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Lending Concentration, Bank Performance and Systemic Risk

Exploring Cross-Country Variation

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Abstract

Using both market-based and annual report-based approaches to measure lending specialization for a broad cross-section of banks and countries over the period 2002 to 2011, this paper is the first to empirically gauge the relationship between bank lending specialization and bank performance and stability in an international sample. Theory suggests that banks might benefit from specialization in the form of higher screening and monitoring efficiency, while a diversified loan portfolio might also enhance stability. This paper finds that sectoral specialization increases volatility and systemic risk exposures, while not leading to higher returns. The paper also documents important time, cross-bank, and cross-county variation in this relationship, which is stronger post 2007, for richer countries, countries without regulatory requirements on diversification, banks with lower market power, and banks with more traditional intermediation models.

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Lending Concentration, Bank Performance and Systemic Risk: Exploring Cross-Country Variation*

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1 Introduction

Sectoral specialization of production and employment varies widely across countries; often, though not exclusively, related to the level of development (Imbs and Wacziarg (2003)). Different degrees of specialization and concentration also have an impact on the scope for and the extent of lending concentration by banks. In turn, lending concentration affects bank risk as well as banking system stability via different and possibly opposing channels. This paper tests these effects empirically and documents how lending specialization is related to bank performance (valuation and returns), bank-specific risk (total volatility), as well as systemic risk (the marginal expected shortfall). While lending specialization has often been flagged by academics and regulators as a critical dimension in banks' performance and stability, research has been hampered by the dearth of data. Using both market-based and annual report-based approaches to measure lending specialization for a broad cross-section of banks and countries over the period 2002 to 2011, this paper is the first to empirically gauge the relationship between bank lending specialization and bank performance and stability.

Lending concentration by banks has two opposing effects on banks' risk-taking incentives and hence on their stability. On the one hand, the traditional portfolio theory view posits that diversification largely eliminates the impact of idiosyncratic shocks on banks' loan portfolio. On the other hand, lending specialization can also result in better screening of potential borrowers and loan applications and more efficient monitoring, hence leading to lower default risk and higher (risk-adjusted) returns. Focused banks will gain expertise in the sectors they lend to, and hence can detect a deterioration of the borrower's business earlier and may react in a timely manner by risk mitigation (for example, by requesting additional collateral). Moreover, a credible threat of better monitoring skills might also prevent risk-shifting by borrowers, as in Stiglitz and Weiss (1981). However, lending concentration or diversification not only affects bank-specific risk, but also the stability of the entire sector. In particular, from a systemic point of view, a third channel may play an important role. In countries where the scope for lending diversification is limited, banks' loan portfolios will be more similar to each other, leading to a more homogeneous financial system. Furthermore, even when diversification is feasible, banks may have incentives to herd, thus causing a lack of diversity. This lack of diversity is potentially more costly for society as it implies that similar institutions will more likely face problems at the same time. On the other hand, recent work has pointed to risks from diversification, if all financial institutions diversify into the same portfolio (Wagner (2010)).

We gauge the relationship between lending specialization and bank performance and stability with two novel data sets. First, we rely on stock return-based indicators of sectoral factor exposures. Using an extended market model, we test whether banks are well diversified and are only exposed to the returns on a broad market index, or whether they additionally exhibit significant exposures to certain sector-specific portfolios. 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 (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)). Second, we also construct a hand-collected database on the sectoral exposures of the largest banks based on the information they report in the notes to their financial statements. 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 317 banks over the period 2007-2011. Both the return-based and accounting-based sectoral exposures are then used to compute several lending specialization indicators, such as focus of the portfolio (standard deviation or HHI of the exposures) or herding with other banks (Euclidean distance measure).

Our main findings are that sectoral specialization ia positively related to bank risk, while not being associated with higher returns. Moreover, it is associated with higher systemic risk exposures as well as increases in total volatility. Hence, it seems that the portfolio diversification gains outweigh the potential benefits of screening and monitoring efficiency in specialized lending. Furthermore, we find that dissimilarity with respect to other banks is also associated with higher risk along all dimensions, in contrast with the theoretical predictions. The results are similar using either the return-based or hand-collected sectoral exposure indicators, notwithstanding differences in sample period (2002-2011 versus 2007-2011), sample size (2030 versus 317 banks) and methodology (bank fixed effects or not).

Sample splits show that our findings hold for the whole sample period, but are stronger for the post-2007 crisis period. A major advantage of our database compared to related studies is its international dimension, which allows examining cross-country differences in the lending specialization-performance relationship. We document that the relationships between sectoral specialization, valuation, volatility and systemic risk contribution are driven by developed countries and countries with no regulatory requirements on diversification, banks operating in more competitive markets and banks focusing on traditional intermediation business. These findings suggest that the regulatory response to our findings cannot be "one size fits all", but rather has to be tailored to bank and country circumstances.

The relationship between lending concentration and bank performance and stability is not only interesting for academics but has been central to policy and regulatory discussions. Historical experience shows that concentration of credit risk in asset portfolios has been one of the major causes of bank distress (e.g. by being overexposed to Enron, Worldcom and the likes). According to a 2004 Basel committee study, credit concentration caused nine of the 13 major banking system crises around the world in the twentieth century, resulting in calls for a revised regulatory approach to sectoral concentration to overcome one of the main shortcomings of the first Basel Accord (i.e. ignoring the potential consequences of this specialization within banks' credit portfolios). Consequently, the second Basel agreement incorporated adjustments regarding the impact of bank lending specialization, though only in the second pillar on the supervisory review process rather than in the first pillar of capital requirements. In "Basel 2.5"[1] and Basel III, there have been no major adjustments regarding concentration risk.

Our paper is related to the literature on lending concentration. Concentration risk could stem from either

[1]"Basel 2.5" is the intermediate change in capital requirements that came into force on December 31, 2011 (e.g. by means of the second and third Capital Requirement Directive in the EU).

imperfect granularity (i.e. exposure to large single names) or imperfect sectoral diversification. Both lead to deviations from the asymptotic single risk factor framework. Empirical evidence for developed countries indicates that the impact on economic capital is larger for sectoral concentration than for name concentration. Using German data (but with a hint that the conclusions are generalizable to other continental European banks), 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. However, there is also theoretical and empirical evidence that shows how lending specialization may be beneficial and reduce risk or increase (risk-adjusted) returns. Winton (2000) shows theoretically that it is likely that the bank's monitoring effectiveness is lower in new sectors, with the effect that diversification lowers average returns on monitored loans, as banks are less likely to improve monitoring incentives, and is more likely to increase the bank's chance of failure. The aforementioned effects theoretically imply a reduction in the probability of default. Empirical evidence by Acharya et al. (2006) for Italy and by Hayden et al. (2007) for Germany documents that specialization in certain industries is indeed 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. 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 lending specialization and bank performance and risk, which also allows testing for cross-country variation in the relationship. While other studies have focussed on banks' diversification in interest and non-interest business, we use unique and novel data to shed light on lending specialization.[2]

[2]See De Jonghe (2010), Demirguc-Kunt and Huizinga (2010) and Stiroh and Rumble (2006), among others, for studies on interest vs. non-interest business of banks.

The remainder of the paper is structured as follows. The next section introduces our sample and unique (hand-collected) data. In Section 3, we outline the methodology and describe the estimated impact of two different sets of specialization measures on bank performance. In Section 4, we exploit the multiple country dimension of the database and examine whether the impact of lending specialization on performance is conditional on certain country-specific or bank-specific characteristics. Section 5 concludes the paper with policy implications and avenues for further research.

2 Data

In the analysis, 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, delisted as well as 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 $12,689$ observations, on $2,005$ banks from 77 countries over the period $2002-2011$. We include commercial banks, bank holding companies, as well as saving banks and cooperatives.

Our independent variables of interest are several proxies of the degree of sectoral specialization of a bank's loan portfolio. These data are not directly available from (commercial) databases for a cross-country sample of banks.[3] Therefore, we take a two-pronged approach. First of all, we rely on return-

[3] Authors of studies on lending concentration have either used confidential data gathered by the central bank's credit register (for single country studies) 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 instutions (which are mainly located in the US). Moreover, the exposures are

based indicators of sectoral factor exposures (subsection 2.1). Secondly, we construct a hand-collected database of the sectoral exposures reported by the largest banks in the notes to their financial statements. The procedure to hand-collect the accounting-based sectoral shares will be exposed in subsection 2.2. To gauge the relationship between sectoral specialization and bank performance, we use various dimensions of bank risk and return. The construction of these dependent variables is described in subsection 2.3. The correlations between both types of sectoral specialization measures as well as their relationship with bank performance measures are described in subsection 2.4.

2.1 A stock return-based approach to measuring banks' sectoral exposures and lending specialization

A bank's stock price is influenced by exposures to systematic risk as well as idiosyncratic news. If a bank holds a well-diversified loan portfolio, then its stock return should mainly co-move with returns on a broad market-wide index. On the other hand, if a bank's loan 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 test whether banks are well diversified and are only exposed to the market index, or whether they additionally exhibit significant exposures to certain sector-specific portfolios (and hence violate the assumption underlying the asymptotic single risk factor framework). 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 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 (2013) to infer European banks' sovereign risk exposure from asset prices. They relate banks' stock returns to yields on German government debt and

then limited to the syndicated loans, which may not be representative for the overall portfolio of commercial and industrial loans.

yields on GIIPS countries' debt, to obtain market-based indicators of banks' exposures to sovereign risk.

