)
Observations	813	813	813	813
R-squared	0.26	0.27	0.24	0.25
Country Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Clustered SE	Bank	Bank	Bank	Bank

Table 3: 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)$_{it}$	0.598**	0.799**	0.619**	0.797**
	(0.280)	(0.308)	(0.272)	(0.307)
Finance and Insurance (=S6)$_{it}$ x OBS$_{it}$		-0.324***		-0.283**
		(0.123)		(0.126)
Finance and Insurance (=S6)$_{it}$ x DISC$_{it}$			0.686**	0.631**
			(0.303)	(0.313)
Off Balance Sheet Size to Total Assets (OBS)$_{it}$		0.067**		0.060**
		(0.027)		(0.027)
Disclosure (DISC)$_{it}$			-0.036	-0.029
			(0.027)	(0.028)
Bank Size$_{it}$	-0.062	-0.041	-0.075	-0.064
	(0.347)	(0.344)	(0.342)	(0.340)
Revenue Diversification$_{it}$	0.175	0.146	0.118	0.092
	(0.291)	(0.295)	(0.272)	(0.276)
Bank Size$_{it}$ x Revenue Diversification$_{it}$	0.875	0.917	1.055	1.107
	(1.603)	(1.596)	(1.580)	(1.577)
Bank Capital$_{it}$	1.564	1.601	1.727	1.722
	(1.370)	(1.371)	(1.375)	(1.375)
Funding Diversification$_{it}$	-0.432	-0.431	-0.474*	-0.471*
	(0.284)	(0.282)	(0.282)	(0.281)
Loans Share$_{it}$	-0.269	-0.272	-0.303	-0.303
	(0.341)	(0.343)	(0.349)	(0.350)
Profitability$_{it}$	-0.087	-0.066	-0.086	-0.068
	(0.258)	(0.256)	(0.255)	(0.254)
Asset Growth$_{it}$	0.077	0.077	0.114	0.115
	(0.126)	(0.128)	(0.124)	(0.126)
Credit Risk$_{it}$	0.071	0.073	0.066	0.069
	(0.052)	(0.051)	(0.052)	(0.052)
Observations	829	829	829	829
Number of bankid	191	191	191	191
R-squared	0.068	0.073	0.077	0.081
Bank Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Clustered SE	Bank	Bank	Bank	Bank

Table 4: 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 10,352 observations, on 1,587 banks from 24 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 Appendix 2.

variable	mean	sd	p5	p50	p95
Panel A: Summary Statistics on franchise value and (systemic) risk					
Total Volatility	39.86	24.66	14.30	32.53	91.66
Franchise Value	1.39	0.91	0.30	1.23	2.96
Systemic Risk Exposure	1.90	2.28	-0.52	1.33	6.62
Panel B: Summary Statistics on Bank Characteristics					
Bank Size	7.79	2.02	5.04	7.36	11.38
Revenue Diversification	0.18	0.13	0.00	0.15	0.42
Bank Capital	0.09	0.04	0.04	0.09	0.18
Funding Diversification	0.90	0.14	0.60	0.95	1.00
Loan Share	0.64	0.15	0.35	0.66	0.84
Profitabilit	0.07	0.13	-0.16	0.09	0.23
Asset Growth	0.11	0.17	-0.07	0.07	0.43
Credit Risk	0.50	0.70	0.00	0.26	1.93

Table 5: 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, credit risk, profitability 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
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.48**		-0.48**	0.01		0.01	-0.05***		-0.05***
	(0.20)		(0.20)	(0.01)		(0.01)	(0.02)		(0.02)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	2.48***		2.48***	-0.03***		-0.03***	0.12***		0.12***
	(0.28)		(0.28)	(0.01)		(0.01)	(0.02)		(0.02)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.02		0.02	-0.00		-0.00	0.08***		0.08***
	(0.24)		(0.24)	(0.01)		(0.01)	(0.02)		(0.02)
$\overline{\text{Specialization}}_i$		-4.29***	-4.94***		0.08***	0.08		-0.56***	-0.73***
		(0.48)	(0.58)		(0.03)	(0.05)		(0.05)	(0.06)
$\overline{\text{Differentiation}}_i$		15.73***	16.59***		-0.05	-0.03		0.11*	0.16**
		(0.54)	(0.90)		(0.03)	(0.04)		(0.06)	(0.07)
$\overline{\text{Financials factor loading}}_i$		1.31**	1.84***		0.06*	0.06*		0.77***	0.88***
		(0.51)	(0.65)		(0.03)	(0.03)		(0.06)	(0.07)
Observations	10,352	10,352	10,352	10,352	10,352	10,352	10,352	10,352	10,352
R-squared	0.53	0.66	0.59	0.40	0.32	0.35	0.33	0.55	0.46
Number of bankid	1,587	1,587	1,587	1,587	1,587	1,587	1,587	1,587	1,587
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	No	No	No	No	No
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Corr(Fit,ν_i)	-0.031			-0.005			-0.020		
Wald test 1 (p-value)			0			0.11			0
Wald test 2 (p-value)			0			0			0
Wald test 3 (p-value)			0.02			0.11			0

