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ORIGINAL ARTICLE

Banks' Specialization versus Diversification in the Loan Portfolio

New Evidence from Germany

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Abstract Do banks with a specialized credit portfolio have superior selection and monitoring abilities? Controlling for the composition of the banks' loan portfolios, we show that specialized banks have lower loan loss rates. We also see that for more focused German banks in our sample period 2003–2011 the standard deviation of loan loss rates seems to be lower. Moreover, the loan loss rate of a given industry in a bank's loan portfolio is lower if the bank has a major exposure to that industry.

Keywords Loan portfolio · Credit risk · Loan losses · Specialization
JEL-Classification G11 · G21 · C23 · C43

1 Introduction

Credit business is a core component of traditional commercial banking. Through careful selection and monitoring of the borrowers a bank can reduce the risk associated with this business. Selection and monitoring abilities depend on the characteristics of the bank with one important feature being the industry concentration within the loan portfolio. The more a bank focuses on certain industries, the more it can acquire industry-specific knowledge and thereby realize specialization benefits, i. e. reduce the credit risk of the loan portfolio. However, a specialized loan portfolio

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harbors increased concentration risks due to higher default correlations of borrowers within a given industry.

In this paper, we investigate the impact of loan portfolio specialization on credit risk. If the risk-return-profile of a loan were exogenous, the credit portfolio risk would be higher for a bank with a less diversified credit portfolio. However, a loan's risk-return-profile is to some extent endogenous, i. e. it can at least in part be influenced by a bank. The question of whether such knowledge gains from loan portfolio specialization exist is at the center of our empirical study.

The main contribution of our analysis stems from using an especially suitable data set. This German data set for the period 2003–2011 comprises of bank loan exposures to the non-financial private sector and the corresponding write-downs, both of which can be broken down into different industries and maturity brackets.

The main results of our study are: Banks with a specialized loan portfolio have, on average, lower loan loss rates after controlling for their portfolio composition. Furthermore, specialized banks even have less unexpected credit risk, as the standard deviation of their loss rates is lower. Making use of our granular data set, we can also prove that the loan loss rate for a given industry is lower if the industry itself is important for the bank. These findings suggest that specialized German banks acquire considerable selection and monitoring abilities that reduce the loan portfolios' credit risk.

The paper proceeds as follows. Sect. 2 discusses the related literature. In Sect. 3, we analyze the relation between loan portfolio specialization and banks' credit risks. Sect. 4 describes the empirical methodology. The data used in this study is presented in Sect. 5, followed by a discussion of results in Sect. 6. Sect. 7 contains robustness checks, and Sect. 8 concludes.

2 Related Literature

Banks with a specialized loan portfolio are expected to have better monitoring abilities (see, for instance, Boot 2000; Carey et al. 1998; Sharpe 1990), which might lower the loan portfolios' credit risk. However, they are confronted with increased credit risk due to industrial concentrations. Acharya et al. (2006) empirically examine the impact of loan portfolio specialization versus diversification on performance indicators of Italian banks. The authors use the Herfindahl-Hirschman Index (HHI) as a measure of loan portfolio specialization across different industries and sectors. They find that industry or sector diversification implies unaffected or marginally increased return and increased credit risk for banks with a moderate downside risk in the loan portfolio, whereas banks with a high credit risk in their loan portfolio experience decreased bank performance through diversification. The authors conclude that "diversification per se is no guarantee of superior performance or greater bank safety and soundness". Recent single country evidence is provided by Tabak et al. (2011) regarding the impact of loan portfolio specialization on Brazilian banks' return and credit risk. They find a positive relationship between bank returns and loan portfolio specialization. In addition, loan portfolio specialization reduces the banks' loan portfolio credit risk. The authors find that sector specialization has an overall positive effect on banks' performance. In contrast, Bebczuk and Galindo (2007) find for Argentina that banks with a diversified credit portfolio have fewer non-performing loans. This effect is mainly driven by larger banks and is especially relevant during times of economic downturn. In the empirical study for Austrian banks by Rossi et al. (2009), the effect of loan diversification on the loan loss provision also moves in the same direction. This means that banks with a concentrated credit portfolio, no matter whether concentration is measured by industry or size, have higher loan loss provisions. However, in their study, only the 100 largest out of almost 1000 banks are included so their results cannot be generalized to the whole Austrian banking system.

For Germany, Behr et al. (2007), Hayden et al. (2007) and Boeve et al. (2010) investigate the impact of industry loan portfolio specialization on the risk and performance of banks. Behr et al. (2007) analyze all German banks between 1993 and 2003 to find out whether a specialization strategy is superior to a diversification strategy in terms of the banks' risk-return characteristics. The authors conclude that a specialized loan portfolio yields a slightly higher return on assets and that a bank specialized in certain industries tends to have lower credit risk in terms of non-performing loans. However, when the standard deviation of the loan loss provision ratio and the respective non-performing loans ratio is used instead as a more straightforward risk measure of a loan portfolio's unexpected credit risk, specialized banks have higher risk than diversified banks. Hayden et al. (2007) analyze loans of 1.5 million euro or more, based on a database from the Deutsche Bundesbank and find that loan portfolio specialization has a positive impact on banks' profitability.

Boeve et al. (2010) analyze German cooperative banks and savings banks from 1995 until 2006. Similar to our approach, the authors separate the bank-specific selection and monitoring abilities. They observe that specialized banks show, on average, a significantly higher monitoring quality. When comparing industry specialization benefits with associated concentration risks using a common credit risk model, the authors find strong evidence that for cooperative banks a higher industry concentration level is, on average, associated with a lower credit risk of the loan portfolio. Results for savings banks, however, depend more on the applied diversification measure. Similar to Boeve et al. (2010), who apply bank-wide distressed loans at annual frequency as broad proxies for banks' actual loan losses, and Behr et al. (2007), who predominantly use loan loss provisions, we contribute to the extant literature by using a more precise proxy of banks' loan losses for the analysis of credit risk. In considerable contrast to the studies mentioned above, we possess a more detailed database. This database comprises of the loan exposures and corresponding write-downs on individual bank-, industry- and maturity-specific levels on a quarterly basis between 2003 and 2011. The data therefore captures the 2008/2009 financial crisis period.

To distinguish the bank-specific selection and monitoring abilities from the composition of the loan portfolio, we follow the basic idea of credit portfolio models (for example, Crouhy et al. 2000; Wilson 1998) which address systematic and idiosyncratic drivers of loan portfolios' default risk. More precisely, our approach, which is based on Memmel et al. (2015), is similar to intensity-based credit portfolio models that apply sector-specific average default rates as systematic factors of credit risk.