In particular, we estimate the following equation for each bank:

$$r_{i,t} = c + \beta r_t^M + \sum_{s=1}^{S} \beta^s r_t^s + \varepsilon_t^i \tag{1}$$

We regress a bank's stock return ($r_{i,t}$) on the returns on a broad market index (r_t^M) as well as on the return to S (=10) different sectoral indices (r_t^s). 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 10 industries: oil & 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 news), we first orthogonalize each of the r_t^s series with respect to market-wide returns (r_t^M) and the financial sector returns.[4] Doing so, we clean the sectoral returns from market-wide news as well as their dependence on financial sector (shocks). Subsequently, we standardize the orthogonalized exposures, which facilitates comparing the exposures to different industries. The estimated β^s coefficients then reflect both the exposure to as well as the riskiness (volatility) of the sectoral shocks. The residual, ε_t^i, captures the idiosyncratic or bank-specific news component. We estimate Equation (1) for each bank and for each year using daily returns, such that we end up with a panel database on sectoral exposures that varies at the bank-year frequency. The panel dataset of estimated exposures consists of $12,689$ bank-year observations, covering $2,005$ banks from 77 countries over a ten year period starting in 2002. 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. Information on the estimated exposures is reported in Table 1.

<Insert Table 1 around here>

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

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 loan 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).

Panel A of Table 1 reports for each estimated factor loading the mean and standard deviation across $12,689$ observations, as well as the 5^{th}, 50^{th}, and 95^{th} percentile of the panel of estimated factor loadings. In panel B, we report for each factor the relative frequency of observing t-statistics in five groups. We consider both conventional significance levels (95%, absolute value of t-statistic above 1.645) as well as a weaker threshold (absolute value of t-statistic in excess of one) to account for the fact that the exposures are estimated over relatively short windows (one year) of daily return data (which can be noisy) and have been orthogonalized (hence estimation error) in a previous step. As illustrated in Panel A, the average and median exposure is close to zero for all but two sectors (i.e. utilities and financials). This indicates that the stock market believes that banks are, on average, not exposed to shocks to these sectors. Unsurprisingly, the exposure to the financial sector is larger and it is more likely that the t-statistic with the associated exposure will exceed 1 or even 1.645 (for 22% of the banks). As indicated in Panel B, for each of the sectoral factor loadings, we find substantial heterogeneity across bank-year pairs and many of these sector exposures are often statistically significant. Specifically, the share of significant t-statistics (at the 5% level) ranges from 15% in the oil&gas and industrial sectors to 28% in the financial sector.

Based on the estimated coefficients of Equation (1), we compute several time-varying bank-specific measures of the intensity of sectoral specialization. More specifically, for each bank and for each year, we calculate the following measures. First, we count the number of sectoral exposures with a t-statistic (in absolute value) larger than one, thus ranging from zero to ten. We label this measure: *Significant Sectoral Factors*. Second, we compute the contribution, of the sectoral factors (excluding the contribution of the financial sector) to the R-squared of the return-generating model (*Sectoral Contribution to* R^2). A larger value indicates a larger exposure to sector-specific news that is not created by economy-wide or financial events. The first two indicators also indicate the extent to which the asymptotic single risk factor assumption is valid for a given bank in a given year. Third, we construct the measure labelled *Dispersion (factors)* which captures the dispersion in the estimated sectoral exposures (standard deviation in the ten β^s coefficients). Fourth, we compute a measure of differentiation (or its opposite: similarity or herding) by banks within a country. For each bank, we compute the Euclidean distance between a bank's estimated sectoral exposures and the country-average (excluding that bank) of the sectoral exposures. The Euclidean distance is computed as follows:

$$Dis\tan ce_{i,j,t} = \sqrt{\sum_{s=1}^{S}\left(\beta^s_{i,j,t} - \frac{1}{I_j}\sum_{i=A}^{I_j}\beta^s_{i,j,t}\right)^2} \tag{2}$$

where I_j is the number of banks in country j. The measure, labelled *Differentiation (factors)*, will be larger the more the bank's sectoral exposures deviate from the average bank in the country. A similar measure has also been used by Cai et al. (2013) to measure bank herding based on syndicated loan exposures.

We report summary statistics on these measures in panel C of Table 1. We find that the average bank has four significant sectoral factor loadings in a given year, that differ substantially from each other (as indicated by the specialization measures) and which lead to a substantial increase in R-square of 7.6% compared to a model that only includes the market factor which has an average R-square of 9% (the financial sector contributes an additional 1%). The average dispersion is 31% and the average bank's differentiation from the country-average is 1.5 factors. More importantly, all measures exhibit substantial variation, which will enable us to assess how these measures are related with our proxies for bank performance and stability.

2.2 Constructing a hand-collected database of reported sectoral exposures

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.[5] 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 and syndicated loan exposures. The former is, however, confidential, only available for few countries and does not allow cross-country comparisons. The latter is limited to very large loans by very large banks. Nevertheless, many banks provide information on their sectoral exposures in the notes to their financial statements.

The 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 hand-collect information on these exposures according to the following procedure. 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. We focus on large, listed banks as these are more likely to publish a detailed report on their website. However, this is not 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 (317 from the 435 banks). To harmonize the heterogeneity in

[5] 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 analyse herding by institutional investors their buy and sell signals.

the sectoral breakdown across banks, we categorize each reported exposure in ten economic sectors based on the one-digit Standard Industrial Classification. Personal/consumer loans, loans to central governments and interbank loans were excluded. 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’).

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 A of Table 2. For each sector, we report the mean, standard deviation, 5^{th}, 50^{th}, and 95^{th} percentile. There is variation in the average exposure across the ten sectors, with the lowest average for the sector “Agriculture, forestry and fishing” and the largest one for “manufacturing”. Within each sector, there is substantial heterogeneity. The value of the 5^{th} percentile is almost always zero, whereas the exposure to manufacturing for the bank at the 95^{th} percentile is 37%.

<Insert Table 2 around here>

Based on these hand-collected exposures, we construct indicators of industrial specialization in lending by banks. These measures are reported in Panel B of Table 2. In particular, we capture various aspects of lending specialization by (i) the dispersion in the reported sectoral exposures (standard deviation of the ten shares), labelled *Dispersion (accounting)*, (ii) the cumulative share of the three largest sectoral exposures (*Sectoral CR3*), (iii) a Hirschmann-Herfindahl index (*Sectoral HHI*) of industrial specialization[6] , and (iv) a proxy for the amount of differentiation (herding) in sectoral exposures at the country level. This measure, *Differentiation (accounting)*, is computed as the Euclidean distance between a bank’s sectoral loan portfolio

[6]The HHI is measured as the sum of the squared sectoral shares. A higher value of the HHI indicates more concentration or inequality. We also compute modified version of the HHI in which we exclude the “Others” category, as this might range from nearly granular to a single exposure. The results are similar for both measures.

and the average bank's sectoral composition (as in Equation 2, but replacing the estimated factors with reported shares). The more similar the exposures, the lower the value of the measure and the higher the exposure to common shocks.

The summary statistics of these measures in Panel B of Table 2 indicate that there is considerable heterogeneity across banks. Specifically, the standard deviation of sectoral exposures, *Dispersion (accounting)*, varies largely with a value of 0.068 at the 5^{th} percentile and a value of 0.184 at the 95^{th} percentile (with a mean of 0.113). The cumulative exposure of the largest three sectors varies from 53% (5th percentile) to 96% (95th percentile), with a mean of 70%. The HHI concentration ratio has an average of 0.227 and a standard deviation of 0.088. Finally, *Differentiation* (accounting) also exhibits substantial cross-sectional variation. The Euclidean distance between a bank's exposure and the country's average exposure ranges from 0.09 to 0.55 (5^{th} and 95^{th} percentile), with a mean of 0.26.

2.3 Measures of bank performance and stability

Using stock return-based measures, we gauge several aspect of bank performance.[7] In particular, we will look at bank valuation, bank risk as well as exposure to systemic risk. More specifically, we will employ the following dependent variables in our analysis. First, bank performance is gauged by the annualized average daily *return* over a calendar year, thus measuring profitability for shareholders. Second, *volatility*, measured as the annualized standard deviation of a bank's daily stock returns over the span of a calendar year, captures

[7] 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) adn 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)).

a bank's total risk exposure. Third, to capture the return-risk trade-off in one metric, we will also 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. (2012)). Mathematically, the MES of bank i at time t is given by the following formula:

$$MES_{i,t}(Q) = E[r_{i,t}|r_{m,t} < VaR^{Q}_{m,t}] \tag{3}$$

where $r_{i,t}$ denotes the daily stock return of bank i at time t, $r_{m,t}$ the return on a stock index at time t and Q is an extreme percentile, such that we look at systemic events. Following common practice in the literature, we compute MES using the opposite of the returns such that a higher MES means a larger systemic risk exposure. In this paper, we measure MES for each bank-year combination and follow common practice by setting Q at 5%. Doing so, $MES_{i,t}$ corresponds with bank i's expected equity loss per dollar in year t conditional on the market experiencing one of its 5% lowest returns in that given year. Conceptually, MES measures the increase in the risk of the system induced by a marginal increase in the weight of bank i in the system.[8] The higher a bank's MES (in absolute value), the higher is the contribution of bank i to the risk of the banking system. We define the banking system as the local, country-specific banking market. In addition, the bank for which we compute the MES is excluded from the banking sector index.[9]

<Insert Table 3 around here>

Summary statistics on these variables are reported in Table 3. The upper panel contains the summary statistics for the full sample. The lower panel reports the summary statistics on the smaller sample of banks

[8]The Expected Shortfall of the market portfolio is given by: $\sum_{i=1}^{N} w_{i,t} E\left[r_{i,t} \middle| r_{m,t} < VaR^{Q}_{m,t}\right]$ and is hence equal to the weighted sum of the MES of all banks in the system. The first derivative of the Expected Shortfall of the market portfolio with respect to $w_{i,t}$ equals the MES of bank i at time t.

[9]We also compute the MES when the global, rahter than 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.

(and shorter period) for which we hand-collect the sectoral exposures. Information on the countries included in the sample as well as the number of bank-year observations by country is reported in Appendix A. Over our larger sample over the period 2002 to 2011, the annualized average stock return was -0.29%, with a volatility of 39.3%. Both variables, however, show a large variation across banks and years. The market-to-bank value of equity shows an average of 1.11, but ranges from 0.01 to 3.10. The average MES with respect to the local market is 2.00. The dependent variables in the smaller and shorter (post-)crisis sample (2007 to 2011) show, on average, worse performance, higher volatility, lower market-to-book value (below one!) and a higher MES. The descriptive statistics in Panel B show a much lower average return of -5.83%, reflecting that the sample period of the smaller sample is dominated by the crisis, a similar average volatility of 42.2%, a low average franchise value of only 0.58 and a MES of 3.94, reflecting the fact that our smaller sample is dominated by large banks.