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 6: Sectoral specialization, sectoral differentiation and financial sector exposure: robustness

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 baseline results and correspond with those reported in Columns 3, 6 and 9 of Table 5. Columns 2, 5 and 8 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 3, 6 and 9 show the baseline estimation on the subsample of the data that is balanced and thus available for 10 years. 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, credit risk, profitability 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	All	moderate growth	balanced panel	All	moderate growth	balanced panel	All	moderate growth	balanced panel
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.48**	-0.47**	0.13	0.01	0.00	0.01	-0.05***	-0.05***	-0.02
	(0.20)	(0.21)	(0.30)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	2.48***	2.13***	2.76***	-0.03***	-0.04***	-0.05***	0.12***	0.09***	0.14***
	(0.28)	(0.30)	(0.42)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.02	0.25	-0.30	-0.00	-0.01	-0.01	0.08***	0.09***	0.08**
	(0.24)	(0.27)	(0.38)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)
$\overline{\text{Specialization}}_{i}$	-4.94***	-4.63***	-7.76***	0.08	0.10**	-0.33***	-0.73***	-0.73***	-1.42***
	(0.58)	(0.63)	(1.01)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.15)
$\overline{\text{Differentiation}}_{i}$	16.59***	17.72***	18.01***	-0.03	-0.03	0.03	0.16**	0.26***	0.63***
	(0.90)	(1.04)	(1.19)	(0.04)	(0.04)	(0.08)	(0.07)	(0.08)	(0.17)
$\overline{\text{Financials factor loading}}_{i}$	1.84***	1.93**	2.06*	0.06*	0.09***	-0.10*	0.88***	0.98***	1.25***
	(0.65)	(0.77)	(1.08)	(0.03)	(0.03)	(0.06)	(0.07)	(0.08)	(0.13)
Observations	10,352	8,119	3,940	10,352	8,119	3,940	10,352	8,119	3,940
R-squared	0.59	0.60	0.59	0.35	0.38	0.44	0.46	0.46	0.48
Number of bankid	1,587	1,517	394	1,587	1,517	394	1,587	1,517	394
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
Panel	RE	RE	RE	RE	RE	RE	RE	RE	RE
Wald test 1 (p-value)	0.00	0.00	0.00	0.11	0.12	0.00	0.00	0.00	0.00
Wald test 2 (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald test 3 (p-value)	0.02	0.04	0.04	0.11	0.01	0.13	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 7: Sectoral specialization, sectoral differentiation and financial sector exposure: time variation