These common factors are represented in the calculations of the loss rates of a hypothetical loan portfolio that has the same industry and maturity composition as that of the bank. The only exception is that the nationwide loss rates are applied. The literature has identified several systematic drivers of credit risk. By examining a panel data set of Italian financial intermediaries, Quagliariello (2007) relates loan loss provisions and non-performing loans to GDP growth. Much like a macroeconomic systematic risk factor, a nationwide driver of credit risk reflecting the business cycle is included in the following analysis. Beyond the general economic cycle, Aretz and Pope (2013) decompose firms' default risk into common factors such as global, country and industry effects by analyzing firms from 24 countries and 30 industries. They find that around 61 % of the systematic variance in changes in firms' default risk is due to global and industry effects. Industry-specific effects as well as regional differences are also included in our analysis. Finally, according to the work by Dennis et al. (2000) on the relationship between maturity and credit risk, the decomposition of our data into different maturity brackets allows us to likewise consider the relevance of banks' maturity composition in this study.

3 Loan Portfolio Specialization and Credit Risk

Loan portfolio specialization is expected to improve selection and monitoring abilities through the build-up of industry-specific knowledge. We examine whether specialized banks – in the sense of industry concentration – exhibit lower loan losses than banks with diversified loan portfolios. Benefiting from our unique database, we control for common risk factors and thereby directly separate the bank-specific selection and monitoring abilities from the composition of the loan portfolio. More precisely, when measuring the performance of an investment fund, a multiple of the return of the market portfolio is subtracted to adjust for the systematic risk. In our case, the loan losses from a hypothetical loan portfolio are subtracted from the bank's actual loan losses. This hypothetical loan portfolio consists of a portfolio with the same industry and maturity composition as that of the bank and its losses are derived by applying the nationwide loss rates. We attribute the difference between the loss rates to the bank's selection and monitoring abilities.

As noted by Acharya et al. (2006), risk is usually defined by unexpected losses and not by expected losses as analyzed above. In our study, we use the standard deviation of loan losses as a proxy for the unexpected portion of credit risk. If specialized banks acquire enough selection and monitoring benefits, an industry-concentrated loan portfolio may even have a lower standard deviation for the loan loss rates. The beneficial effects due to specialization not only exist, which can be measured by reduced expected losses, but they also more than outweigh the negative effects due to specialization, which stem from foregone diversification.

Furthermore, we investigate in greater detail the composition of each individual bank's total loan exposure. In particular, we develop the new idea that loan exposures to a relatively large industry within a bank's loan portfolio compared to a relatively small industry are, on average, accompanied by greater attention and increased monitoring. Similar to the line of argument concerning bank size and credit risk, a better monitoring ability is generated, for example, by a higher number of cases or larger volumes from the more important industries. This might especially be the case for regional banks that predominantly serve the small and medium-sized enterprises. We expect that the corresponding monitoring benefits reduce, on average, the respective loan losses. Thus the banks' loss rates for industries where they have large exposures are compared with the loss rates of banks that have small exposure in these industries. We control for the composition of the loan portfolios, thereby separating the effects of selection and monitoring abilities. Suppose, for example, that the industry "construction" accounts for 30 % of the lending of Bank A and for 2 % of the lending of Bank B. We then would expect that loss rates for construction firms are lower, on average, in Bank A than in Bank B.

4 Empirical Methodology

Classical portfolio theory according to Markowitz (1952) suggests optimal portfolio selection through diversification to address the typical trade-off between portfolio risk and expected return. However, data limitations concerning the calculation of risk, return and default correlations hinder this model's applicability to financial intermediation.[1] More importantly, in contrast to the Markowitz model, credit risk is at best to some extent exogenous because banks can influence the expected return of a granted loan by monitoring it closely. As a consequence, banks usually adopt simpler strategies to allocate their loan portfolios. The Herfindahl-Hirschman Index (HHI) comprises naïve diversification in a specialization measure and has been widely used in the loan portfolio specialization literature.

Note that we use the HHI and other specialization measures to capture the banks' loan portfolio concentrations with respect to certain industries. This implies that concentration risks due to a bank's focus on certain borrowers, such as one large firm within an industry, are not captured by the measures used in this paper. The information available in the Bundesbank's borrowers statistics simply does not contain a respective breakdown into different borrowers within an industry allowing for such an analysis.

We define $X_{i,t,j,k}$ as the accounting value (in euro) of the loan exposure of bank i at quarterly time t to industry j in maturity bracket k. Correspondingly,

$$X_{i,t,j} := \sum_{k=1}^{3} X_{i,t,j,k} \tag{1}$$

[1] The data frequency of the default data is not high enough to enable reliable estimates of the default correlations between our 27 industries. In some papers, e. g. Duellmann and Masschelein (2007), one obtains default correlations by using stock returns of listed firms of the respective industries. However, one also has to note that in several industries, for example in agriculture in Germany, the number of listed firms is insufficient and not representative for the firms in the banks' credit portfolios.

denotes the accounting value (in euro) of the loan exposure of bank i at time t to industry j where the loans are aggregated over the three maturity brackets. Further,

$$x_{i,t,j} := \frac{X_{i,t,j}}{\sum_{j=1}^{27} X_{i,t,j}} \tag{2}$$

defines the share of loans granted by bank i at time t to industry j. Since the borrowers statistics provide quarterly data, the specialization measures can be calculated on a quarterly basis. Note that we measure specialization, in accordance with the literature (see the works mentioned above), by the portfolio shares and not by the euro amounts of the respective exposures.

As the leading naïve diversification measure, the Herfindahl-Hirschman Index (HHI) is defined by

$$HHI_{i,t} := \sum_{j=1}^{27} (x_{i,t,j})^2 \tag{3}$$

The *HHI* is equal to 1 when all loan exposures are granted to a single industry, and it equals 1/27 when all 27 industries that will be considered in our empirical analysis have identical loan exposures.

The empirical analysis investigates the impact of loan portfolio specialization on banks' credit risk, approximated by the historic loan losses, adjusted for the composition of the loan portfolio and further bank-specific control variables. The bank-wide loss rate serves as a dependent variable in our study and is based on data from the borrowers statistics. The notations in (4)–(11) follow Memmel et al. (2015).

To start with, $C_{i,t,j,k}$ denotes the change in value (in euro) of bank i's loans from $t-1$ to t to industry j in maturity bracket k. This leads to the bank-wide change in value, defined as

$$C_{i,t} := \sum_{j=1}^{27} \sum_{k=1}^{3} C_{i,t,j,k} \tag{4}$$

The bank-wide loss rate is then calculated on a quarterly basis as a moving average, where we multiply the moving averages by 4 to obtain annualized values

$$q_{i,t} := \frac{4 \cdot \sum_{m=0}^{3} C_{i,t-m}}{0.5 \cdot X_{i,t} + X_{i,t-1} + X_{i,t-2} + X_{i,t-3} + 0.5 \cdot X_{i,t-4}} \tag{5}$$

Hence $q_{i,t}$ is the weighted average of the losses in the current and three previous quarters, where the weights are the portfolio sizes in a quarter. We use this method to calculate the average in order to avoid extreme values which can potentially arise when a bank's loan portfolio has almost shrunk to nothing.