2.4 Relating performance to specialization: Exploring pairwise correlations

In the three previous subsections, we introduced the performance metrics as well as two sets of sectoral specialization indicators, respectively based on return-based sectoral factor exposures and accounting-based sectoral lending shares. In this subsection, we present a first exploration of the relationship between these variables by means of pairwise correlations. We repeat, for convenience, the definitions of the above-mentioned measures in Table 4.

<Insert Table 4 around here>

Table 5 contains three panels of correlation matrices. In the upper panel A, we report the correlation coefficients among and between the performance measures and the sectoral specialization measures based on factor loadings (large sample). In the middle panel B, we report the correlation coefficients among and between the performance measures and the sectoral specialization measures based on accounting exposures (small sample). In panel C, we report the correlation coefficients among and between all sectoral specialization measures (for the small sample). The number-letter combination in the column headers (which differ by panel) correspond with a variable in the rows. In each panel the correlation coefficient as well as the p-value are reported.

<Insert Table 5 around here>

Focussing first on the pairwise correlations between factor-based specialization measures and bank performance, we find that *Dispersion* and *Differentiation* correlate negatively with average stock returns and positively with total volatility. *Sectoral Contribution to* R^2 correlates negatively and significantly with returns, while *Sectoral Factors* correlates positively and significantly with volatility. The franchise value (market value or net worth scaled by book value of equity) is a market-based risk-adjusted return indicator. The negative (positive) relation of sectoral specialization and average return (volatility) translates into a negative relationship between sectoral specialization, as measured by *Sectoral Contribution to* R^2, *Dispersion* and *Differentation* and the franchise value. Finally, significant sectoral exposures, dispersion and differentiation are all correlated with a higher exposure to systemic risk, as measured by the marginal expected shortfall. All pairwise correlation coefficients between the four return-based sectoral specialization measures are positive (except one) and significant. However, the correlation is far from perfect, indicating that the information content of each of these measures is slightly different.

The correlation coefficients in the middle panel B indicate that the accounting-based lending dispersion, concentration or differentiation measures are also positively and significantly correlated with total volatility and MES, even though the data source is different, the sample period is shorter and the set of banks is smaller. None of the specialization measures is significantly correlated with average return. In contrast to panel A, we find in panel B that the franchise value is positively correlated with lending specialization. Note that this opposite result is most likely caused by the franchise value measure. The signs of the correlation between the franchise value and each of the three other performance metrics is also reversed in panel B compared to panel A (while the sign of the correlation coefficients between these three is the same in both panels). We conjecture that this is driven by the fact that the smaller sample is driven by the crisis experience. Furthermore, each of the four accounting-based specialization measures is positively and significantly related with one another. The correlation coefficients for the first three indicators (dispersion, sectoral CR3 and sectoral HHI) are high and above 85%. Only the accounting differentiation measure seems to capture a somewhat different aspect.

Finally, in the lower panel C of Table 5, we report the pairwise correlation coefficients between all the specialization indicators. While the correlation is almost always strongly positive and significant within a group, it is low and mostly insignificant across both groups. The market-based measures *Significant Sectoral Factors* and *Dispersion (factors)* are uncorrelated with each of the four accounting measures. The measures *Differentiation (factors)* is positively and significantly related with three accounting-based lending specialization measures. In contrast, the *Sectoral Contribution to* R^2 is negatively and significantly related to three accounting-based sectoral specialization measures. This suggests that the market-based and accounting-based measures capture different dimensions of lending specialization, as we already alluded to above. The market-based measures have the advantage that they can also capture exposures of banks through market and hedging operations in addition to asset-based exposures. On the other hand, these measures might include noise if stock market participants are not able to make an accurate assessment. The accounting-based measures are direct indicators of loan portfolio exposures, but do not capture hedging operations that banks might be able to undertake. Recognizing the differences between these two approaches, we gauge the relationship between sectoral specialization and bank performance across these two different groups of indicators and samples.

3 Results

The contribution of this paper is to assess how lending specialization affects bank performance. To that end, we will relate both the return-based and the accounting-based measures of sectoral specialization to the variables that capture the various dimensions of bank performance, while controlling for other bank characteristics that may affect bank performance. More specifically, we will estimate regressions of the following form:

$$Performance_{i,t} = \beta_1 \cdot Specialization_{i,t-1} + X_{i,t-1}\beta_{controls} + u_i + v_t + \varepsilon_{i,t} \tag{4}$$

The independent variables are lagged one year to mitigate concerns of reverse causality. We winsorize all variables at the 1 and 99 percentile level to mitigate the impact of outliers. Next to the set of control variables, discussed below, we also include year fixed effects as well as bank fixed effects. The standard errors are clustered at the bank level. Before gauging the relationship between sectoral specialization and bank performance, we will first present the results of a regression of each dependent variable on the set of control variables only (i.e. without a specialization measure). This serves two purposes. First, it further describes the data and facilitates comparability with other papers. Second, in a subsequent subsection, we will add the various sectoral specialization indicators one-by-one and will for the sake of space omit the reporting of the results on the control variables.

3.1 Initial regressions: Leveling the playing field

In Table 6, we show the results of regressing each dimension of bank performance on the set of control variables. The control variables, of which the summary statistics are reported in Table 3, capture various dimensions of a bank's business model that might influence performance and stability. First of all, we include bank size and non-interest income. The former is computed as the natural logarithm of total assets expressed in 2007 US dollars.[10] We measure a bank's share of non-interest income to total operating income, by dividing other operating income (which comprises trading income, commissions and fees as well as all

[10]While most of the bank-specific variables are ratios, variables in levels (such as size) are expressed in 2007 US dollars (millions). Furthermore, bank size is highly correlated with many other bank characteristics, affecting the point estimates and the magnitude of the standard errors. We therefore orthogonalize bank size with respect to all other control variables.

other non-interest income) by the sum of interest income and other operating income. The other bank-specific variables are proxies for leverage (capital-to-asset ratio), the funding structure (share of deposits in sum of deposits and money market funding)[11], asset mix (loans to assets ratio), profitability (return-on-equity), annual growth in total assets as well as expected credit risk (Loan Loss Provision to Total Assets). These variables are often used in other studies that gauge the performance and stability of banks, including Demirguc-Kunt and Huizinga (2010), Laeven and Levine (2009) or Beck et al. (2013).

<Insert Table 6 around here>

In the left hand side part of Table 6, we report the regression results of the full sample, that will be used when analyzing the impact of the factor-based specialization measures. We find that larger banks have lower returns on average but also less volatile returns, have lower market-to-book values, and higher MES. Similarly, banks with higher non-interest income shares have lower but also less volatile returns, have lower market-to-book values, and higher MES, although the last two results are not significant. Better capitalized banks have higher returns, higher market-to-book values and lower MES, while the relationship with volatility is not significant. Banks with higher loan-to-asset ratios have higher average but also more volatile returns, have higher market-to-book values and lower MES. Banks with higher returns on equity in the previous period have lower average but also less volatile returns, have lower market-to-book values and higher MES. Banks with higher asset growth in the previous period experience higher returns and higher market-to-book values. Banks with higher loan loss provisions, finally, have lower average returns, lower market-to-book values and higher MES. The R^2 vary substantially across the four regressions, with our control variables explaining the highest share of variation in the market-to-book value regression (76.8%), while they only explain 34% in the average return regression. The reported findings are, in general, as

[11] Using several proxies for access to deposits and the use of bank deposits, Han and Melecky (2013) find that greater access to bank deposits can make the deposit funding base of banks more resilient in times of financial stress and will hence also affect bank performance and banks' exposure to systemic risk.

expected and in line with other studies.

In the right hand side part of Table 6, we report the regression results for the smaller sample and shorter (crisis and post-crisis) period. The results are mostly different, except for total volatility. Recall that the sample now only spans five years, of which a large part is dominated by the global financial crisis. Moreover, the combination of a short sample period and bank fixed effects gives less power to solely rely on the within variation to identify significant relationships. This is also apparent from the fact that the R^2 stays high (due to the bank and year fixed effects), irrespective of the lack of significant bank-specific characteristics. Hence, irrespective of the quality of the return-based versus accounting-based measures, it will be harder to identify significant relationships for the latter compared to the former, given the shorter and smaller sample.

3.2 Lending specialization and bank performance

To gauge the relationship between lending specialization and bank performance and fragility, we add each of the four return-based sectoral specialization indicators, discussed above, one-by-one to the regression setup reported in the previous subsection. This results in 16 different specifications. We summarize the results in Table 7, reporting only the information of interest. More specifically, for each regression, we only report the coefficient and t-statistic on the return-based sectoral specialization indicator as well as the number of observations and the adjusted R^2 of the regression. In each regression, we add the control variables and bank and year fixed effects as in Table 6. The standard errors are clustered at the bank level. The table is constructed so that each of the four sectoral specialization indicators is reported in a different column. The dependent variable varies by block of rows.

<Insert Table 7 around here>

We do not find any significant relationship between annualized average returns and lending specialization of banks. In all four regressions with returns as dependent variable is the standard error of the lending specialization variable higher than the coefficient, leading to t-statistics well below one (in absolute value).

Specializing in specific sectors is therefore not reflected in stock returns. There is a significant relationship between the volatility of stock returns and lending specialization, as indicated in the second block of results. Specifically, banks whose returns react more to sectoral indices (i.e. where sectoral factors contribute more to the R^2), for which we find a higher dispersion of sectoral betas in the return regression, and which show a higher factor-based differentiation (i.e. Euclidian distance from the country's average exposure) have more volatile stock returns. Lending specialization is thus associated with higher stock volatility. There is a significant, negative relationship between banks' market-to-book values and lending specialization, as documented in the third row of results. Specifically, banks with a higher number of significant sectoral betas, whose returns react more to sectoral indices (i.e. where sectoral factors contribute more to the R^2), for which we find a higher dispersion of sectoral betas in the return regression, and which show a higher Euclidian distance from the country's average exposure have lower market-to-book values. Lending specialization thus seems to undermine market value.