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 baseline results and correspond with those reported in Columns 3, 6 and 9 of Table 5. Columns 2, 5 and 8 show the baseline estimation on the subsample from 2003 to 2007, while columns 3, 6 and 9 show the baseline estimation on the subsample from 2008 to 2012. 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, credit risk, profitability 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	All	pre 2008	post 2007	All	pre 2008	post 2007	All	pre 2008	post 2007
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.48**	0.07	-0.14	0.01	0.00	0.00	-0.05***	0.00	-0.02
	(0.20)	(0.16)	(0.31)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	2.48***	-0.07	1.09***	-0.03***	0.01	-0.02***	0.12***	-0.00	0.09***
	(0.28)	(0.37)	(0.33)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.02	-0.24	-0.17	-0.00	-0.01	-0.00	0.08***	0.08***	-0.02
	(0.24)	(0.34)	(0.25)	(0.01)	(0.02)	(0.00)	(0.02)	(0.03)	(0.02)
$\overline{\text{Specialization}}_{i}$	-4.94***	-3.31***	-6.64***	0.08	0.05	0.09	-0.73***	-0.43***	-1.31***
	(0.58)	(0.55)	(0.98)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.12)
$\overline{\text{Differentiation}}_{i}$	16.59***	12.34***	17.93***	-0.03	0.06	-0.10**	0.16**	0.19***	0.17
	(0.90)	(1.03)	(1.30)	(0.04)	(0.05)	(0.04)	(0.07)	(0.05)	(0.11)
$\overline{\text{Financials factor loading}}_{i}$	1.84***	0.50	3.91***	0.06*	0.12**	0.02	0.88***	0.57***	1.32***
	(0.65)	(0.76)	(1.02)	(0.03)	(0.05)	(0.04)	(0.07)	(0.05)	(0.12)
Observations	10,352	5,268	5,084	10,352	5,268	5,084	10,352	5,268	5,084
R squared	0.59	0.45	0.58	0.35	0.23	0.30	0.46	0.56	0.44
Number of bankid	1,587	1,451	1,204	1,587	1,451	1,204	1,587	1,451	1,204
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
Panel	RE	RE	RE	RE	RE	RE	RE	RE	RE
Wald test 1 (p-value)	0.00	0.00	0.00	0.11	0.66	0.28	0.00	0.00	0.00
Wald test 2 (p-value)	0.00	0.00	0.00	0.00	0.39	0.00	0.00	0.00	0.00
Wald test 3 (p-value)	0.02	0.52	0.00	0.11	0.03	0.66	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 8: Sectoral specialization, sectoral differentiation and financial sector exposure: country variation

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 baseline results and correspond with those reported in Columns 3, 6 and 9 of Table 5. Columns 2, 5 and 8 provide estimation results for the subsample of US banks. Columns 3, 6 and 9 represent results for a sample excluding US banks. 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, credit risk, profitability 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	All	US	Non-US	All	US	Non-US	All	US	Non-US
$\overline{\overline{\text{Specialization}}}_{it-1}$	-0.48**	-0.70***	-0.99***	0.01	0.00	0.03***	-0.05***	-0.05**	-0.09***
	(0.20)	(0.25)	(0.27)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
$\overline{\overline{\text{Differentiation}}}_{it-1}$	2.48***	1.92***	2.03***	-0.03***	-0.03***	-0.01	0.12***	0.07***	0.18***
	(0.28)	(0.34)	(0.46)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
$\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.02	-0.66**	0.91**	-0.00	0.00	-0.02	0.08***	0.01	0.21***
	(0.24)	(0.28)	(0.39)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
$\overline{\text{Specialization}}_{i}$	-4.94***	-3.80***	-5.09***	0.08	-0.02	0.24**	-0.73***	-0.71***	-0.76***
	(0.58)	(0.73)	(0.73)	(0.05)	(0.05)	(0.10)	(0.06)	(0.08)	(0.08)
$\overline{\text{Differentiation}}_{i}$	16.59***	15.98***	13.88***	-0.03	-0.02	0.00	0.16**	0.17*	0.30***
	(0.90)	(1.02)	(1.33)	(0.04)	(0.04)	(0.08)	(0.07)	(0.09)	(0.10)
$\overline{\text{Financials factor loading}}_{i}$	1.84***	0.78	6.57***	0.06*	0.04	0.17	0.88***	0.79***	0.83***
	(0.65)	(0.74)	(1.03)	(0.03)	(0.03)	(0.10)	(0.07)	(0.09)	(0.11)
Observations	10,352	6,431	3,921	10,352	6,431	3,921	10,352	6,431	3,921
R-squared	0.59	0.70	0.49	0.35	0.44	0.36	0.46	0.42	0.52
Number of bankid	1,587	1,041	546	1,587	1,041	546	1,587	1,041	546
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
Panel	RE	RE	RE	RE	RE	RE	RE	RE	RE
Wald test 1 (p-value)	0	0.00	0	0.11	0.91	0.00	0.00	0.00	0.00
Wald test 2 (p-value)	0	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.00
Wald test 3 (p-value)	0.02	0.02	0.00	0.11	0.42	0.08	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: $\overline{\overline{\text{Financials factor loading}}}_{it-1} - \overline{\text{Financials factor loading}}_{i} = 0$.