To separate the bank-specific selection and monitoring abilities from the composition of the loan portfolio, common factors of credit risk, such as a nationwide factor and industry- and maturity-specific factors, are included in the empirical analysis. These common factors are calculated from a hypothetical loan portfolio that has the same industry and maturity composition as that of the bank, but where nationwide loss rates are applied. The loss rate of the hypothetical loan portfolio is calculated on a quarterly basis as

$$hq_{i,t}^{ind\times mat} = \sum_{j=1}^{27} \sum_{k=1}^{3} w_{i,t,j,k} \cdot Q_{t,j,k}^{ind\times mat} \tag{6}$$

with $w_{i,t,j,k}$ as the weight according to the industry- and maturity-specific share of loans made by bank i at time t with respect to the bank's whole loan exposure and $Q_{t,j,k}^{ind\times mat}$ as time-, industry- and maturity-specific nationwide loss rate. For a more detailed description, see Memmel et al. (2015). The loss rate of the hypothetical loan portfolio can be decomposed into the following common factors:

$$hq_{i,t}^{ind\times mat} = Q_t + \Delta hq_{i,t}^{ind} + \Delta hq_{i,t}^{mat} \tag{7}$$

with Q_t as the nationwide loss rate of the entire loan portfolio at time t, and the industry and maturity adjustment factors

$$\Delta hq_{i,t}^{ind} \equiv hq_{i,t}^{ind} - Q_t \tag{8}$$

respectively

$$\Delta hq_{i,t}^{mat} \equiv hq_{i,t}^{ind\times mat} - hq_{i,t}^{ind} \tag{9}$$

Q_t is a nationwide factor reflecting the phase of the overall credit cycle. The expression $\Delta hq_{i,t}^{ind}$ provides the industry factor, i. e. the differences in the loss rate of the hypothetical portfolio that are due to bank i's deviations in the industry composition. The maturity factor $\Delta hq_{i,t}^{mat}$ is calculated similarly to account for the maturity structure. Thus, the hypothetical loan portfolio loss rates are those of a portfolio where a bank's portfolio weights and the nationwide loss rates are applied. As a result, beyond a nationwide factor, industry-specific effects and the impact of the loan portfolio's maturity composition can be considered.

Cooperative banks and savings banks dominate the German banking market by number of institutions. Their credit business by and large is restricted to their home region. Therefore, it may be argued that naïve diversification as measured by the HHI is not a relevant benchmark, because these banks' loan portfolios and loss rates will more or less mirror the regional economy. To take this issue into account, for regional banks, differences in the loan portfolios' loss rates due to regional effects are similarly included in the analysis in a robustness check. The region-specific loss rate is defined as

$$Q^{reg}_{R(i),t} := \frac{\sum_{\text{bank } i \text{ is in region } R} C_{i,t}}{\sum_{\text{bank } i \text{ is in region } R} X_{i,t}} \tag{10}$$

with R denoting the ten postcode areas. Hence, the regional factor is defined as

$$\Delta Q^{reg}_{R(i),t} \equiv Q^{reg}_{R(i),t} - Q_t \tag{11}$$

and denotes the difference between the loss rate in bank i's postal code area and the nationwide loss rate, and is set to zero for nationwide banks. As another robustness check we also have replaced the *HHI* by a distance measure calculating the deviation of a bank's loan portfolio composition from the overall regional loan portfolio.

Our research question could be subject to a reverse causality issue. A bank may decide to focus its loan portfolio specifically on industries that are less exposed to risk, i. e. those characterized by comparatively low loan loss rates. In this case, lower risk industries would affect the bank's industry concentration level. However, the decision of the bank's loan portfolio management to focus – for whatever reasons – on specific industries or sectors is already included on the right-hand side of our estimation equation. The inclusion of common risk factors explicitly controls for the composition of the loan portfolio. Consequently we only examine that excess return, which can be attributed to the bank's selection and monitoring abilities. Put differently, a bank specialized in low risk industries must have loss rates even below the low overall loss rates of these industries in order to reap specialization benefits. In our view, this approach effectively eliminates the reverse causality concern.

A lower loss rate could, on average, result from the borrowers' good quality and not from the banks' selection and monitoring abilities. Similarly to the above reasoning, the common risk factors included in our study take the average loss rate in a specific industry (and thus the performance of the corresponding borrowers) into account. Therefore, if a bank has better than average borrowers, this is indeed related to superior debtor selection.

In addition, banks' total assets *(LN_TA)*, risk-weighted assets over total assets *(RWA_TA)*, the borrowers' average tangible asset ratio *(AVA)*, the return-on-assets *(ROA)* or, alternatively, return-on-equity *(ROE)* as well as the employee ratio *(ER)* are included as bank-specific control variables, denoted by $X_{a,i,t}$ ($a = 6, \ldots, 10$). See Table A1 in the Appendix for further definitions of the variables. These bank-specific controls taken mainly from the prudential information system are available on a yearly basis only, which restricts our analysis to $t = 4, 8, 12, .., T$ with $T = 36$. This leads us to the following regression for the empirical analysis of the question of whether loan portfolio specialization reduces credit risk:

$$q_{i,t} = \beta_0 + \beta_1 Q_t + \beta_2 \Delta hq_{i,t}^{ind} + \beta_3 \Delta hq_{i,t}^{mat} + \beta_4 \Delta Q_{R(i),t}^{reg} + \beta_5 HHI_{i,t} + \sum_{a=6}^{10} \beta_a X_{a,i,t} + \epsilon_{i,t} \quad (12)$$

with the dependent variable $q_{i,t}$ as the bank-wide yearly loss rate at time t regressed on loan portfolio specialization (β_5) while controlling for the composition of the loan portfolio $(\beta_1$ to $\beta_4)$ and including further bank-specific control variables $(\beta_6$ to $\beta_{10})$.