Finally, we find a significant relationship between the MES and our different measures of lending specialization. Specifically, banks with more specialized lending portfolios according to our four indices have a higher MES, thus contribute more to systemic fragility than other banks. In contrast to the theoretical predictions, we find that differentiation (a larger distance, hence less herding) leads to more realized tail risk, a more volatile stock and a lower market-to-book value. One potential explanation for this finding is in the information content of this specific application of the distance measure. It measures the extent to which the estimated sectoral factor exposures differ from the average of the estimated factor exposures in the country. It misses hence a large part of herding or similarity to common shocks (which will be in the exposure to the market factor). In addition, finding that more similar exposures lead to lower risk might already reflect the idea the government will be more likely to step in if the likelihood of multiple banks facing distress is higher (Acharya and Yorulmazer (2007)).

The economic significance of our findings varies across the different regressions. A standard deviation in the three significant sectoral specialization indicators is associated with a three to 16% increase in the standard deviation of total volatility. A standard deviation in the four sectoral specialization indicators is associated with one to seven percent decrease in the standard deviation of the franchise value. Finally, a standard deviation in the four sectoral specialization indicators is associated with a one to 18% increase in the standard deviation of MES.

Table 8 reports the results for the lending specialization indicators based on the hand-collected reported exposures and are organized in a similar fashion as Table 6. We add each of the four accounting-based sectoral specialization indicators (as specified in Subsection 2.2) one-by-one to the regression setup reported in the introduction to Section 3, resulting in 16 different specifications. Unlike in Table 6, we no longer include bank fixed effects due to the very limited within variation in each of the lending specialization indicators.

<Insert Table 8 around here>

Our results show no significant relationship between lending specialization and average annualized returns, which is consistent with the pairwise correlation results (see panel B of Table 5) and the results in Table 7. None of the four lending specialization variables enters significantly at conventional levels. Lending specialization is thus not reflected in stock returns. We find a significant relationship between three out of four lending specialization indicators and the volatility of stock returns. Specifically, banks with a higher dispersion and a higher concentration of sectoral portfolio shares, as measured both by the CR3 and the HHI, show a higher volatility of stock returns. On the other hand, we do not find any significant relationship between lending specialization and market-to-book values of banks. Banks with sectorally more specialized lending portfolios are thus not traded with a discount. Hence, the results in the pairwise correlation table (panel B of Table 5) might have been spurious and disappear after properly controlling for other factors that affect the franchise value. Finally, accounting-based sectoral specialization is significantly and positively related to MES in both a regression and pairwise correlation framework.

In summary, both total volatility and the systemic risk exposures are higher for banks with a more specialized (less diversified) sectoral business loan portfolio. The results for our herding measure are, as with the market-based similarity measures, opposite (whenever significant) to the theoretical predictions. The more the bank's sectoral loan portfolio differs from the average bank in the country the riskier the bank is perceived to be. Our results are based on a very broad cross-section of countries and banks, especially the large sample with return-based exposure data. Pooling these banks and countries and testing for a linear relationship between banks' sectoral specialization and their performance might mask significant variation across banks, across countries and over time. We will explore such variation in the next section.

4 Lending Specialization and Bank Performance: Cross-country Heterogeneity

To the best of our knowledge, we are the first to examine lending concentration using an international sample of banks. Most previous studies relied on proprietary data from a central bank and were hence restricted to one country. This feature of the sample creates the opportunity to directly examine how the impact of lending specialization on bank performance varies with bank and country characteristics. Moreover, we will also exploit that our return-based sample covers a long time period (of ten years) including the global financial crisis. In particular, we will examine whether the relationships are different in (i) the pre-crisis versus (post-)crisis period, (ii) developed versus developing countries and (iii) countries with and without explicit guidelines on bank asset diversification, (iv) banks above and below the median size, (v) banks above and below the median Lerner index of market power, (vi) banks below and above the loan-asset ratio, and (vii) banks below and above the median of non-interest income share, where the last two are indicators of the extent to which banks engage in traditional intermediation business.

More specifically, we will estimate equations of the following form:

$$
\begin{aligned}
Performance_{i,t} = \; & \beta_1^{below} \cdot Specialization_{i,t-1} \cdot I(Y < Y^{median}) + \\
& \beta_1^{above} \cdot Specialization_{i,t-1} \cdot I(Y \geq Y^{median}) + \\
& X_{i,t-1}\beta_{controls} + u_i + v_t + \varepsilon_{i,t}
\end{aligned} \tag{5}
$$

In order to exploit sufficient cross-country and cross-time variation, we use our larger and longer sample to explore whether the relationship between lending specialization and performance of banks varies depending on the characteristics Y. Specifically, we interact the (factor-based) lending specialization indicators with two dummy variables that split the sample according to characteristic Y. Results are reported in Table 9. We focus on two specific measures of performance – the market-to-book value (panel A) and the Marginal Expected Shortfall (panel B). As before, we only report the information of interest, i.e. the coefficient of each of the two sub-groups and their t-statistics, as well as the number of observations, the R^2 and the p-value of a test whether $\beta_1^{below} = \beta_1^{above}$. To facilitate the comparison with the previous results, we reproduce, in the first column, the results without the sample split.

First, we split the sample into the period before and after the on-set of the Global Financial Crisis. The relationship between lending specialization and bank performance might vary between the pre- and the crisis periods for two reasons. First, different monetary regimes may affect the amount and quality of loans outstanding. The pre-crisis era is characterized by cheap credit, massive loan growth and a riskier pool of borrowers (Buncic and Melecky (2013)). During and after the crisis, banks have been applying stricter lending standards. Second, after the meltdown of 2007/8, the stock market might perceive lending specialization differently, incorporating the lessons from the crisis. We therefore test whether the relationship between the market-to-book value and the different measures of lending specialization varies across the periods 2002 to 2006 and 2007 to 2011. We find that in most cases, the negative relationship between lending specialization and market-to-book values is more pronounced for the crisis period than for the pre-crisis period. Specifically, the number of *Significant Sectoral Factors* and *Differentiation* from other banks enter negatively and significantly only for the crisis period, but not for the pre-crisis period. The *Dispersion* of sectoral factor exposures enters significantly for both periods but with a larger coefficient estimate for the crisis period. Only in the case of the *Sectoral Contribution to* R^2 does the pre-crisis interaction enter significantly and with a larger coefficient than the crisis-interaction. Overall, the negative relationship between the risk-adjusted returns of banks and lending specialization seems to be stronger for the (post-)crisis than the pre-crisis period.

The results in panel B of Table 9 show that the positive relationship between the MES and lending specialization is in most cases more pronounced for the post-crisis than the pre-crisis period. Specifically, the number of *Significant Sectoral Factors,* the *Sectoral Contribution to* R^2 and the *Dispersion* enter with substantially larger coefficients for the crisis than for the pre-crisis period. The number of *Significant Sectoral Factors* enters even negatively and significantly for the pre-crisis period. Only in the case of sectoral *Differentiation* from the country-average does the pre-crisis coefficient enter with a larger coefficient than the crisis-interaction. Overall, this suggests that while our results are not driven by the crisis period, they are more pronounced for this period. Since the start of the global financial crisis, lending specialization and the resulting exposures to certain sectors is perceived to be more detrimental for both value as well as exposure to systemic risk.

The second sample split is based on GDP per capita. As documented by Imbs and Wacziarg (2003), sectoral specialization varies across countries at different income levels, with important repercussions for sectoral specialization by the financial system.[12] Economically less developed economies feature a higher

[12]In addition, lending concentration may also be more prevalent in emerging market economies due to different ownership structures compared to Anglo-Saxon countries. In the latter, firms in general have dispersed shareholders and own other firms (if any) via subsidiaries. In emerging market economies, on the other hand, firms are often held in groups with complicated ownership structures. La Porta et al. (1999) document that approximately 25 percent of the firms in a sample of rich countries are members of pyramids. Lins (2003) reports statistics for 18 emerging markets and reports that 66% of the firms for which the management group is the largest blockholder of the control rights of a firm use pyramids to increase their control rights.

degree of specialization, which might make sectoral specialization of banks more of a necessity and less damaging for systemic stability.[13] On the other hand, the positive effect of lending specialization on bank performance might be more pronounced at higher levels of economic development, where banks have the necessary expertise and institutional background to exploit such economies of scale. We therefore split our sample into countries below and above the median GDP per capita (Slovak Republic in 2005, with a value of 6775 for GDP per capita (constant 2000 US$)). Lending specialization is penalized more strongly in countries with high GDP per capita, both in terms of franchise value and MES. The impact of sectoral factor specialization on the market-to-book value (MES) is more negative (positive) in developed versus developing countries, for each of the four market-based sectoral specialization measures. In fact, in developing countries, there is often an insignificant or even a positive (negative) and significant effect of specialization on market-to-book-value (MES). The negative effects of banks' sectoral specialization on performance and contribution to systemic risk are therefore stronger in more developed countries, outweighing any benefits that might arise from loan specialization. On the other hand, there is only limited evidence of negative effects of sectoral specialization for banks in developing countries, a finding that has important implications for the regulatory reform debate on the global level.