Appendix

Appendix 1: references to sectoral concentration in earning calls transcripts

In this appendix, we provide examples of how information on sectoral concentration appears in transcripts of earnings calls. In particular:

- Example 1 shows how banks inform their analysts, shareholders, etc. on the sectoral composition of the loan portfolio.
- Example 2 provides evidence that banks effectively communicate about changes in their sectoral exposures.
- Examples 3 and 5 indicate that banks communicate about concentration risk in their portfolio and the hedging techniques they use.
- Examples 4 and 5 indicate that analysts are concerned about the composition and evolution of the loan portfolio.
- Example 6 shows how analysts at rating agencies use sectoral concentration risk as a motivation for a rating downgrade of a bank.

Example 1: Itau-Unibanco Brazil

- Q3 2016 earnings call, includes discussion on sectoral split-up of loan portfolio.
- Slide 51: Credit portfolio by business sector and credit concentration

Credit Portfolio Breakdown

Companies Credit Portfolio by Business Sector [1]

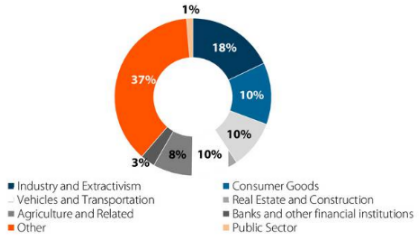
In R$ millions, end of period	3Q16	2Q16	change	
Public Sector	**4,421**	**4,460**	**(39)**	**-0.9%**
Private Sector | Companies	**331,890**	**338,170**	**(6,281)**	**-1.9%**
Real Estate	25,075	24,635	440	1.8%
Vehicles and auto parts	19,096	19,701	(605)	-3.1%
Food and beverage	17,758	18,589	(831)	-4.5%
Agribusiness and fertilizers	16,127	15,952	175	1.1%
Transportation	14,359	15,312	(953)	-6.2%
Energy and water treatment	13,629	14,220	(590)	-4.1%
Banks and other financial institutions	13,325	14,849	(1,524)	-10.3%
Petrochemical and chemical	11,032	11,220	(189)	-1.7%
Steel and metallurgy	10,532	11,069	(536)	-4.8%
Infrastructure work	10,142	10,098	44	0.4%
Sugar and Alcohol	9,519	9,568	(49)	-0.5%
Telecommunications	9,023	9,842	(819)	-8.3%
Mining	8,383	8,486	(103)	-1.2%
Oil and gas	7,211	7,041	170	2.4%
Capital Assets	7,064	7,695	(631)	-8.2%
Construction Material	6,936	7,043	(107)	-1.5%
Pharmaceutical and cosmetics	6,503	6,498	6	0.1%
Electronic and IT	5,992	5,973	19	0.3%
Clothing and footwear	5,011	4,934	76	1.5%
Services - Other	40,237	39,657	580	1.5%
Commerce - Other	18,732	18,547	185	1.0%
Industry - Other	7,747	7,342	404	5.5%
Other	48,457	49,900	(1,443)	-2.9%
Total	**336,310**	**342,630**	**(6,320)**	**-1.8%**

Credit Concentration [2]

R$ million

	Loan, lease and other credit operations		Loan, lease, other credit operations and securities of companies and financial institutions	
	Risk	% of Total	Risk	% of Total
Largest Debtor	4,081	0.7%	8,051	1.2%
10 largest debtors	31,716	5.6%	46,432	7.0%
20 largest debtors	48,564	8.6%	74,939	11.4%
50 largest debtors	80,974	14.3%	118,925	18.0%
100 largest debtors	109,131	19.2%	156,470	23.7%

(2) Includes endorsements and sureties



(1) Includes endorsements and sureties. Industry and Extractivism = Steel and Metallurgy + Capital Assets + Petrochemical and Chemical + Energy and sewage + Oil and gas. Consumer Goods = Food and beverage + Clothing and footwear + Pharmaceuticals and cosmetics + Entertainment and tourism. Vehicles and Transportation = Transportation + Vehicles and autoparts. Real Estate and Construction = Real estate agents + Construction material + Infrastructure work. Agriculture and Related = Agribusiness and fertilizers + Sugar and alcohol + Pulp and paper. Other = Other + Electronic and IT.

Itaú Unibanco Holding S.A. page 51 Itaú

- https://seekingalpha.com/article/4017476-itau-unibanco-holding-s-2016-q3-results-earnings-call-slides

Example 2: Commerzbank

- Q3 2016 earnings conference call.
- CFO Stephan Engels discussing changes in loan portfolio (page 2/7):

> "Our management team reduced the ACR shipping exposure from more than 20 billion EaD end of 2010 to 5 billion as of Q3 2016, the team will further use their experience to successfully manage the portfolio in this market environment."