To empirically examine the unexpected credit risk, we use the standard deviation of loan losses as a proxy for the unexpected part of credit risk and apply the following cross-sectional regression:

$$\widehat{\sigma}_{lr}^i = \gamma_0 + \gamma_1 \widehat{\sigma}_{cf}^i + \gamma_2 \overline{HHI_i} + \sum_{a=3}^{7} \gamma_a \bar{X}_{a,i} + v_i \quad (13)$$

with $\widehat{\sigma}_{lr}^i$ as the standard deviation of the loss rates of bank i over time. The variable $\overline{HHI}_{\mathrm{i}}$ denotes the serial average of the specialization measure *HHI* for bank i. $\bar{X}_{a,i}$ reflects the serial averages of the bank-specific control variables. To control for the volatility of the reference loan portfolio with the same composition as that of the bank, i. e. $\widehat{\sigma}_{cf}^i$ in Equation (13), we conduct a separate fixed effects regression according to (14) which includes the bank-wide loss rates as dependent variables and the common risk factors as independent ones:

$$q_{i,t} = \beta_0 + \beta_1 Q_t + \beta_2 \Delta hq_{i,t}^{ind} + \beta_3 \Delta hq_{i,t}^{mat} + \beta_4 \Delta Q_{R(i),t}^{reg} + \epsilon_{i,t} \quad (14)$$

We estimate regression (14) and calculate the standard deviations of the predicted dependent variable for each bank over time which, in turn, serves as explanatory variable $\widehat{\sigma}_{cf}^i$ in Equation (13).

To analyze the individual bank's loan exposures in more detail, we investigate a bank's largest and smallest industry-specific loan exposures. To this end, we divide a bank's loan portfolio at time t into two sub-portfolios. The first sub-portfolio $(L_{i,t})$ includes the bank's largest industry-specific loan exposures in descending order aggregated up to a share of loan exposures just below 50%. The remaining (small) industry-specific loan exposures are included in the second loan portfolio $(S_{i,t})$. As a result, within a bank's loan portfolio, industry-specific loan exposures contribute to either the upper or the lower half of the portfolio size distribution. For simplicity, in the text below these two sub-portfolio groups are referred to as the largest and smallest industry-specific loan exposures.

For each of the two sub-portfolios, the actual and the hypothetical loss rates are considered, i. e. the loss rate based on the bank's portfolio weights and the nationwide loss rate of the sub-portfolio, leading to $r^L_{i,t}$ and $r^S_{i,t}$, respectively (see below). The corresponding variable of interest is calculated both for each year separately ($\widehat{\Delta}_t$) and the overall sample ($\widehat{\Delta}$). Accordingly, we define

$$\widehat{\Delta}_t = \sum_{i=1}^{N} \left(r^L_{i,t} - r^S_{i,t} \right) \tag{15}$$

for each quarter $t = 4, 8, \ldots, 36$, with

$$r^L_{i,t} = \frac{\sum_{j \in L_{i,t}} C_{i,t,j}}{\sum_{j \in L_{i,t}} X_{i,t,j}} - \frac{\sum_{j \in L_{i,t}} Q^{ind}_{t,j} \cdot X_{i,t,j}}{\sum_{j \in L_{i,t}} X_{i,t,j}} \tag{16}$$

and with a corresponding definition for $r^S_{i,t}$ as well, and

$$\widehat{\Delta} = \sum_{t} \widehat{\Delta}_t \tag{17}$$

By subtracting the hypothetical from the actual loss rates in (16) we control for the composition of the loan portfolio.

5 Data

We use the borrowers statistics (*Kreditnehmerstatistik*) provided by the Deutsche Bundesbank as our main database, which is not publicly available. This database differentiates between loans using three different maturity brackets. Loans up to one year are short-term, loans made for more than one year and up to five years are medium-term, and loans made for more than five years are long-term. Since the end of 2002, short-, medium- and long-term loan exposures to the real economy and the respective changes in the valuations of these loans are reported on a quarterly basis by all German banks.

As favored by the Deutsche Bundesbank (2009), write-downs and write-ups are defined as "valuation [...] changes caused by individual value adjustments and any write-downs/write-ups of non-performing debt".[2] One considerable advantage of the database is that it allows loan exposures and, different from previous studies, valuation changes to be broken down into different industries, sectors (i. e. loans to enterprises, households and non-profit institutions), and maturity brackets.[3] It should be noted that lending to monetary financial institutions (MFIs) and to all layers of government are excluded from this database. Long-term mortgage loans (both private and corporate), which constitute a substantial chunk of loans to the real economy, are also not included in our analysis. This is because their loss rates are considerably smaller than the ones of the other loans. Robustness checks show that the inclusion of these mortgage loans does not qualitatively change the results.

Table 1 lists the composition of the database in terms of industries and sectors. Besides the sector of corporate borrowers, which can be broken down into 23 industries, two further sectors, i. e. private borrowers (which can be broken down into three subgroups) and non-profit institutions are examined, resulting in the 27 "industries" mentioned earlier.

The borrowers statistics collects valuation changes as net write-downs; for example, a negative value is reported if write-downs exceed write-ups, in this case, the value is used as gross write-downs. A positive value is reported if write-ups exceed write-downs, in this case we set the value to zero. We do so because we want to obtain an estimate for the gross write-downs, since it seems that banks carry out gross write-downs in a timely manner whereas the write-ups can be somewhat delayed. This weakens the serial connection of net write-downs with the corresponding default.

The bank-wide loss rates are presented in Table 2 for the whole sample and both nationwide and regional banks. The whole sample of 13,605 observations shows a median loss rate of 1.01 % over our observation period from 2003 to 2011. For the sub-sample of regional banks, the distribution is also broken down into size quintiles according to the loan portfolio exposure. Interestingly, regional banks in the 4th size quintile show the highest loss rates, whereas banks with the smallest loan portfolios, which are supposed to be less able to diversify credit risk, show somewhat lower loss rates in the extreme percentiles.

The prudential information system *(Bankaufsichtliches Informationssystem, BAKIS)*, which is a proprietary database provided by the Deutsche Bundesbank and the German Federal Financial Supervisory Authority *(BaFin)* for regular banking supervision, contains – along with other information – balance sheet data on a yearly basis and is used here as a source for bank-specific control variables. As one major variable in the context of banking, the natural logarithm of a bank's total assets *(LN_TA)* is included as a common control variable for bank size.

[2] When writing down loan exposures, the banks take into account the collateral for the loan so that the write downs – seen as the absolute value – are smaller in case there is valuable collateral. However, banks tend to make the write-downs conservative in the sense that the final write-downs seem to be smaller than the first write-downs, documented by the large number of positive write-ups.

[3] However, the data is not available for single loans. For each bank and each quarter, we have the exposures and the valuation changes broken down into 81 sub-portfolios (27 industries multiplied by three maturity brackets).