In column (3), we split the sample according to whether banks in a country are subject to specific regulatory guidelines regarding asset diversification. On the one hand, such guidelines might mitigate the negative impact of specialization by forcing diversification along other dimensions, including geographical. On the other hand, such diversification rules might be the result of a sectorally very specialized banking sector. The information is taken from the World Bank questionnaire on Bank Regulation and Supervision (Cihak et al. (2012) and Barth et al. (2013)), which asks: "Are there any regulatory rules or supervisory guidelines regarding asset diversification?". Countries with no such guidelines are in the below group,

[13]On the other hand, Brown (2013) shows that household income reductions due to banking crisis are more significant in the middle-income countries than in the high-income countries, and are mostly due to the labour market channel.

whereas countries that answer 'YES' to the question are in the above (median) group. In our sample, the number of countries having such rules or guidelines varies over time. In the early years 50% of the countries had guidelines, whereas to the end of the sample period approximately 66% of the countries in our sample have guidelines. Regarding the franchise value, we find that lending specialization (each of the four measures) leads to a lower market-to-book ratio in countries with no explicit rules or guidelines on asset diversification. In contrast, in countries that do have such guidelines, we find a significantly positive or insignificant effect. Similarly, regarding the exposure to systemic risk, we also find that the impact is much more positive in countries without rules or guidelines. This result could indicate that stock market investors trust lending and sectoral specialization more whenever there are regulatory rules or there is a supervisor monitoring the exposure limits. In the absence of such rules or supervisory oversight, stock market investors seem to put more faith in the risk diversification gains rather than the specialization skills in screening and monitoring.

In column (4), we split the sample according to bank size, with the median bank size being $4,023$ million US$ (ln(TA)=8.30). On the one hand, larger banks might be better able to exploit economies of scale as well as benefits of risk management and diversification, so that the overall effect of sectoral specialization might be lower. On the other hand, smaller banks might be forced to specialize in niche markets and might adopt the necessary risk management tools to do so. The results in Panel A results suggest that the effect of sectoral specialization on banks' franchise value is not significantly different for large and small banks. The coefficient estimates of *Sectoral Contribution to* R^2, *Dispersion* and *Differentiation* enter negatively and significantly. While the coefficient estimates are larger for smaller banks, the difference to the coefficient estimates for large banks is not significant in any of the regressions. The results in Panel B suggest that specialization by large banks has in three out of four cases a larger effect on MES than specialization by small banks. With the exception of *Sectoral Contribution to* R^2, the coefficient estimate for large banks enters with a significantly larger positive coefficient than for small banks. This suggest that if larger banks specialize into specific sectors, this has more systemic repercussions.

In column (5) we split the sample according to banks' market power, as gauged by the Lerner index, which is the relative markup of price over marginal cost. The median Lerner index in our sample is 24.8%. On the one hand, banks with more market power might be better able to benefit from sectoral specialization as they can offset risks stemming from lack of diversification with higher pricing power as well as better screening (see e.g. Petersen and Rajan (1995) who show that more competition reduces relationship lending, and Hauswald and Marquez (2006) who show that competition reduces lending to informationally opaque borrowers). In addition, many papers find that more competition (less pricing power) leads to more risk-taking by banks (see, e.g., Beck et al. (2013)). Specialization may then be perceived as a risky gamble by low market power banks. On the other hand, banks in more competitive environment might be able to tap more sophisticated hedging and other risk management tools to counter the effect of sectoral specialization. The results in Panel A suggest that the negative effect of sectoral specialization on the franchise value is significantly stronger for banks in more competitive environments. In all four row blocks does the coefficient for banks below the median Lerner index enter negatively and significantly larger than for banks with a Lerner index above the median. The results in Panel B provide mixed evidence on the relative importance of market power for the relationship between sectoral specialization and MES. In the case of Significant Sectoral Factors and *Sectoral Contribution to* R^2, the coefficient for banks with market power below the median is significantly more positive than for banks with market power above the median. There is no significant difference in the case of Dispersion, where the coefficients for both banks with high and low market power enter positively and significantly, while in the case of Dispersion from the average sectoral specialization, the positive and significant relationship between sectoral specialization and MES is stronger for banks with high market power. This suggests that it is banks with high market power and specializing away from the country average that add to systemic risk more than other banks.

Finally, we also inspect whether a bank's business focus in lending and traditional intermediation income affects the specialization-performance relationship. In column (6), we split the sample according to the loan-asset ratio (median value = 65%). Banks with a higher loan-asset ratio and thus more traditional business model focusing on financial intermediation might suffer more from sectoral specialization as they have less opportunities to diversify along other dimensions, as for example non-lending activities. The results in column (6) confirm this conjecture, as for three of the four sectoral specialization measures, the coefficient estimates enters with a higher coefficient in the regressions of *Franchise Value* and MES. The only exception is *Differentiation* from the country-average, where there is no significant difference between banks below and above the median of the loan-asset ratio. Finally, in column (7) we split the sample according to the median non-interest income share. The intuition behind this sample split is similar to the split according to the loan-asset ratio; banks with a higher non-interest income share and thus less of a focus on traditional intermediation business might be less affected by sectoral specialization. The results in column (7), however, do not provide any evidence to this effect, with most coefficients not being significantly different for banks below and above the sample median of the non-interest income share.

5 Conclusions

This paper gauges the relationship between sectoral specialization of banks and their performance and contribution to systemic risk. While theory and previous country-specific evidence provides ambiguous findings, our results, based on a broad cross-country and cross-bank sample show that banks with higher sectoral specialization have higher volatility, lower market-book values and a higher contribution to systemic risk, while there is no significant relationship with profitability. Critically, we find significant variation in these relationships over time, across countries and across banks. The relationship between sectoral specialization, volatility and risk holds across our sample period 2001 to 2011, but is stronger for the post-crisis period starting in 2007. The relationship is stronger for more developed economies and for countries without regulatory rules on diversification. We also find that the relationship between sectoral contribution and systemic risk contribution is larger for larger banks and banks with more market power, while the relationship between sectoral specialization and the market-book values is stronger for banks in more competitive environments. Finally, we find some evidence that the relationship is stronger for banks with more traditional intermediation models.

Our findings are a first attempt at empirically gauging the relationship between sectoral specialization and bank performance and risk, using novel data and approaches. While a first exploration, they provide already some important policy messages. First, while there seem to be no significant benefits in terms of profitability from diversifying or specializing, sectoral specialization brings with it significant risks. However, these risks vary significantly across countries, across market structures and banks' business models. Any regulatory response to sectoral specialization has to take this variation into account.

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Table 1: Sectoral factor loadings and return-based sectoral specialization measures

This table contains information on sectoral factor exposures, their significance 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 on a broad market index as well as on the return to 10 different sectoral indices. 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 12,689 bank-year observations, covering 2,005 banks from 77 countries over a ten year period starting in 2002. Panel A reports for each estimated factor loading the mean and standard deviation across 12,689 observations, as well as the fifth, fiftieth and ninety-fifth percentile of the panel of estimated factor loadings. In panel B, we report for each factor the relative frequency of observing t-stats in five groups. Based on the estimated sectoral exposures, we compute four time-varying bank-specific measures of the intensity of sectoral specialization of which summary statistics are reported in panel C. A detailed description of the construction of these four measures is provided in the text as well as in Table 4.

Panel A: Summary Statistics on Sectoral Factor Loadings					
variable	mean	sd	p5	p50	p95
1= Oil & gas (OILGS)	0.002	1.010	-1.442	-0.008	1.495
2= Basic materials (BMATR)	-0.006	0.854	-1.226	0.012	1.087
3= Industrials (INDUS)	0.008	0.586	-0.787	0.000	0.840
4= Consumer goods (CNSMG)	0.004	0.646	-0.903	0.002	0.885
5= Healthcare (HLTHC)	-0.007	0.739	-1.131	-0.001	1.105
6= Consumer services (CNSMS)	0.006	0.611	-0.873	0.005	0.873
7= Telecommunications (TELCM)	-0.009	0.468	-0.756	0.000	0.693
8= Utilities (UTILS)	0.021	0.442	-0.627	0.024	0.651
9= Technology (TECNO)	0.009	0.955	-1.354	0.000	1.381
10= Financials(FINAN)	0.094	0.308	-0.234	0.037	0.604

Panel B: Frequency table of t-stats of sectoral factor loadings					
	t<-1.65	-1.65<=t<-1	-1<=t<1	1<t<1.65	1.65<=t
1= Oil & gas (OILGS)	0.082	0.109	0.628	0.111	0.070
2= Basic materials (BMATR)	0.085	0.099	0.608	0.116	0.092
3= Industrials (INDUS)	0.076	0.107	0.632	0.108	0.076
4= Consumer goods (CNSMG)	0.085	0.109	0.598	0.110	0.099
5= Healthcare (HLTHC)	0.081	0.111	0.617	0.111	0.080
6= Consumer services (CNSMS)	0.092	0.109	0.585	0.116	0.099
7= Telecommunications (TELCM)	0.088	0.105	0.620	0.110	0.076
8= Utilities (UTILS)	0.064	0.095	0.608	0.125	0.107
9= Technology (TECNO)	0.091	0.107	0.605	0.114	0.084
10= Financials(FINAN)	0.061	0.086	0.518	0.120	0.216

Panel C: Sectoral Specialization Indicators based on Factor Loadings					
	mean	sd	p5	p50	p95
Significant Sectoral Factors	3.980	3.134	0.000	3.000	9.000
Sectoral Contribution to R^2	0.076	0.061	0.016	0.053	0.214
Dispersion (factors)	0.314	0.221	0.080	0.256	0.773
Differentiation (factors)	1.462	1.290	0.305	1.073	4.045

Note: 12689 observations, on 2005 banks from 77 countries, 2002-2011

Table 2: Sectoral Exposures: Hand-collected from banks' websites

We hand-collect information on sectoral exposures from the notes to the banks' financial statements. We focus on large, listed banks as these are more likely to publish a detailed report on their website. The data collection yields a panel of accounting-based sectoral exposures at the bank-year level for the years 2007-2011, covering 1426 observations on 317 banks from 57 countries. Summary statistics on these self-reported exposures are reported in panel A. For each sector, we report the mean, standard deviation, as well as the fifth, fiftieth and ninety-fifth percentile. Based on the hand-collected accounting-based sectoral exposures, we compute four time-varying bank-specific measures of the intensity of sectoral specialization of which summary statistics are reported in panel B. A detailed description of the construction of these four measures is provided in the text as well as in Table 4.

Panel A: Sectoral Allocation of Corporate Loans					
variable	mean	sd	p5	p50	p95
S1 "Agriculture, Forestry and Fishing"	0.023	0.042	0.000	0.006	0.100
S2 "Mining & Construction"	0.070	0.069	0.000	0.055	0.215
S3 "Manufacturing"	0.165	0.112	0.019	0.146	0.374
S4 "Transportation, communication, Electric, Gas and Sanitary service"	0.083	0.079	0.000	0.059	0.239
S5 "Wholesale trade and Retail trade"	0.136	0.103	0.000	0.118	0.346
S6 "Finance and Insurance"	0.091	0.108	0.000	0.051	0.319
S7 "Real estate"	0.129	0.140	0.000	0.095	0.441
S8 "Services"	0.109	0.101	0.000	0.094	0.314
S9 "Public administration"	0.044	0.076	0.000	0.009	0.183
S10 "Other industries"	0.149	0.164	0.000	0.091	0.466

Panel B: Sectoral Specialization Indicators					
	mean	sd	p5	p50	p95
Dispersion (accounting)	0.113	0.037	0.068	0.105	0.184
Sectoral CR3	0.697	0.125	0.529	0.674	0.961
Sectoral HHI	0.227	0.088	0.142	0.199	0.404
Differentiation (accounting)	0.263	0.136	0.090	0.240	0.547

Note: 1426 observations, 317 banks from 57 countries, 2007-2011)

Table 3: Summary Statistics

This table contains summary statistics on the performance measures and the control variables for two samples. In panel A, the sample consists of 12689 observations, on 2005 banks from 77 countries, 2002-2011. This larger sample corresponds with the sample for which we can estimate the return-based sectoral specialization measures. The sample in panel B is smaller (1426 observations), covers less banks (317) from less countries (57) over a shorter sample period (2007-2011). This smaller sample coincides is the sample for which we have hand-collected the accounting-based sectoral exposures. In each panel, we provide summary statistics (mean, standard deviation as well as the fifth, fiftieth and ninety-fifth percentile) on four performance measures and eight control variables. The last column of the lower panel contains the p-values of a difference in means test for the mean of the small sample versus the mean of its complementary part of the full sample. A detailed description of the construction of these measures is provided in the text as well as in Table 4 (for the performance measures).

Panel A: Large sample: 12689 observations, on 2005 banks from 77 countries, 2002-2011

variable	mean	sd	p5	p50	p95
Return	-0.29	44.34	-83.24	4.50	62.34
Volatility	39.33	24.35	13.50	32.57	89.48
Franchise Value	1.11	1.23	0.01	0.86	3.10
MES	2.00	2.30	-0.45	1.44	6.77
Bank Size (ln of total assets in 2007 US$)	9.23	3.19	5.32	8.30	15.09
Non-Interest Income Share (as a share of Interest Income and Non-Interest Income)	0.19	0.14	0.00	0.17	0.43
Equity to Total Assets	0.09	0.06	0.04	0.09	0.18
Share of Deposits in Deposits and Money Market Funding	0.88	0.15	0.56	0.94	1.00
Loans to Total Assets	0.63	0.15	0.33	0.65	0.84
Return on Equity	0.08	0.15	-0.16	0.10	0.26
Growth in Total Assets	0.12	0.19	-0.07	0.07	0.43
Loan Loss Provisions to Total Assets	0.55	0.83	0.00	0.29	2.09

Panel B: Small sample: 1426 observations, on 317 banks from 57 countries, 2007-2011

variable	mean	sd	p5	p50	p95	p-value($! = mean$)
Return	-5.83	49.06	-98.44	0.00	69.00	0.000
Volatility	42.21	20.10	18.25	38.41	80.39	0.000
Franchise Value	0.58	1.03	0.00	0.18	2.02	0.000
MES	3.94	2.51	0.44	3.53	9.12	0.000
Bank Size (ln of total assets in 2007 US$)	13.02	2.24	9.47	13.14	16.50	0.000
Non-Interest Income Share (as a share of Interest Income and Non-Interest Income)	0.20	0.12	0.05	0.18	0.41	0.000
Equity to Total Assets	0.08	0.04	0.03	0.07	0.14	0.000
Share of Deposits in Deposits and Money Market Funding	0.84	0.15	0.54	0.89	0.99	0.000
Loans to Total Assets	0.59	0.14	0.33	0.62	0.78	0.000
Return on Equity	0.10	0.14	-0.06	0.11	0.27	0.000
Growth in Total Assets	0.12	0.18	-0.06	0.07	0.40	0.930
Loan Loss Provisions to Total Assets	0.58	0.78	0.01	0.33	1.84	0.198

Table 4: Data dictionary: Variables, Labels and Source

This table contains information on the labels and definitions of the independent variables of interest (panel A and panel B) and the dependent variables (panel C). In the upper panel A, we describe the sectoral specialization indicators based on factor loadings. In the middle panel, we label and define the sectoral specialization indicators based on accounting data. In the lower panel, we label and define the four performance metrics.

Variable Label	Variable definition	Units and source
	Panel A: Sectoral Specialization Indicators based on Factor Loadings	
Significant Sectoral Factors	Number of factor loadings with an abs(t-stat)>1	
Sectoral Contribution to R^2	Contribution to R2 of the sectoral factors	
Dispersion (factors)	Dispersion (st.dev) of sectoral betas	
Differentiation (factors)	Euclidean distance between bank's return-based exposures and country's average exposures (excluding bank in average)	
	Panel B: Sectoral Specialization Indicators based on Accounting data	
Dispersion (accounting)	Dispersion (st.dev) of sectoral acc. Exposures	
Sectoral CR3	Cumulative exposure of largest three acc. Exposures	
Sectoral HHI	Concentration (HHI) of sectoral acc. Exposures	
Differentiation (accounting)	Euclidean distance between a bank's exposures and the country's average exposures (excluding bank in average)	
	Panel C: Performance Measures	
Return	Annualized Average Daily Stock Return	
Volatility	Annualized Volatility of Daily Stock Return	
Franchise Value	Market-to-Book value of Equity	
MES	Marginal Expected Shortfall (5%, wrt LOCAL banking sector)	

Table 5: Correlation matrices

This table contains three panels of correlation matrices. In each panel, the pairwise correlation coefficients as well as the p-value are reported. In panel A, we report the correlation coefficients among and between the performance measures and the sectoral specialization measures based on factor loadings (corresponding with the larger sample of 12634 observations). In panel B, we report the correlation coefficients among and between the performance measures and the sectoral specialization measures based on accounting exposures (smaller sample of 1392 observations). In panel C, we report the correlation coefficients among and between all sectoral specialization measures. The number-letter combination in the column headers (which differ by panel) correspond with a variable in the rows.

Correlation between performance measures and Sectoral Specialization Indicators based on Factor Loadings (large sample: 12634 obs.)

Variables	A1	A2	A3	A4	A5	A6	A7	A8
Return (=A1)	1.000							
Volatility (=A2)	-0.398	1.000						
	(0.000)							
Franchise Value (=A3)	0.071	-0.212	1.000					
	(0.000)	(0.000)						
MES (=A4)	-0.269	0.406	-0.146	1.000				
	(0.000)	(0.000)	(0.000)					
Significant Sectoral Factors (=A5)	0.010	0.026	-0.001	0.129	1.000			
	(0.247)	(0.004)	(0.918)	(0.000)				
Sectoral Contribution to R^2 (=A6)	-0.036	-0.011	-0.034	0.378	0.289	1.000		
	(0.000)	(0.220)	(0.000)	(0.000)	(0.000)			
Dispersion (factors) (=A7)	-0.065	0.437	-0.168	0.229	0.507	0.205	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Differentiation (factors) (=A8)	-0.093	0.330	-0.114	0.049	0.413	-0.017	0.777	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.053)	(0.000)	

Correlation between performance measures and Sectoral Specialization Indicators based on Accounting Data (small sample: 1392 obs.)

Variables	B1	B2	B3	B4	B5	B6	B7	B8
Return (=B1)	1.000							
Volatility (=B2)	-0.327	1.000						
	(0.000)							
Franchise Value (=B3)	-0.082	0.066	1.000					
	(0.002)	(0.013)						
MES (=B4)	-0.406	0.746	0.109	1.000				
	(0.000)	(0.000)	(0.000)					
Dispersion (accounting) (=B5)	-0.008	0.060	0.073	0.094	1.000			
	(0.752)	(0.025)	(0.007)	(0.000)				
Sectoral CR3 (=B6)	-0.003	0.068	0.080	0.080	0.923	1.000		
	(0.896)	(0.011)	(0.003)	(0.003)	(0.000)			
Sectoral HHI (=B7)	-0.012	0.054	0.069	0.097	0.983	0.875	1.000	
	(0.646)	(0.044)	(0.010)	(0.000)	(0.000)	(0.000)		
Differentiation (accounting) (=B8)	-0.051	0.099	0.202	0.109	0.586	0.569	0.606	1.000
	(0.056)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Correlation between Sectoral Specialization Indicators based on Factor Loadings and Accounting Data (small sample: 1363 obs.)

Variables	C1	C2	C3	C4	C5	C6	C7	C8
Significant Sectoral Factors (=C1)	1.000							
Sectoral Contribution to R^2 (=C2)	0.206	1.000						
	(0.000)							
Dispersion (factors) (=C3)	0.531	0.227	1.000					
	(0.000)	(0.000)						
Differentiation (factors) (=C4)	0.365	-0.058	0.595	1.000				
	(0.000)	(0.031)	(0.000)					
Dispersion (accounting) (=C5)	-0.010	-0.048	0.016	0.054	1.000			
	(0.720)	(0.078)	(0.545)	(0.046)				
Sectoral CR3 (=C6)	-0.009	-0.067	0.024	0.081	0.923	1.000		
	(0.741)	(0.013)	(0.377)	(0.003)	(0.000)			
Sectoral HHI (=C7)	-0.009	-0.026	0.014	0.036	0.983	0.875	1.000	
	(0.743)	(0.341)	(0.593)	(0.189)	(0.000)	(0.000)		
Differentiation (accounting) (=C8)	-0.021	-0.143	0.001	0.059	0.586	0.569	0.606	1.000
	(0.433)	(0.000)	(0.976)	(0.028)	(0.000)	(0.000)	(0.000)	

Table 6: Drivers of Bank Performance

This table shows the results of regressing a bank performance metric (return, volatility, franchise value or MES) on the set of control variables. In the left hand side, we report the regression results of the full sample. In the right hand side, we report the regression results for the smaller sample. The control variables capture various dimensions of a bank's business model that might influence performance and stability. Size is computed as the natural logarithm of total assets expressed in 2007 US dollars. We measure a bank's share of non-interest income to total operating income, by dividing other operating income (which comprises trading income, commissions and fees as well as all other non-interest income) by the sum of interest income and other operating income. The other bank-specific variables are proxies for leverage (capital-to-asset ratio), the funding structure (share of deposits in sum of deposits and money market funding), asset mix (loans to assets ratio), profitability (return-on-equity), annual growth in total assets as well as expected credit risk (Loan Loss Provision to Total Assets). The independent variables are lagged one year to mitigate concerns regarding reverse causality. We winsorize all variables at the 1 and 99 percentile level to mitigate the impact of outliers. Next to the set of control variables, we also include year fixed effects as well as bank fixed effects. The standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	Large sample: 2005 banks from 77 countries, 2002-2011				Small sample: 317 banks from 57 countries, 2007-2011			
VARIABLES	Return	Volatility	Franchise Value	MES	Return	Volatility	Franchise Value	MES
Bank Size (orthogonalized)	-27.106***	-5.951***	-0.361***	0.369***	-3.732	-7.765*	-0.394**	-0.744
	(2.345)	(1.410)	(0.065)	(0.108)	(11.415)	(4.703)	(0.194)	(0.484)
Non-Interest Income Share	-53.127***	-12.370***	-0.401	0.095	-46.249	-24.336*	-1.084**	-1.882
	(8.744)	(4.378)	(0.256)	(0.333)	(35.211)	(13.977)	(0.445)	(1.442)
Equity to Total Assets	347.149***	9.705	2.594***	-4.355***	228.280	-53.338	6.207	-3.813
	(40.019)	(20.894)	(0.897)	(1.628)	(177.442)	(69.831)	(3.770)	(7.752)
Share of Deposits in Total Funding	104.780***	18.038***	1.186***	-1.606***	-16.731	1.381	0.890	1.997
	(10.310)	(6.032)	(0.317)	(0.501)	(53.604)	(19.886)	(0.643)	(2.064)
Loans to Total Assets	95.833***	23.674***	2.046***	-2.358***	-15.038	58.200**	0.509	5.356*
	(13.524)	(8.153)	(0.381)	(0.616)	(56.507)	(25.054)	(1.113)	(2.775)
Return on Equity	-88.137***	-50.317***	-1.060***	1.131**	-21.656	-48.328***	-1.013	-2.265
	(10.284)	(6.046)	(0.301)	(0.461)	(44.945)	(17.685)	(0.994)	(1.974)
Growth in Total Assets	16.432***	2.301	0.498***	0.039	0.303	9.959**	0.162	0.963*
	(3.328)	(1.813)	(0.083)	(0.154)	(12.494)	(4.765)	(0.164)	(0.538)
Loan Loss Provisions to Total Assets	-14.579***	0.751	-0.281***	0.308***	5.087	-3.075	-0.223**	-0.252
	(1.400)	(0.772)	(0.039)	(0.058)	(5.900)	(2.270)	(0.097)	(0.227)
Constant	-126.296***	5.803	-0.959**	3.797***	37.860	32.410*	0.442	0.606
	(16.156)	(9.854)	(0.478)	(0.773)	(44.691)	(17.494)	(0.595)	(2.067)
Observations	12689	12689	12684	12689	1426	1426	1426	1426
Adjusted R-squared	0.340	0.616	0.768	0.607	0.398	0.736	0.796	0.747
Bank Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Lending Specialization and Bank Performance: Evidence from Stock Return-based Sectoral Specialization Measures

To gauge the relationship between lending specialization and bank performance and fragility, we add each of the four return-based sectoral specialization indicators one-by-one to a regression of each of the four dependent variables on the control variables (as reported in the left hand side part of Table 6). This results in 16 different specifications. We summarize the results by reporting only the information of interest. More specifically, for each regression, we only report the coefficient and t-statistic on the return-based sectoral specialization indicator as well as the number of observations and the adjusted R-squared of the regression. The table is constructed as follows. Each of the four sectoral specialization indicators is reported in a different column. The dependent variable varies by block of rows. The sample consists of 12689 observations, on 2005 banks from 77 countries, 2002-2011.

	Return			
	Significant Sectoral Factors	Sectoral Contribution to R^2	Dispersion (factors)	Differentiation (factors)
Coeff	0.093	-6.287	-1.245	-0.052
t-statistic	0.789	-0.601	-0.497	-0.139
Observations	12689	12639	12689	12689
Adjusted R-squared	0.340	0.341	0.340	0.340
	Volatility			
	Significant Sectoral Factors	Sectoral Contribution to R^2	Dispersion (factors)	Differentiation (factors)
Coeff	0.043	11.583***	17.284***	1.788***
t-statistic	0.818	2.616	14.266	9.228
Observations	12689	12639	12689	12689
Adjusted R-squared	0.616	0.619	0.631	0.622
	Franchise Value			
	Significant Sectoral Factors	Sectoral Contribution to R^2	Dispersion (factors)	Differentiation (factors)
Coeff	-0.004*	-0.988***	-0.391***	-0.039***
t-statistic	-1.950	-5.949	-9.532	-6.391
Observations	12684	12634	12684	12684
Adjusted R-squared	0.768	0.771	0.771	0.769
	MES			
	Significant Sectoral Factors	Sectoral Contribution to R^2	Dispersion (factors)	Differentiation (factors)
Coeff	0.011**	6.981***	1.259***	0.080***
t-statistic	2.169	14.190	12.560	5.388
Observations	12689	12639	12689	12689
Adjusted R-squared	0.607	0.620	0.616	0.608

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; t-stats based on robust standard errors clustered at bank level
Each regression includes control variables, bank and year fixed effects.

Table 8: Lending Specialization and Bank Performance: Evidence from Accounting-based Sectoral Specialization Measures

To gauge the relationship between lending specialization and bank performance and fragility, we add each of the four accounting-based sectoral specialization indicators one-by-one to a regression of each of the four dependent variables on the control variables (as reported in the right hand side part of Table 6). The only difference with respect to Table 6 is that we do not include bank fixed effects due to the lack of within bank variation in the sectoral specialization measures. This results in 16 different specifications. We summarize the results by reporting only the information of interest. More specifically, for each regression, we only report the coefficient and t-statistic on the accounting-based sectoral specialization indicator as well as the number of observations and the adjusted R-squared of the regression. The table is constructed as follows. Each of the four sectoral specialization indicators is reported in a different column. The dependent variable varies by block of rows. The regressions are based on a smaller sample (compared to table 7) of 1426 observations, covering 317 banks from 57 countries over the period 2007-2011.

	Return			
	Dispersion (accounting)	Sectoral CR3	Sectoral HHI	Differentiation (accounting)
Coeff	12.288	2.317	4.880	-6.599
t-statistic	0.450	0.271	0.425	-0.813
Observations	1426	1426	1426	1392
Adjusted R-squared	0.413	0.413	0.413	0.410

	Volatility			
	Dispersion (accounting)	Sectoral CR3	Sectoral HHI	Differentiation (accounting)
Coeff	32.380*	12.301**	11.772*	7.272
t-statistic	1.938	2.311	1.722	1.383
Observations	1426	1426	1426	1392
Adjusted R-squared	0.416	0.419	0.416	0.417

	Franchise Value			
	Dispersion (accounting)	Sectoral CR3	Sectoral HHI	Differentiation (accounting)
Coeff	-0.790	-0.435	-0.265	0.490
t-statistic	-0.664	-1.235	-0.523	1.319
Observations	1426	1426	1426	1392
Adjusted R-squared	0.273	0.275	0.273	0.274

	MES			
	Dispersion (accounting)	Sectoral CR3	Sectoral HHI	Differentiation (accounting)
Coeff	6.221***	1.759**	2.551***	0.821
t-statistic	2.689	2.410	2.703	1.144
Observations	1426	1426	1426	1392
Adjusted R-squared	0.360	0.359	0.360	0.365

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; t-stats based on robust standard errors clustered at bank level
Each regression includes control variables and year fixed effects.

Table 9: Sample splits: panel A (Franchsie Value) and panel B (MES)

This table contains information on how the impact of lending specialization on banks' franchise value and marginal expected shortfall varies with country- and bank characteristics. The dependent variable in Panel A is the market-to-book value of equity (franchise value). It is the Marginal Expected Shortfall in Panel B. Each panel is constructed in a similar fashion. Each panel consists of four subpanels corresponding with a return-based sectoral specialization measure. The regression setup differs in only one dimension from the one in table 7 and 8. We now interact the (factor-based) lending specialization indicators with two dummy variables that split the sample according to the characteristic mentioned in the column title. For example, in the first subpanel, the independent variable of interest is the number of significant sectoral factor exposures. The baseline result, which is also in Table 6, is repeated in the first column. This is the 'unconditional' effect. In subsequent columns, we examine whether the effect of the number of significant factors on the MES varies over time (the period 2002-2006 versus 2007-2012) or with country characteristics: developed vs. developing countries (sample split according to median value of GDP per capita), and countries with no guidelines on asset diversification (below) or with guidelines (above). We also examine the scope for differential effects of lending specialization on franchise value and MES for (i) large versus small banks, banks with market power (the Lerner index), banks with a focus on lending (loan-to-asset ratio), and banks with a focus on non-tradition banking (non-interest income share) We only report the coefficients of interest and the associated t-statistic. Significance at the conventional levels is indicated with *** (1 per cent), ** (5 per cent) or * (10 per cent). We also report the number of observations and R-square. Furthermore, the last row in each block reports the p-value of a t-test for the equality of the coefficient below or above the sample mean. In each regression, we include a set of control variables (as in table 6) as well as bank and time fixed effects. Standard errors are clustered at the bank level.

Panel A: Franchise Value (Market to Book value of Equity)

		pre/post 2007	GDP per capita	Asset Diversification	Size	Market Power	Loan/Asset	NII-share
				Significant Sectoral Factors				
Significant Sectoral Factors (=X1)	-0.004*							
t-stat	-1.950							
X1 * [column title below median]		0.003	0.004	-0.017***	-0.004	-0.014***	-0.000	-0.007***
t-stat		0.971	0.811	-6.028	-1.252	-5.303	-0.154	-2.580
X1 * [column title above median]		-0.011***	-0.006**	0.012***	-0.005	0.005**	-0.008***	-0.001
t-stat		-3.707	-2.542	3.557	-1.551	2.041	-2.971	-0.373
Observations	12684	12684	12684	12684	12684	12684	12684	12684
Adjusted R-squared	0.768	0.769	0.768	0.770	0.768	0.769	0.768	0.768
p-value(below=above)		0.003***	0.082*	0.000***	0.800	0.000***	0.042**	0.163
				Sectoral Contribution to R^2				
Sectoral Contribution to R^2 (=X2)	-0.988***							
t-stat	-5.949							
X2 * [column title below median]		-1.510***	1.801***	-1.630***	-1.232***	-1.404***	-0.682***	-1.081***
t-stat		-6.943	4.144	-9.164	-5.292	-7.198	-3.283	-5.534
X2 * [column title above median]		-0.759***	-1.328***	0.989***	-0.789***	-0.616***	-1.199***	-0.766***
t-stat.		-3.676	-7.440	3.485	-3.666	-3.407	-6.658	-4.064
Observations	12634	12634	12634	12634	12634	12634	12634	12634
Adjusted R-squared	0.771	0.771	0.772	0.774	0.771	0.771	0.771	0.771
p-value(below=above)		0.007***	0.000***	0.000***	0.137	0.000***	0.010***	0.151
				Dispersion (factors)				
Dispersions (factors) (=X3)	-0.391***							
t-stat	-9.532							
X3 * [column title below median]		-0.247***	-0.111*	-0.546***	-0.418***	-0.501***	-0.340***	-0.381***
t-stat		-3.884	-1.662	-10.922	-7.448	-10.489	-6.968	-7.530
X3 * [column title above median]		-0.470***	-0.445***	-0.045	-0.361***	-0.239***	-0.437***	-0.348***
t-stat		-8.263	-9.487	-0.782	-6.882	-5.077	-9.056	-7.368
Observations	12684	12684	12684	12684	12684	12684	12684	12684
Adjusted R-squared	0.771	0.772	0.772	0.774	0.771	0.772	0.772	0.771
p-value(below=above)		0.013**	0.000***	0.000***	0.431	0.000***	0.063*	0.580
				Differentiation (factors)				
Differentiation (factors) (=X4)	-0.039***							
t-stat	-6.391							
X4 * [column title below median]		-0.012	-0.009	-0.060***	-0.044***	-0.059***	-0.036***	-0.037***
t-stat		-1.249	-0.856	-7.482	-5.028	-8.178	-4.587	-4.706
X4 * [column title above median]		-0.052***	-0.046***	0.007	-0.033***	-0.010	-0.042***	-0.037***
t-stat		-6.668	-6.571	0.766	-3.996	-1.262	-5.424	-4.507
Observations	12684	12684	12684	12684	12684	12684	12684	12684
Adjusted R-squared	0.769	0.770	0.770	0.771	0.769	0.770	0.769	0.769
p-value(below=above)		0.001***	0.002***	0.000***	0.368	0.000***	0.529	0.964

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; t-stats based on robust standard errors clustered at bank level
Each regression includes control variables, bank and year fixed effects.

Panel B: Marginal Expected Shortfall

		pre/post 2007	GDP per capita	Asset Diversification	Size	Market Power	Loan/Asset	NII-share
Significant Sectoral Factors								
Significant Sectoral Factors (=X1)	0.011**							
t-stat	2.169							
X1 * [column title below median]		-0.028***	-0.013	0.026***	0.005	0.018***	-0.002	0.011*
t-stat		-4.400	-1.068	3.978	0.754	2.624	-0.231	1.732
X1 * [column title above median]		0.046***	0.017***	-0.009	0.017**	0.003	0.023***	0.009
t-stat		5.771	3.400	-1.359	2.127	0.515	3.523	1.477
Observations	12689	12689	12689	12689	12689	12689	12689	12689
Adjusted R-squared	0.607	0.609	0.607	0.608	0.607	0.607	0.607	0.607
p-value(below=above)		0.000***	0.022**	0.000***	0.234	0.080*	0.006***	0.821
Sectoral Contribution to R^2								
Sectoral Contribution to R^2 (=X2)	6.981***							
t-stat	14.190							
X2 * [column title below median]		1.168**	-3.072***	8.607***	8.289***	8.607***	4.531***	6.994***
t-stat		2.110	-3.294	17.023	13.514	14.488	7.971	11.817
X2 * [column title above median]		9.537***	8.188***	1.970***	5.899***	5.524***	8.720***	5.975***
t-stat.		16.552	15.998	3.789	8.641	10.859	15.579	10.702
Observations	12639	12639	12639	12639	12639	12639	12639	12639
Adjusted R-squared	0.620	0.631	0.624	0.627	0.621	0.623	0.623	0.619
p-value(below=above)		0.000***	0.000***	0.000***	0.007***	0.000***	0.000***	0.085*
Dispersion (factors)								
Dispersions (factors) (=X3)	1.259***							
t-stat	12.560							
X3 * [column title below median]		0.746***	0.338*	1.477***	0.883***	1.274***	1.032***	1.077***
t-stat		5.329	1.782	12.570	6.785	10.546	8.952	8.324
X3 * [column title above median]		1.541***	1.472***	0.770***	1.657***	1.238***	1.466***	1.238***
t-stat		11.571	13.268	5.858	11.112	10.524	11.056	10.229
Observations	12689	12689	12689	12689	12689	12689	12689	12689
Adjusted R-squared	0.616	0.617	0.617	0.618	0.617	0.616	0.617	0.615
p-value(below=above)		0.000***	0.000***	0.000***	0.000***	0.785	0.003***	0.295
Differentiation (factors)								
Differentiation (factors) (=X4)	0.080***							
t-stat	5.388							
X4 * [column title below median]		0.110***	0.014	0.106***	0.048**	0.063***	0.063***	0.054***
t-stat		4.577	0.513	5.867	2.456	3.506	3.487	2.829
X4 * [column title above median]		0.065***	0.099***	0.024	0.121***	0.104***	0.096***	0.095***
t-stat		3.501	5.948	1.093	5.247	5.539	4.809	4.877
Observations	12689	12689	12689	12689	12689	12689	12689	12689
Adjusted R-squared	0.608	0.608	0.608	0.609	0.608	0.608	0.608	0.608
p-value(below=above)		0.145	0.008***	0.002***	0.015**	0.066*	0.169	0.110

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; t-stats based on robust standard errors clustered at bank level
Each regression includes control variables, bank and year fixed effects.

A List of countries and number of bank-year observations by country

Country	Large Sample	Small sample	Country	Large Sample	Small sample
ARGENTINA	62	15	MACEDONIA (FYROM)	8	0
AUSTRALIA	59	25	MALAYSIA	108	5
AUSTRIA	70	16	MEXICO	65	10
BAHRAIN	42	10	MOROCCO	37	3
BANGLADESH	128	0	NIGER	2	0
BELGIUM	26	10	NIGERIA	6	2
BERMUDA	20	4	NORWAY	146	25
BOSNIA AND HERZEGOVINA	6	0	OMAN	28	5
BOTSWANA	9	0	PAKISTAN	122	0
BRAZIL	145	10	PERU	59	10
BULGARIA	21	0	PHILIPPINES	93	14
CANADA	103	0	POLAND	120	51
CHILE	57	25	PORTUGAL	51	15
CHINA	62	58	QATAR	35	15
COLOMBIA	60	17	ROMANIA	35	5
CROATIA	96	10	RUSSIAN FEDERATION	65	40
DENMARK	331	10	SAUDI ARABIA	74	33
ECUADOR	35	0	SERBIA	14	0
EGYPT	66	1	SINGAPORE	37	15
FINLAND	18	9	SLOVAKIA	23	4
FRANCE	247	24	SLOVENIA	24	0
GERMANY	109	15	SOUTH AFRICA	64	20
GREECE	82	20	SPAIN	93	15
HONG KONG SAR, CHINA	87	35	SRI LANKA	56	0
HUNGARY	14	0	SWEDEN	40	20
ICELAND	4	0	SWITZERLAND	114	10
INDIA	272	70	TAIWAN, CHINA	222	45
INDONESIA	122	17	THAILAND	119	34
IRELAND	10	5	TUNISIA	47	0
ISRAEL	80	30	TURKEY	100	45
ITALY	205	30	UGANDA	6	0
JAPAN	915	290	UKRAINE	26	0
JORDAN	53	9	UNITED ARAB EMIRATES	93	34
KAZAKHSTAN	26	10	UNITED KINGDOM	77	20
KENYA	71	0	UNITED STATES OF AMERICA	6426	113
KOREA REPUBLIC OF	74	0	VENEZUELA	106	8
KUWAIT	41	13	VIETNAM	0	3
LEBANON	44	14	ZIMBABWE	7	0
LITHUANIA	48	0			
LUXEMBOURG	21	5			

Large sample: 12689 observations, on 2005 banks from 77 countries, 2002-2011
Small sample: 1426 observations, on 317 banks from 57 countries, 2007-2011