- https://seekingalpha.com/article/4020247-commerzbank-ag-crzbf-q3-2016-results-earnings-call-transcript?all=true&find=commerzbank%2Bearnings

Example 3: Bank of Montreal Financial Group

- Q2 2005 conference call.
- Bob McGlashan, BMO Financial Group - EVP, Head of Corporate Risk Management discusses hedging of concentration risk:

> "On slide 9, you'll see the allocation of our credit protection portfolio by industry. We are active in the use of single name credit default swaps to mitigate risk related to specific credit exposures and indexed credit default swaps to mitigate sectoral risk concentrations."

- Yvan Bourdeau - BMO Nesbitt Burns - President, COO discusses sectoral specialization

> "Thank you Bob. Moving to slide 10, our CDS or trading book is predominantly in a loan protection position. As illustrated on the slide, our industry exposure is well diversified with significant concentration of risk in only 3 particular industries."

- https://www.bmo.com/bmo/files/speech/3/1/Q2%202005%20Transcript.pdf

Example 4: ING

- Q2 2015 conference call, analyst requests info on sectoral lending strategies.
- Tarik El Mejjad (Bank of America Merrill Lynch)

"And my second question is on your loan growth and industry lending. Can you please give us more detail on what sectors are working well and how you manage still to grow, although oil and gas is not doing well? I know that you are diversified but if you can explain us what other factors are."

- https://www.ing.com/web/file?uuid=b23fb012-464c-4751-95cb-9535840efac2&owner=b03bc017-e0db-4b5d-abbf-003b12934429&contentid=37490

Example 5: IDFC Limited

- Q3 2015 earnings conference call, discussion between analyst and bank representatives.
- Jai Mundhra (CRISIL rating agency):

  "Sure. My next question is with respect to the concentration guidelines in terms of the loan exposure that applies to banks. So how do you actually plan to meet that thing because I believe banks have certain sector over sectoral concentration guidelines?"

- reply of Pavan Kaushal (Chief Risk Officer, IDFC):

  "As we become a bank obviously we will carnation the existing book. But like Vikram mentioned earlier we are going to be putting on other types of assets whether they are corporate loans or consumer and rural and over a period of time this diversification will come in."

- Sunil Kakar (group CFO):

  "So let me also clarify as far as I know that if the Board approves the sectoral guidelines and therefore there is no RBI-mandated percentage sectoral exposure."

- Pavan Kaushal:

  "The mandates are all from the Board and as the Reserve Bank obviously has approved our demerger, it is fully aware about our current portfolio concentrations."

- https://www.idfc.com/pdf/quarterly_results/FY_15/Q3/IDFC_9MFY15_Concall_Transcript.pdf

Example 6: Diamond Bank PLC

- S&P Global Ratings today lowered its long- and short-term counterparty credit ratings on Nigeria-based Diamond Bank PLC to 'B-/C' from 'B/B'.
- The downgrade by S&P is partly related to their concerns on sectoral concentration risk.

  "We think Diamond's asset quality and earnings stability is vulnerable to further contraction in Nigeria's economy over the next 12 months, especially given itsbalance sheet concentrations, including:

  - Sizable sectoral concentration on oil and gas (31% of total loans and 12% of NPLs), most of which has been restructured over the past 12 months by extending the tenor of loans;
  - Exposure to other cyclical sectors, such as general commerce, manufacturing, and real estate and construction, which together accounted for 40% of total loans and 62% of NPLs as of March 31, 2016."

- https://www.proshareng.com/news/Investors%20NewsBeat/Diamond-Bank-Lowered-To--B--C--On-Reduced-Earnings-and-Rising-FX-Liquidity-Risk/31463

Table A1: List of countries and number of bank-year observations by country

Country	Bank-year observations Full sample	Bank-year observations Accounting subsample
ARGENTINA	63	6
BRAZIL	156	8
CHILE	58	22
DENMARK	335	10
FRANCE	249	21
GERMANY	111	14
HONG KONG	90	33
INDIA	280	64
INDONESIA	101	17
ISRAEL	80	29
ITALY	209	15
JAPAN	918	283
MALAYSIA	108	
MEXICO	65	8
NORWAY	149	17
PAKISTAN	125	
SRI LANKA	59	
SWITZERLAND	115	8
TAIWAN	224	45
THAILAND	119	34
TURKEY	102	45
UNITED ARAB EMIRATES	99	34
UNITED STATES OF AMERICA	6,431	95
VENEZUELA	106	5

Full sample: 10,532 observations, on 1,587 banks from 24 countries, 2002-2011.
Accounting subsample: 813 observations, on 188 banks from 21 countries, 2007-2011.