Table 1 Share of Lending by Industries

Item	Borrowers	Dec. 2003 (%)	Dec. 2011 (%)
Enterprises		*69.4*	*71.9*
1	Agriculture, forestry, fishing and aquaculture	1.5	2.1
2	Electricity, gas and water supply; refuse disposal, mining and quarrying	3.2	6.5
3	Chemical industry, manufacture of coke and refined petroleum products	0.9	0.7
4	Manufacture of rubber and plastic products	0.6	0.5
5	Manufacture of other non-metallic mineral products	0.5	0.3
6	Manufacture of basic metals and fabricated metal products	1.7	1.7
7	Manufacture of machinery and equipment; manufacture of transport equipment; repair and installation of machinery and equipment	2.1	2.4
8	Manufacture of computer, electronic and optical products	1.1	0.9
9	Manufacture of wood and wood products; manufacture of pulp, paper and paper products, printing; manufacture of furniture	1.9	1.3
10	Textiles, apparel and leather goods	0.4	0.2
11	Manufacture of food products and beverages; manufacture of tobacco products	1.4	1.1
12	Construction	2.9	2.9
13	Wholesale and retail trade; repair of motor vehicles and motorcycles	9.5	7.2
14	Transportation and storage; post and telecommunications	4.1	4.0
15	Financial intermediation (excluding MFIs) and insurance companies services	3.9	14.6
16	Housing enterprises	4.8	4.3
17	Holding companies	3.3	3.1
18	Other real estate activities	9.0	6.3
19	Hotels and restaurants	1.2	0.9
20	Information and communication; research and development; membership organizations; publishing activities; other business activities	4.7	4.1
21	Health and social work (enterprises and self-employment)	3.9	3.6
22	Rental and leasing activities	2.0	0.8
23	Other service activities	4.5	2.3

Table 1 Share of Lending by Industries (Continued)

Private households		29.8	27.4
24	Instalment loans (excluding housing loans)	10.7	11.8
25	Other loans (excluding housing loans)	6.6	4.2
26	Housing loans	12.6	11.4
Non-profit institutions			
27	Non-profit institutions	0.8 %	0.7 %

This table shows the shares of lending to German borrowers (excluding MFIs and government; long-term mortgage loans are also not included), broken down into enterprises, private households and non-profit institutions at end-2003 and end-2011

Table 2 Summary Statistics of Bank-wide Loss Rates

Banks	Number of observations	Bank-wide loss rate (in %) Percentile			
		99th	95th	90th	Median
Nationwide	387	4.82	2.77	2.11	0.55
Regional	13,218	5.05	3.54	2.75	1.03
1st size quintile	2,580	4.93	3.43	2.57	0.83
2nd	2,624	4.86	3.35	2.58	0.94
3rd	2,639	5.14	3.66	2.84	1.09
4th	2,689	5.17	3.74	3.00	1.15
5th	2,686	5.16	3.50	2.71	1.08
Whole sample	13,605	5.04	3.53	2.73	1.01

This table shows the bank-wide loss rates (per annum, excluding loans to MFIs and government; long-term mortgage loans are also not included) for the period 2003–2011. For regional banks, the bank-wide loss rates are broken down into loan portfolio size quintiles. The 1st quintile corresponds to the smallest and the 5th quintile represents the largest size quintile, respectively

Following Rossi et al. (2009), we consider the overall quality of a bank's loan portfolio. This is due to the fact that a highly diversified loan portfolio of risky assets may have a different impact on the bank-wide loss rate than a specialized loan portfolio which focuses on almost risk-free assets. As risk-weighted assets are both a proxy for the size as well as for the risk position of a bank, the risk-weighted assets over total assets ratio *(RWA_TA)* is included to ensure that the variable captures only the banks' loan quality. This prevents any multicollinearity with the banks' total assets. One aim of banking regulation is that increased risk-taking results in higher risk-weighted assets. Therefore, we expect a positive relationship between risk-weighted assets over total assets and credit risk, although it is known that the regulatory risk-weights are only an imperfect risk measure. In addition, we include the average ratio of the borrowers' tangible assets *(AVA)* in our regressions. We calculate this ratio for each bank and each point in time. It is calculated as the weighted ratio of the tangible assets in relation to the borrowers' total assets where the weights are the individual banks' credit exposures to the 27 industries under investigation. This variable is a further measure of the credit quality because

Table 3 Descriptive Statistics of the HHI and Bank-specific Control Variables, for 2003, 2011 and the 2003-2011 Period

Variable	Mean	SD	P5	P95
HHI				
2003–2011	0.1564	0.1364	0.0764	0.4123
2003	0.1532	0.1290	0.0777	0.3772
2011	0.1571	0.1370	0.0753	0.4377
Ln (total assets) (LN_TA)				
2003–2011	6.3003	1.5028	4.0921	8.7402
2003	6.1164	1.4668	3.8813	8.5183
2011	6.9334	1.4906	4.6579	9.3978
Risk weighted assets/total assets (RWA_TA)				
2003–2011	0.5859	0.1345	0.3613	0.7828
2003	0.6245	0.1206	0.4193	0.7999
2011	0.5351	0.1461	0.3036	0.7569
Ratio of tangible assets (AVA)				
2003–2011	0.2644	0.0374	0.2108	0.3290
2003	0.2602	0.0284	0.2219	0.3077
2011	0.2938	0.0385	0.2357	0.3574
Return-on-assets (ROA)				
2003–2011	0.26 %	0.59 %	0.02 %	0.67 %
2003	0.22 %	0.38 %	0.02 %	0.54 %
2011	0.28 %	0.55 %	0.00 %	0.71 %
Employee ratio (ER)				
2003–2011	0.2430	0.0980	0.0908	0.3609
2003	0.2697	0.0982	0.1321	0.3879
2011	0.2134	0.1002	0.0447	0.3089

This table shows summary statistics of the explanatory variables. "SD" means standard deviation, "P5" and "P95" mean the fifth and the 95th percentile, respectively

a borrower's credit loss given default tends to be lower as the amount of tangible assets the borrower possesses increases.

Moreover, we anticipate increased risk to be accompanied by increased returns. We therefore include return-on-assets *(ROA)* and, alternatively, return-on-equity *(ROE)* in our model. By doing so, we also control for potentially higher compensation for riskier loans. As a further characteristic influencing the monitoring quality, Behr et al. (2007) suggest that the employee ratio *(ER,)* calculated as the average number of employees over total assets, is an appropriate proxy, since the build-up of industry-specific knowledge is assumed to be personnel-intensive. We likewise include the ER in our analysis and expect a negative relationship with credit risk due to the expected specialization benefits. Table 3 displays summary statistics for these variables.

To merge quarterly data taken from the borrowers statistics with annual data from the prudential information system, we calculate the four-quarter sum of write-offs and write-downs and moving averages of the loan exposures, which is also the reason why our regressions do not start until end-2003. *BAKIS* also provides information on mergers and acquisitions. Despite on-going consolidation trends in the German banking market, the numbers of regional banks, branches of foreign banks, and banks with special functions increased in our study over the observation period. A common procedure for handling mergers is applied: at the time of any type of acquisition or merger, a new (third) bank is constructed, which is why the number of banks in our sample exceeds the number of existing banks.