Table A2: 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), the bank-specific control variables (panel C) as well as the country characteristics used in the sample splits (panel D).

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
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
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 A3: Sectoral specialization, sectoral differentiation and financial sector exposure: full baseline regression results

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. The results correspond to those shown in columns 3, 6 and 9 of Table 5, but also shows the results for the control variables. 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)
Panel	RE	RE	RE
$\overline{\text{Specialization}}_{it-1}$	-0.48**	0.01	-0.05***
	(0.20)	(0.01)	(0.02)
$\overline{\text{Differentiation}}_{it-1}$	2.48***	-0.03***	0.12***
	(0.28)	(0.01)	(0.02)
$\overline{\text{Financials factor loading}}_{it-1}$	0.02	-0.00	0.08***
	(0.24)	(0.01)	(0.02)
$\overline{\text{Specialization}}_{i}$	-4.94***	0.08	-0.73***
	(0.58)	(0.05)	(0.06)
$\overline{\text{Differentiation}}_{i}$	16.59***	-0.03	0.16**
	(0.90)	(0.04)	(0.07)
$\overline{\text{Financials factor loading}}_{i}$	1.84***	0.06*	0.88***
	(0.65)	(0.03)	(0.07)
$\overline{\text{Revenue Diversification}}_{it-1}$	3.95	0.51***	-0.64**
	(3.24)	(0.16)	(0.28)
$\overline{\text{Bank Capital}}_{it-1}$	-113.73***	-2.37***	2.66**
	(12.24)	(0.51)	(1.05)
$\overline{\text{Funding Diversification}}_{it-1}$	0.22	0.17	-0.46
	(3.69)	(0.16)	(0.36)
$\overline{\text{Loans Share}}_{it-1}$	0.84	0.22	-0.44
	(4.04)	(0.18)	(0.34)
$\overline{\text{Profitability}}_{it-1}$	-31.95***	0.19	-0.33
	(3.22)	(0.13)	(0.28)
$\overline{\text{Asset Growth}}_{it-1}$	-1.87	0.24***	0.34**
	(1.38)	(0.05)	(0.13)
$\overline{\text{Credit Risk}}_{it-1}$	4.58***	-0.10***	0.20***
	(0.50)	(0.02)	(0.04)
$\overline{\text{Bank Size}}_{it-1}$	-3.99**	-0.03	0.05
	(1.90)	(0.07)	(0.17)
$\overline{\text{Bank Size x Revenue Diversification}}_{it-1}$	-13.97*	0.12	-0.73
	(7.40)	(0.29)	(0.61)
$\overline{\text{Revenue Diversification}}_{i}$	4.68	0.57***	1.17***
	(2.95)	(0.22)	(0.32)
$\overline{\text{Bank Capital}}_{i}$	-40.61***	-1.99***	-0.75
	(6.83)	(0.46)	(0.79)
$\overline{\text{Funding Diversification}}_{i}$	1.35	0.39	-1.38***
	(2.81)	(0.27)	(0.32)
$\overline{\text{Loans Share}}_{i}$	1.78	-0.77***	-0.61**
	(2.13)	(0.17)	(0.26)
$\overline{\text{Profitability}}_{i}$	-46.78***	2.65***	1.66***
	(5.33)	(0.38)	(0.48)
$\overline{\text{Asset Growth}}_{i}$	6.62***	0.89***	-0.09
	(2.52)	(0.20)	(0.28)
$\overline{\text{Credit Risk}}_{i}$	4.38***	0.13**	0.43***
	(0.91)	(0.05)	(0.10)
$\overline{\text{Bank Size}}_{i}$	-144.00	0.56	4.47
	(118.83)	(11.92)	(13.66)
$\overline{\text{Bank Size x Revenue Diversification}}_{i}$	11.04	5.82***	-1.87
	(25.22)	(1.96)	(2.54)
Observations	10,352	10,352	10,352
Number of bankid	1,587	1,587	1,587
R-squared	0.59	0.35	0.46
Bank Controls	Yes	Yes	Yes
Bank Fixed Effects	No	No	No
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table A4: Correlation table: within and between

This Table shows the correlation between (i) total volatility, (ii) banks' franchise value, and (iii) systemic risk exposure and bank sector specialization, bank sector differentiation and financial sector exposure. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Total Volatility$_{it}$	1								
(2) Franchise Value$_{it}$	-0.28***	1							
(3) Systemic Risk exposure$_{it}$	0.38***	-0.07***	1						
(4) $\overline{\overline{\text{Specialization}}}_{it-1}$	0.02**	0.01	-0.01	1					
(5) $\overline{\overline{\text{Differentiation}}}_{it-1}$	0.15***	-0.14***	0.06***	0.22***	1				
(6) $\overline{\overline{\text{Financials factor loading}}}_{it-1}$	0.04***	-0.05***	0.04***	-0.00	0.03***	1			
(7) $\overline{\text{Specialization}}_{i}$	-0.02**	-0.07***	-0.35***	0	0	0	1		
(8) $\overline{\text{Differentiation}}_{i}$	0.40***	-0.10***	-0.08***	0	0	0	0.28***	1	
(9) $\overline{\text{Financials factor loading}}_{i}$	0.03***	0.11***	0.27***	0	0	0	-0.23***	-0.08***	1

(obs=10352)

Table A5: Sectoral specialization, sectoral differentiation and financial sector exposure: one-by-one inclusion

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; when we include them individually rather than jointly. The methodology used is the hybrid model as in columns 3, 6 and 9 of Table 5, but we include each independent variable of interest indiviudally. Standard errors are clustered at the bank level. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	Total Volatility			**Franchise Value**			**Systemic Risk exposure**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{\text{Specialization}}_{it-1}$	0.19			0.00			-0.02		
	(0.19)			(0.01)			(0.02)		
$\overline{\text{Differentiation}}_{it-1}$		2.33***			-0.03***			0.11***	
		(0.27)			(0.01)			(0.02)	
$\overline{\text{Financials factor loading}}_{it-1}$			0.03			-0.00			0.08***
			(0.24)			(0.01)			(0.02)
$\overline{\text{Specialization}}_{i}$	-0.89			0.06			-0.82***		
	(0.67)			(0.05)			(0.06)		
$\overline{\text{Differentiation}}_{i}$		14.95***			-0.01			-0.12*	
		(0.90)			(0.03)			(0.07)	
$\overline{\text{Financials factor loading}}_{i}$			1.51*			0.05*			1.00***
			(0.83)			(0.03)			(0.08)
Observations	10,352	10,352	10,352	10,352	10,352	10,352	10,352	10,352	10,352
R squared	0.511	0.577	0.510	0.351	0.351	0.351	0.415	0.375	0.426
Number of bankid	1,587	1,587	1,587	1,587	1,587	1,587	1,587	1,587	1,587
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Sectoral specialization, sectoral differentiation and financial sector exposure: 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 the error-in-variables estimator of Erickson et al. (2014). We separately estimate a fixed effects and a between effects version of the model using this estimator as there is no hybrid error-in-variables estimator available. 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	3rd order cumulant	3rd order moment	3rd order cumulant	3rd order moment	3rd order cumulant	3rd order moment
$\overline{\text{Specialization}}_{it-1}$	-3.51***		0.12		-0.61***	
	(1.04)		(0.15)		(0.20)	
$\overline{\text{Differentiation}}_{it-1}$	13.73***		-0.46		2.18***	
	(3.73)		(0.54)		(0.73)	
$\overline{\text{Financials factor loading}}_{it-1}$	-0.68		-0.06		0.04	
	(1.03)		(0.05)		(0.22)	
$\overline{\text{Specialization}}_{i}$		-6.18***		0.05		-0.48**
		(1.74)		(0.26)		(0.23)
$\overline{\text{Differentiation}}_{i}$		19.26***		0.05		-0.82
		(5.51)		(0.91)		(0.73)
$\overline{\text{Financials factor loading}}_{i}$		-2.73		-0.09		0.57*
		(3.83)		(0.20)		(0.32)
Observations	10,352	1,587	10,352	1,587	10,352	1,587
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	No	Yes	No	Yes	No
Country Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	Yes	No	Yes	No	Yes	No