We summarize savings banks, cooperative banks, and regional private commercial banks as regional banks which operate in areas around their headquarters. For these banks, regional effects are included with the help of the postcode system, utilizing the fact that there are ten relatively equally populated postcode areas in Germany. All other banks, especially the big banks but also the central institutions of savings banks and cooperative banks, are expected to operate on a nationwide basis. To moderately correct for outliers, observations with bank-wide loss rates above the 99th percentile are deleted from the overall dataset.

6 Results

In our regression (12), we explore the relationship between a bank's loss rate within its credit portfolio and the overall specialization of this portfolio. The variable of central interest is the specialization measure *HHI*, which shows significance at the 1 % level with a negative sign for all banks as well as (at least at the 10 % level) for nationwide and for regional banks (Table 4). This suggests that higher loan portfolio specialization – after controlling for the portfolio composition – couples with a lower loan loss rate showing that credit portfolio specialization is beneficial when considering the expected losses. This finding confirms earlier results by Behr et al. (2007).

The effect of the industry concentration is also not negligible from an economic point of view: If the *HHI* in the credit portfolio increases by one standard deviation (i. e. by 0.1364, see Table 3), then the portfolio loss rate goes down, on average, by 15 basis points. This reduction seems considerable, given the median loss rate of 1.01 % p. a. However, due to the pronounced skewness of the distribution, the reduction of 15 basis points is relatively small when we look at the higher percentiles (Table 2). For all banks, the model explains about 6 % of the serial variation and about 10 % of the cross-sectional variation in the bank-wide loss rate. The explanatory power varies approximately in the same range for regional banks as these constitute the majority in the dataset, whereas the R-squared within (R-squared between) is estimated at about 16 % (20 %) for nationwide banks. The common factors of the hypothetical portfolio, namely the nationwide (Q_t), the industry-specific ($\Delta hq_{i,t}^{ind}$), the maturity-specific ($\Delta hq_{i,t}^{mat}$) as well as the regional factors ($\Delta Q_{R(i),t}^{reg}$) are all positive and highly significant, showing that they are indeed risk drivers.

Turning to the bank-specific control variables, the employee ratio *(ER)* merits some remark. We find a strong statistically positive relationship with the bank-wide loss rate for regional banks. This implies that, while controlling for the riskiness of the loan portfolio, a higher number of employees relative to the bank's total assets is

Table 4 Regression Results for the Bank-wide Loss Rate

Variables	Bank-wide loss rate All banks	Nationwide banks	Regional banks
Q	0.676***	0.818***	0.668***
	(0.044)	(0.285)	(0.045)
Δhq^{ind}	0.554***	0.804***	0.534***
	(0.084)	(0.254)	(0.089)
Δhq^{mat}	0.663***	0.905***	0.647***
	(0.109)	(0.387)	(0.117)
ΔQ^{reg}	0.102***		0.101***
	(0.042)		(0.042)
HHI	*–0.014****	*–0.009**	*–0.014****
	(0.003)	*(0.005)*	*(0.004)*
LN_TA	0.002**	0.002	0.002*
	(0.001)	(0.002)	(0.001)
RWA_TA	–0.007***	–0.007*	–0.008***
	(0.002)	(0.004)	(0.002)
AVA	–0.021***	–0.005	–0.022***
	(0.006)	(0.025)	(0.006)
ROA	–0.068***	0.053*	–0.109***
	(0.030)	(0.031)	(0.026)
ER	0.010***	0.011*	0.011***
	(0.004)	(0.007)	(0.004)
Constant	–0.001	–0.018	0.001
	(0.008)	(0.025)	(0.008)
R-squared (within)	6.3 %	16.0 %	6.2 %
R-squared (between)	9.6 %	19.6 %	10.5 %
Number of Observations	13,605	387	13,218
Number of banks	2,077	91	1,986

This table shows regression results from a standard fixed effects estimation equation with robust standard errors. The dependent variable is the bank-wide loss rate. The right-hand side of the regression equation is based on common risk factors, a specialization measure (HHI), and various bank-specific control variables, see Table A1. Yearly data is used. Time and group indices are suppressed for simplicity
***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors are shown in parentheses

accompanied by a higher loss rate on average for regional banks. In comparison to the results by Behr et al. (2007), who include a similar set of bank-specific control variables and find a negative relationship between the *ER* and loan loss provision and non-performing loan ratios, the outcome is somewhat surprising.

Omitted variables might limit the validity of our findings. For example, the existence of market power may have an impact on a bank's credit risk. In general, a bank that exercises market power in a certain industry should be able to charge higher spreads or choose less risky loans, which leads to relatively less credit risk on average. Since bank-specific characteristics such as market power are rather difficult

Table 5 Regression Results for the Standard Deviation of the Bank-wide Loss Rate

	SD (Bank-wide loss rate)		
Variables	All banks	Nationwide banks	Regional banks
$\widehat{\sigma}_{cf}$	1.2203***	2.0443***	1.1528***
	(0.1506)	(0.4916)	(0.1553)
HHI	*–0.0038****	*0.0059*	*–0.0023*
	(0.0012)	*(0.0039)*	*(0.0015)*
LN_TA	–0.0003***	0.0012**	–0.0003***
	(0.0001)	(0.0005)	(0.0001)
RWA_TA	–0.0032***	0.0093**	–0.0037***
	(0.0011)	(0.0046)	(0.0012)
AVA	–0.0031	0.0240*	–0.0070
	(0.0050)	(0.0136)	(0.0059)
ROA	–0.2616***	–0.1800	–0.2598***
	(0.0570)	(0.2900)	(0.0578)
ER	0.0018	0.0048	0.0020
	(0.0016)	(0.0087)	(0.0017)
Constant	0.0099***	–0.0224***	0.0113***
	(0.0016)	(0.0083)	(0.0017)
R-squared (between)	13.1 %	77.4 %	10.8 %
Number of banks	933	31	902

This table shows regression results from a cross-sectional regression. The dependent variable is the standard deviation of the bank-wide loss rate. The right-hand side of the regression equation is based on the standard deviation of the hypothetical portfolios loss rates, the average values of the HHI and bank-specific control variables, see Table A1. Group indices are suppressed for simplicity
***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors are shown in parentheses

to measure precisely in practice, we assume them to be captured in the bank fixed effects.

The results displayed in Table 5 reveal evidence concerning the impact of loan portfolio specialization on the unexpected part of credit risk, measured by the standard deviation of the bank-wide loss rates. To obtain a reliable estimate of the standard deviation that is comparable in the cross-section of banks, we consider only banks for which we have nine observations and then conduct cross-sectional regressions.

The variable $\widehat{\sigma}^{i}_{cf}$ denotes the standard deviation of the common systematic risk factors and thereby controls for the volatility of the reference loan portfolio with the same composition as that of the bank. For the samples of all banks and the regional banks, this coefficient is not statistically different from one, which is the theoretically expected value. An increase in the standard deviation of the systematic risk factors by one basis point, for example, implies an increase of about 1.2 basis points in the standard deviation of the loan losses.

Behr et al. (2007) observe increased loan portfolio credit risk for specialized banks measured by the standard deviation of the loan loss provision ratio and the standard deviation of the non-performing loan ratio. This typical risk-return trade-

Table 6 Results of a Sample t-Test

	Number of observations Variable: $\widehat{\Delta}$	Mean	SE	t-value
Overall sample	13,605	–0.0085***	0.000364	23.4818
By year	Variable: $\widehat{\Delta_t}$			
2003	1,529	–0.0044***	0.001495	2.9160
2004	1,625	–0.0076***	0.000982	7.7141
2005	1,582	–0.0101***	0.001108	9.0731
2006	1,578	–0.0109***	0.001106	9.8708
2007	1,600	–0.0083***	0.000906	9.1167
2008	1,571	–0.0084***	0.000882	9.4857
2009	1,587	–0.0083***	0.000909	9.1769
2010	1,561	–0.0102***	0.001103	9.2730
2011	972	–0.0087***	0.001248	6.9794

This table shows the results of a sample t-test for the variable $\widehat{\Delta}$ (see Sect. 5). Results are displayed for the overall sample and by year, period 2003–2011

*** denotes statistical significance at the 1 percent level

off vanishes in our study when their proxies are replaced by the superior data now available. We find evidence for the overall sample that banks with an industry concentrated loan portfolio (higher *HHI*) – after controlling for the portfolio composition – have a lower unexpected part of credit risk than diversified banks, as their standard deviation of the loan losses is lower. However, as Table 5 shows, the corresponding coefficient becomes insignificant for the subsamples of regional and nationwide banks. Whereas the first findings show that specialization is beneficial concerning expected losses in the banks' credit portfolio (Table 4), the results above show that these beneficial effects seem to even outweigh the negative specialization effects concerning unexpected losses.

Above, we have raised the idea that the largest industry-specific loan exposures are accompanied by increased monitoring experience or monitoring intensity by the loan officers and therefore show lower loss rates on average. The empirical procedure described in the previous section, Equations (15)–(17), leads for bank i at time t to a comparison of the loss rates of the largest industry-specific loan exposures and the smallest industry-specific loan exposures, while controlling each time for the nationwide loss rates of the respective portfolios. The differences in the loss rates can be compared by a simple t-test of $\widehat{\Delta}$ for the overall sample and $\widehat{\Delta_t}$ for a t-test in each year (Table 6 for the results of the t-test statistics).

The test statistic for the overall sample reveals that $\widehat{\Delta_t}$ is statistically significantly smaller than zero. Moreover, the corresponding means are statistically significantly smaller than zero for each year considered. These results confirm that banks gain increased knowledge and experience concerning their largest industry-specific loan exposures and thereby reduce the associated loan losses through corresponding monitoring benefits.

7 Robustness Checks

We report results for an unbalanced panel in this paper to avoid any potential bias that might be generated due to defaulted banks dropping out of the sample. The explanatory power of the overall model is even higher for a balanced panel than for an unbalanced panel which is stated, not reported. Nevertheless, our regression results remain qualitatively the same, as can be seen from regression results available upon request.

The HHI measures portfolio specialization with respect to naïve diversification. However, naïve diversification does not account for the relative importance of several industries and sectors in an economy. Pfingsten and Rudolph (2004) and Kamp et al. (2005) develop distance measures that describe the composition of a loan portfolio by comparing its distance to a benchmark portfolio. For such a benchmark one may either choose the national loan portfolio (Table 1) or the regional loan portfolios. Choosing the latter takes into account that regional banks cannot select the industry composition of their loan portfolios completely arbitrarily. They are restricted to the regional economy, but can still specialize to some extent by deviating from this benchmark. The results, not reported here, remain qualitatively the same when distance measures (instead of the naïve specialization measure HHI) are applied.

As regards the 2008/2009 financial crisis period, the average bank-wide loss rate over time did not show a similar increase compared to the 2003 recession. This is mainly due to the fact that the German real economy only exhibited a short and moderate slump in growth and the majority of banks included in our data set were adversely affected only through second-round effects. According to the empirical analysis in our study, the results on loan portfolio specialization hold throughout the 2008/2009 financial crisis period and also for a 2008–2010 sub-sample. A financial crisis dummy that is included in our regressions, which is not shown here, turns out to be insignificant.

Table 7 presents the average loss rates for the different industries, broken down into two cases. The loss rates in the first case are the average loss rates in the event that the industry under consideration belongs to the sub-portfolio of the largest industries in a given bank's loan portfolio. The loss rates in the second case are defined accordingly for the smallest industries. For example, where construction belongs to a bank's largest industries (first case), the loss rate is, based on simple average, 2.14 %, whereas in the second case where construction belongs to a bank's smallest industries, the loss rate is, on average, 2.39 %. In general, the average loss rates of the largest industry-specific loan exposures are lower than the average loss rates of the smallest industry-specific loan exposures (with the two exceptions being the industries "Wholesale and retail trade; repair of motor vehicles and motorcycles" and "Textiles, apparel and leather goods"). As one would expect, the last column in Table 7 reveals that some industries and sectors are important for a majority of banks, for instance the instalment loans to private households, while several industries are often far less important in the banks' credit portfolios, such as loans to the industry "Textiles, apparel and leather goods".

We also look at maturity diversification within specific industries. The question of whether the maturity structure of loans is different depending on bank specialization

Table 7 Average Loss Rate (in %) by Industry

Item	Borrower	If the industry is important for a bank	Otherwise	Share of banks for which the industry is important (in %)
	Enterprises			
1	Agriculture, forestry, fishing and aquaculture	0.53	1.18	21.09
2	Electricity, gas and water supply; refuse disposal, mining and quarrying	0.34	1.31	5.15
	Manufacturing			
3	Chemical Industry, manufacture of coke and refined petroleum products	0.00	3.72	0.08
4	Manufacture of rubber and plastic products	1.31	3.75	0.22
5	Manufacture of other non-metallic mineral products	2.14	2.56	0.10
6	Manufacture of basic metals and fabricated metal products	1.98	2.50	3.86
7	Manufacture of machinery and equipment; manufacture of transport equipment; repair and installation of machinery and equipment	1.62	2.75	0.79
8	Manufacture of computer, electronic and optical products	0.87	2.38	0.23
9	Manufacture of wood and wood products; manufacture of pulp, paper and paper products, printing; manufacture of furniture	2.16	2.42	1.57
10	Textiles, apparel and leather goods	3.62	3.31	0.18
11	Manufacture of food products and beverages; manufacture of tobacco products	1.70	2.34	0.68
12	Construction	2.14	2.39	13.33
13	Wholesale and retail trade; repair of motor vehicles and motorcycles	2.06	1.99	58.88
14	Transportation and storage; post and telecommunications	0.91	1.98	1.59
15	Financial intermediation (excluding MFIs) and insurance companies services	0.28	1.85	3.24
	Services (including self-employment)			
16	Housing enterprises	1.09	2.39	9.82
17	Holding companies	0.74	3.25	1.51
18	Other real estate activities	1.35	2.29	16.10
19	Hotels and restaurants	2.58	2.77	2.85
20	Information and communication; research and development; membership organizations; publishing activities; other business activities	1.37	1.77	9.51
21	Health and social work (enterprises and self-employment)	0.77	0.99	5.15
22	Rental and leasing activities	0.29	2.17	0.57
23	Other service activities	1.34	2.12	3.38

Table 7 Average Loss Rate (in %) by Industry (Continued)

	Private households			
24	Instalment loans (excluding housing loans)	0.68	1.18	75.54
25	Other loans (excluding housing loans)	1.75	2.05	41.43
26	Housing loans	0.54	0.99	76.24
	Non-profit institutions			
27	Non-profit institutions	0.17	0.92	0.34

This table shows the average loss rate (in %) by industry where the industry is important for a bank and where this is not the case. The important (otherwise) industry-specific loss rates are calculated as unweighted means over all banks and the observation period 2003–2011. The classification is done according to the following procedure: a bank's loan portfolio at time t is divided into two subportfolios. The first subportfolio includes the bank's largest industry-specific loan exposures in descending order aggregated up to a share of loan exposures just below 50 %. The remaining (small) industry-specific loan exposures are included in the second loan portfolio. Correspondingly, industry-specific loan exposures are important for a bank or otherwise. The last column displays the share of banks (in %) for which the industry is important

is investigated. Assuming that higher bank specialization is accompanied by increased experience or intensified monitoring, a specialization strategy might change a bank's monitoring activity. We find that a higher loan portfolio specialization decreases the portion of short- and medium-term loans while increasing the portion of long-term loans. This could indicate that increased experience as well as close monitoring and supervision fosters greater confidence in the borrower not to default on its loan and thus favors longer-term loan contracts. Another explanation for our finding might be related to the corporate finance literature that understands long-term debt as a probable collateralized obligation. In this case, industry concentration would be driven by the presence of collateral. However, this is not necessarily a driving factor here since other industry-specific characteristics such as longer-term investment perspectives in the chemical industry might also influence a specialization strategy in longer-term maturities. The analysis of general driving factors for the maturity composition goes beyond the scope of this paper.

Aretz and Pope (2013) reveal that global, country and industry effects are common factors driving firms' default risk. Similar to our regional factor based on the postal code areas, regional GDP growth on the district level (*Landkreise*) might be an important variable reflecting regional differences in the business cycle. Memmel et al. (2015) conduct an analysis which is related to our approach in terms of data and methodology. The authors focus on the common drivers of a loan portfolio's default risk, which are also used in our study, and find no significant explanatory power for the inclusion of regional GDP growth.

The hypothetical loan portfolio loss rates used above are those of a portfolio where the bank's portfolio weights and the nationwide loss rates are applied. This might be problematic for the majority of banks in our data set as regional banks generally operate in the close vicinity of their location. Replacing the nationwide loss rates with the regional loss rates in the calculation of the hypothetical loss rates does not deliver significantly different results, which are available upon request.

While the tangible assets ratio is included as a further control variable in this study, the issue to separate the impact of an exogenous increase in concentration on banks' loan loss rates might also be addressed by means of a difference-in-difference approach (Atanasov and Black 2014). However, within our observation period between 2003 and 2011, no regulatory changes in law concerning banks' industry concentration in particular have occurred, which would allow for this sound identification strategy.

8 Conclusions

Examination of the effects of a bank's loan portfolio specialization versus diversification is an important topic in the banking literature. For stocks and bonds, the benefits of portfolio diversification are not questioned, not least because it is a pivotal feature of modern finance. However, concerning the loans in a bank's credit portfolio, their return and risk parameters are not completely exogenous (as it can be assumed for stocks), but can at least in part be determined by the respective bank.

Our data set is particularly well-suited for addressing this question as we utilize not only the disaggregated loan exposures, but also the corresponding write-downs. In other words, these loan exposures and their corresponding write-downs are broken down into the same sectors, industries, and maturity brackets.

We find that specialized banks exhibit, on average, both a lower credit risk in general and a lower unexpected portion of this risk if controlled for the portfolio composition. Apparently, banks build up industry-specific knowledge. Closer examination of the loss rates within a bank's loan portfolio reveals that the loss rate of a given industry in a bank's loan portfolio is lower if the bank has major exposures to this industry. This result holds both for the overall sample period and annually. These findings suggest that specialized German banks acquire considerable selection and monitoring abilities that reduce their loan portfolio's credit risk beyond associated industry concentration risks.

With regard to implications concerning the trade-off between specialization and diversification in the banks' credit portfolios, our analysis suggests the following: Allowing banks to realize benefits from loan portfolio specialization enhances bank stability given that this specialization results in a more efficient allocation of credit risk. However, when assessing the effects on bank stability, it is necessary to bear in mind that, in our study, we analyze the relationships around the mean of the distribution, not in the tail, and that diversification in the credit portfolio becomes especially important in extreme events. Consequently, our findings do not necessarily imply that specialized portfolios ought to be given a discount when calculating regulatory capital requirements.

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Appendix

Table A1 Definitions of Variables

Variable	Definition
Q	Nationwide loss rate of the entire loan portfolio at time t, i. e. nationwide write-downs/nationwide loan exposure
Δhq^{ind}	Industry factor, i. e. deviations in the loss rate of a hypothetical portfolio that are due to bank i's deviation in the industry composition
Δhq^{mat}	Maturity factor, i. e. deviations in the loss rate of a hypothetical portfolio that are due to bank i's deviation in the maturity composition
ΔQ^{reg}	Regional factor, i. e. deviations in the loss rate of a hypothetical portfolio that are due to bank i's deviation in the regional composition
HHI	Herfindahl-Hirschman Index, i. e. [1/27; 1]
LN_TA	Natural logarithm of total assets (total assets in € million)
RWA_TA	Risk-weighted assets (in € million)/total assets (in € million)
AVA	Average ratio of the borrowers' tangible assets
ROA	Return-on-Assets, i. e. net income (in € million)/total assets (in € million)
ER	Average number of employees/total assets (total assets in € million)

Time and group indices are suppressed for simplicity

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