Table A7: Sectoral concentration and stock returns during the financial crisis

This Table shows the impact of bank sector specialization, bank sector differentiation and financial sector exposure on buy-and-hold returns during the Global Financial crisis. We mimic the setup of Beltratti and Stulz (2012) and measure buy-and-hold returns over the period ranging from July 2007 to December 2008. In the first column, we only include the variables of interest. In subsequent columns, we also include control variables. In columns 3 and 4, we extend the period over which we measure the buy-and-hold return with three and six months, respectively. ***, ** and * denote p<0.01, p<0.05 and p<0.1 respectively.

	Buy-and-Hold Return 07/2007 to 12/2008 (1)	Buy-and-Hold Return 07/2007 to 12/2008 (2)	Buy-and-Hold Return 07/2007 to 03/2009 (3)	Buy-and-Hold Return 07/2007 to 06/2009 (4)
Specialization	0.108	-0.598	1.030	1.667
	(1.229)	(1.182)	(1.020)	(1.100)
Differentiation	-4.299**	-4.433**	-3.559*	-4.407**
	(2.139)	(2.112)	(1.932)	(1.972)
Financials factor loading	-5.098**	-5.033*	-6.653***	-5.785**
	(2.581)	(2.627)	(2.251)	(2.604)
Bank Size		-57.276**	-50.388**	-56.667***
		(22.336)	(20.467)	(21.617)
Bank Size x Revenue Diversification		74.282	57.202	63.552
		(61.718)	(60.976)	(59.847)
Revenue Diversification		-7.891	-10.456	-1.048
		(10.631)	(9.759)	(10.268)
Bank Capital		4.522	24.572	0.590
		(32.420)	(29.640)	(31.365)
Funding Diversification		19.274*	16.507*	14.289
		(10.250)	(9.043)	(10.218)
Loans Share		-41.660***	-38.051***	-44.038***
		(9.542)	(8.544)	(9.035)
Profitability		-9.681	-21.514	-14.492
		(19.660)	(16.377)	(17.196)
Asset Growth		-13.948	-13.862*	-14.411*
		(9.618)	(7.655)	(8.119)
Credit Risk		-3.858	-4.698	-3.131
		(3.503)	(3.041)	(3.224)
Observations	881	881	874	871
R-squared	0.159	0.232	0.269	0.329
Country Fixed Effects	Yes	Yes	Yes	Yes

Table A8: Sectoral concentration and bank ownership

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. We use the between estimator setup to investigate whether or not our between (long-run) results could be affected by omitting a time-invariant proxy for ownership. We control for ownership structure using Laeven and Levine (2009)'s primary measures of ownership structure, which are the cash flow rights that the largest owner gets from his control rights, as well as the control rights themselves. These variables are only available for a subset of banks for the year 2001. For each dependent variable, we show three regression specifications using identical samples: one with the cash flow rights variable, one with the control rights variable and one without these (the benchmark). ***, ** 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)
$\overline{\text{Specialization}}_i$	-8.01***	-8.04***	-8.11***	0.36	0.37	0.36	-1.74***	-1.71***	-1.74***
	(2.28)	(2.31)	(2.29)	(0.26)	(0.27)	(0.27)	(0.30)	(0.31)	(0.31)
$\overline{\text{Differentiation}}_i$	16.65***	16.59***	15.98***	0.39	0.42	0.40	0.96**	1.03**	1.00**
	(3.01)	(3.07)	(3.10)	(0.35)	(0.35)	(0.36)	(0.40)	(0.41)	(0.42)
$\overline{\text{Financials factor loading}}_i$	10.08***	10.11***	10.37***	-0.39	-0.41*	-0.40	1.24***	1.21***	1.22***
	(2.07)	(2.10)	(2.09)	(0.24)	(0.24)	(0.24)	(0.28)	(0.28)	(0.28)
Cash flow rights (2001)		0.00			-0.00			-0.00	
		(0.03)			(0.00)			(0.00)	
Control rights (2001)			0.03			-0.00			-0.00
			(0.03)			(0.00)			(0.00)
Observations	717	717	717	717	717	717	717	717	717
Number of bankid	101	101	101	101	101	101	101	101	101
R-squared	0.92	0.92	0.92	0.76	0.76	0.76	0.91	0.91	0.91
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes