DEUTSCHE
BUNDESBANK
EUROSYSTEM

Do specialization benefits outweigh concentration risks in credit portfolios of German banks?

Rolf Böve

(zeb/rolfes.schierenbeck.associates, Münster)

Klaus Düllmann

(Deutsche Bundesbank)

Andreas Pfingsten

(University of Münster)

Discussion Paper

Series 2: Banking and Financial Studies

No 10/2010

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0
Telex within Germany 41227, telex from abroad 414431

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978-3–86558–656–8 (Printversion)
ISBN 978-3–86558–657–5 (Internetversion)

Abstract

Lending specialization on certain industry sectors can have opposing effects on monitoring (including screening) abilities and on the sectoral concentration risk of a credit portfolio. In this paper, we examine in the first part if monitoring abilities of German cooperative banks and savings banks increase with their specialization on certain industry sectors. We observe that sectoral specialization generally entails better monitoring quality, particularly in the case of the cooperative banks. In the second part we measure the overall effect of better monitoring and the associated higher sectoral credit concentrations on the credit risk of the portfolio. Our empirical results suggest that specialization benefits overcompensate the impact of higher credit concentrations in the case of the cooperative banks. For savings banks, the results on the net effect depend on how specialization is measured. If specialization is gauged by Hirschman Herfindahl indices, the net effect is an increase of portfolio risk due to the higher sectoral concentration. If specialization is instead measured by distance measures, portfolio risk decreases as the impact of better monitoring abilities prevails.

Key Words:
bank lending, loan portfolio, diversification, expected loss, savings banks, cooperative banks, concentration, economic capital, credit risk.

JEL Classification: G11, G21.

Non-technical summary

Previous empirical work indicates that banks specializing in specific industry sectors in their corporate lending possess above average screening and monitoring abilities. This means that they can better assess the credit quality of their borrowers and and monitor it up to maturity. Specialization in industry sectors can have opposing effects on the credit risk of a portfolio. On the one hand, portfolio risk *ceteris paribus* decreases because of below-average default probabilities and above-average recovery rates at default, both due to better knowledge and information. On the other hand, the higher portfolio share of certain sectors due to the specialization *ceteris paribus* increases sector concentration and the credit risk of the portfolio. In this discussion paper, we analyze which of the two effects prevails. We thereby bring together two strands of literature: empirical work on specialization benefits that has hitherto been concerned with the expected loss and the literature on risk modelling for credit portfolios that is concerned with the occurrence of rare but severe losses, i.e. an extreme quantile of the distribution. The first-time use of portfolio risk models and the value-at-risk measure in this context is a prerequisite in order to capture the concentration risk that materializes exactly in rare and severe loss events and which has been disregarded in the first strand of the literature.

The discussion paper makes two important research contributions: In the first part, the impact of specialization on the screening and monitoring abilities is analyzed empirically. In the second part, we explore the overall impact of specialization benefits and the higher sectoral concentration involved on the credit risk of the portfolio. The empirical analyses are based on yearly single bank data of German cooperative banks and savings banks for the time period from 1995 to 2006.

The results support the hypothesis that specialized cooperative banks and savings banks can reap significant monitoring benefits. This finding is confirmed by various robustness checks using different indicator variables. The results differ between cooperative banks and savings banks concerning the overall effect of monitoring benefits and higher sectoral concentration on portfolio risk. For cooperative banks, a higher degree of specialization reduces the portfolio risk in spite of a higher sectoral concentration in a statistically and economically significant way. In the case of savings banks, the results instead depend strongly on the applied specialization measure. For the Herfindahl-Hirschman-Index as specialization measure, the portfolio risk is overall increased due to specialization whereas it is reduced for distance measures. The results are distinctly less significant compared with those for cooperative banks. In summary, we find empirical support that it is possible for at least a substantial number of banks to overcompensate the higher sectoral concentration risk implied by a specialized lending strategy through the associated monitoring benefits.

Nichttechnische Zusammenfassung

Frühere empirische Forschungsarbeiten liefern Hinweise, dass Banken, die sich im Firmenkundenkreditgeschäft auf bestimmte Branchen spezialisieren, über überdurchschnittliche Screening- und Monitoring-Fähigkeiten verfügen. Dies bedeutet, dass sie besser als nicht spezialisierte Institute die Kreditqualität ihrer Kreditnehmer beurteilen und für die Dauer der Kreditbeziehung verfolgen können. Branchen-Spezialisierung kann allerdings gegenläufige Auswirkungen auf das Kreditrisiko des Portfolios haben. Einerseits verringert sie *ceteris paribus* das Portfoliorisiko aufgrund von im Mittel niedrigeren Ausfallwahrscheinlichkeiten und höheren Verwertungserlösen bei Kreditausfällen als Folge der Wissens- und Informationsvorteile. Andererseits verstärken die aufgrund der Spezialisierung höheren Portfolioanteile einzelner Sektoren *ceteris paribus* die Sektorkonzentration und erhöhen damit das Kreditrisiko des Portfolios. In dem vorliegenden Diskussionspapier untersuchen wir, welcher dieser beiden Effekte überwiegt. Damit werden zwei Literaturstränge verbunden: empirische Arbeiten zu Spezialisierungsvorteilen, die als Zielgröße den erwarteten (mittleren) Verlust verwenden, und die Literatur zur Risikomodellierung von Kreditportfolien, die sich mit dem Eintritt seltener, aber dafür hoher Verluste, d.h. mit einer Flanke der Verlustverteilung beschäftigt. Die erstmalige Verwendung von Portfoliorisikomodellen und des Value-at-Risk-Maßes ist in diesem Zusammenhang eine Voraussetzung, um die im ersten Literaturstrang vernachlässigten Konzentrationsrisiken, die gerade bei seltenen, hohen Verlustereignissen schlagend werden, angemessen zu erfassen.

Das Diskussionspapier liefert zwei wesentliche Forschungsbeiträge: Im ersten Teil wird der Einfluss der Branchenspezialisierung auf die Screening- und Monitoring-Fähigkeiten empirisch untersucht. Im zweiten Teil untersuchen wir den Gesamteffekt aus Spezialisierungsvorteilen und der damit verbundenen höheren Sektorkonzentration auf das Kreditrisiko des Portfolios. Die empirischen Untersuchungen basieren auf jährlichen Einzelbankdaten für deutsche Kreditgenossenschaften und Sparkassen im Zeitraum von 1995 bis 2006.

Die Ergebnisse stützen die Hypothese, dass spezialisierte Kreditgenossenschaften und Sparkassen Monitoring-Vorteile besitzen. Dies wird durch zahlreiche Robustheitsprüfungen unter Verwendung unterschiedlicher Kennziffern bestätigt. Bezüglich des Gesamteffektes aus Monitoring-Vorteilen und höheren Sektorkonzentrationen auf das Portfoliorisiko weichen die Ergebnisse für Kreditgenossenschaften und Sparkassen voneinander ab. Ein höherer Spezialisierungsgrad senkt bei Kreditgenossenschaften trotz der höheren Sektorkonzentration das Portfoliorisiko in statistisch und ökonomisch signifikantem Umfang. Im Falle der Sparkassen hängen die Resultate dagegen stark von dem verwendeten Spezialisierungsmaß ab. Bei Herfindahl-Hirschman-Indizes als Spezialisierungsmaß erhöht sich im Gesamteffekt das Portfoliorisiko mit der Spezialisierung, während es für Distanzmaße sinkt. Im Vergleich zu den Kreditgenossenschaften sind diese Ergebnisse deutlich weniger signifikant. Zusammenfassend finden wir empirische Anhaltspunkte dafür, dass zumindest eine größere Anzahl von Kreditinstituten es schaffen, das höhere Sektorkonzentrationsrisiko aus einer spezialisierten Kreditvergabestrategie durch die damit verbundenen Monitoring-Vorteile mehr als auszugleichen.

Contents

Do specialization benefits outweigh concentration risks in credit portfolios of German banks?[1]

1 Introduction

Two important drivers of credit risk in bank lending are the banks' screening and monitoring abilities and their credit concentrations in industry sectors. These risk drivers have opposing effects on portfolio risk: Whereas better screening and monitoring abilities *ceteris paribus* reduce risk, it is *ceteris paribus* increased by sectoral concentrations. To achieve superior screening and monitoring abilities, a bank might specialize on certain industries in lending and hereby raise its sectoral concentration. This means a specialized bank might reduce its credit risk by a better monitoring quality, but, at the same time, increase its credit risk by a higher concentration. This paper sets out to explore empirically, first, the impact of industry specialization on banks' screening and monitoring abilities and, second, which of the effects prevails in the net impact on the credit risk of the portfolio. The sample of banks comprises savings banks and cooperative banks in Germany. Both groups of banks are particularly suited for the purpose of the paper: Their proximity to their client base should help to reap monitoring benefits, while their geographical lending constraints may lead to sectoral concentrations.

The hypothesis of client-focused banks having superior screening and monitoring abilities is based on their comparative advantage in overcoming information asymmetries between bank and borrower due to the proximity to their client base.[2] A deeper understanding of the borrower's business might have the following implications:[3]

---

[1]For helpful comments on this and earlier versions of this paper, we are indebted to Christoph Memmel as well as to participants of the Finance Research Seminar in Muenster, the 15th Annual Meeting of the German Finance Association in Muenster, the 66th Annual Meeting of the Association of University Professors of Management in Berlin, the 11th Symposium on Finance, Banking, and Insurance in Karlsruhe, and the 1st Rostock Conference on Services Research.

[2]A survey of financial intermediation may be found in Freixas and Rochet (2008), Greenbaum and Thakor (2007), and Allen and Santomero (1998).

[3]Banks which practice relationship lending might also reduce information asymmetries. The empirical results by Degryse and Ongena (2003) for the Norwegian bank market suggest a linkage between diversification and relationship lending and confirm the theoretical analysis by Boot and Schmeits (2000). However, for the German bank market the appropriate investigations are lacking. We do not examine the

- Better screening abilities reduce the problem of adverse selection[4] and allow a better assessment of the collateral value.

- Specialized banks 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 (monitoring in a narrow sense).[5]

- Specialized banks are more successful in workout processes.[6]

Both screening and monitoring influence the probability of default (PD) and the loss given default (LGD) of the borrowers in the bank's portfolio. Superior industry knowledge may also entail a more efficient workout process and, hence, higher recovery rates. As we cannot clearly differentiate between screening and monitoring abilities in our empirical analysis and as we also assume a strong positive correlation between them, the term "monitoring" refers in this paper to both aspects.

Previous empirical work suggests that specialization entails a higher monitoring quality. The work by Acharya et al. (2006), Kamp (2006), and Hayden et al. (2007) provides empirical evidence that specialization on certain industries is accompanied by lower loan loss rates. Furthermore, Acharya et al. (2006), Kamp (2006), and Craigwell et al. (2006) reveal empirically that lending to industries serviced by a bank for the first time is linked to higher loan loss rates. Both results can be seen as an indication of superior monitoring abilities of specialized banks although they may be influenced by a tendency of specialized banks to focus their lending on low-risk industries. This tendency seems reasonable as banks seeking for a diversified loan portfolio in order to protect themselves against high unexpected losses are more willing to lend to risky industries.[7]

In contrast to monitoring abilities, credit concentrations in industrial sectors or in single borrowers *ceteris paribus* increase portfolio risk. Higher sectoral concentrations increase default correlations in the portfolio because borrowers' default events are generally more

possible relation between relationship lending and specialization as we do not use single borrower data in our investigations.

[4]See, for example, Akerlof (1970) and Hauswald and Marquez (2006).

[5]Better monitoring might prevent risk-shifting by borrowers. See Stiglitz and Weiss (1981).

[6]Franks et al. (2004) and Grunert and Volk (2005) show that a deeper relationship between bank and customer goes along with a higher recovery rate, possibly because of a faster workout process.

[7]Empirical evidence for this relation in the case of cooperative banks may be found in Böve and Pfingsten (2008).

correlated if they are in the same sector than if they are in different sectors. Therefore, regulators demand that this risk needs to be considered in banks' risk management.[8] Düllmann and Masschelein (2007) confirm in an empirical analysis that the impact of sectoral concentrations is substantial in real banks' credit portfolios. Whereas monitoring abilities are commonly measured by profits and average losses, i.e. in the middle of the loss distribution, risk concentrations only become relevant in its adverse tail, i.e. for rare events.

Rossi et al. (2009) find that a higher sectoral diversification reduces realized risk measured by the amount of provisions for bad loans. While this result is subject to the critique that concentration materializes only in the tail of a loss distribution, they also find that an increase in diversification reduces the amount of capital actually required by managers. Summarizing they find support for the *classical diversification hypothesis* that risk-adjusted returns are higher for well-diversified portfolios. They do not differentiate banks, however, with respect to their monitoring benefits obtained from specialization.

Empirical work that addresses the net effect of superior monitoring abilities of specialized banks and the associated sectoral concentrations on the credit risk of a loan portfolio is missing. Only the theoretical work by Winton (1999) includes monitoring incentives and recommends diversification strategies solely for banks with medium high portfolio risk. In order to close this gap, we examine in this paper whether the positive relationship between specialization level in corporate lending and portfolio risk still holds if the assumption of a constant monitoring quality is abandoned and different degrees of monitoring quality depending on the specialization level are considered. In order to conduct this analysis, we have chosen a two-stage procedure. In the first part, we examine the relation between specialization level and monitoring quality. The results of this empirical analysis are used as input parameters for the second analysis, which clarifies the relation between specialization level and portfolio risk.

Our empirical analysis is based on annual bank proprietary data from 1995 to 2006 and comprises the primary institutions of German savings and cooperative banks. The measurement of the specialization level uses the borrower statistic, which includes the loan exposures of each German bank in corporate banking broken down into 23 industry sectors.

[8] See Bundesanstalt für Finanzdienstleistungsaufsicht (2009), BTR 1.1, and Basel Committee on Banking Supervision (2006).

The main results of the paper are: Specialized banks show, on average, a higher monitoring quality than diversified banks. This relationship is stronger for cooperative banks than for savings banks in Germany. Incorporating these specialization benefits into the examination of portfolio risk, we find a negative relationship between specialization level and portfolio risk in the case of the cooperative banks, i.e. the specialization benefits overcompensate the negative concentration effects. For savings banks, we have to differentiate between the results for naive specialization measures and distance measures. Specialization measured by Hirschman Herfindahl indices is accompanied by a higher portfolio risk, whereas specialization measured by distance measures is accompanied by a lower portfolio risk.

The remainder of the paper is organized as follows. In section 2, we examine the relationship between specialization level and monitoring quality. After the introduction of our main variables (section 2.1), the empirical design (section 2.2), and our data sources (section 2.3), we present and interpret the empirical results (section 2.4.1), and check for robustness (section 2.4.2). In section 3, we examine the relationship between specialization level and portfolio risk. Firstly, we introduce the applied credit model. After the description of the calibration and the empirical design, we present and interpret the results. Section 4 summarizes and concludes.

2 Measurement of specialization benefits

2.1 Key Variables

2.1.1 Measurement of the specialization level

In order to measure monitoring benefits of specialized banks, we revert to the specialization measures used by Kamp (2006). For measuring naive diversification the Hirschman Herfindahl Index (HHI) is a very popular key index.[9] In our case it is calculated for bank b at time t as

[9] In addition to the HHI there are further concentration measures, for example the Gini-coefficient and the Shannon entropy, used by Kamp (2006).

$$HHI_{(b,t)} := \sum_{i=1}^{23} x_{(b,i,t)}^2 \tag{1}$$

where $x_{(b,i,t)}$ stands for the proportion of industry i as a share of the corporate loans of bank b at time t. The *HHI* values range from $\frac{1}{23}$ for the most diversified (equal shares in all 23 sectors) to 1 for the most concentrated (single sector) portfolio.

In addition to the calculation of the *HHI* based on loan volumes we evaluate a weighted HHI (HHI^w), which is based on the loan volumes weighted by the insolvency rates of each industry, i.e.

$$HHI_{(b,t)}^w := \sum_{i=1}^{23} \left(\frac{IR_{(i,t)} \cdot X_{(b,i,t)}}{\sum_{j=1}^{23} IR_{(j,t)} \cdot X_{(b,j,t)}} \right)^2, \tag{2}$$

where $\mathrm{X}_{(b,i,t)}$ denotes the loan amount of bank b in industry i at time t and $IR_{(i,t)}$ denotes the insolvency rate of industry i at time t in Germany. This definition takes into account that the level of knowledge and effort exerted for monitoring should reflect the level of potential loss. The higher the risk, the more endeavours there are to monitor. If an industry constitutes a major part of the risk weighted loan exposure, this should be reflected in the specialization level.[10]

The *HHI* (HHI^w) has been criticized as a specialization measure because of its equal weighting of the industries although the industries differ greatly in loan volume and importance for the lending business. In particular, the explanatory power of the *HHI* depends on the chosen industry classification. Hence, Pfingsten and Rudolph (2004) recommend distance measures to benchmark portfolios as reasonable alternative key figures. These measures have already been used in papers by Kamp (2006) and Norden and Szerencses (2005). Our benchmarks are the national lending composition by industry (*nation*) and the regional lending compositions (*region*) by industry.[11] Each bank b is assigned to one region.[12] Since the investigation focuses on savings banks and cooperative banks, the re-

[10] We revert to the insolvency rates of the industries because of a lack of single borrower data.

[11] For the motivation of the benchmarks, see Kamp (2006). For the calculation of the regional benchmarks, we use the same banks as mentioned in footnote 13.

[12] The banks are assigned to 182 different regions in total. According to Kötter and Wedow (2006), local savings and cooperative banks grant, on average, 80% of their loan portfolio to customers within these regions.

gional benchmarks represent an indicator of lending in the relevant business district. We define $X^{nation}_{(i,t)}$ and $X^{region_b}_{(i,t)}$, respectively, as the sums of the loan amounts in the industry i at time t at the national level and the level of the region, respectively, where the head office of bank b is located.[13] $x^{\cdot}_{(\cdot,\cdot)}$ indicates the corresponding proportions. We adopt the standardized sum of the absolute differences between the bank portfolio and the benchmark portfolio as the distance measure:[14]

$$D^{type}_{(b,t)} := \frac{1}{2}\sum_{i=1}^{23} |x_{(i,b,t)} - x^{type_b}_{(i,t)}|, \tag{3}$$

where $type$ = nation or region. The values range from 0 to 1 and can be interpreted as the part of the loan portfolio which has to be rearranged to replicate the structure of the benchmark portfolio.

In the case of all specialization measures, high values imply a high level of specialization and low values indicate a high level of diversification. We stress that a high level of specialization is not necessarily a result of the bank's strategy. In fact, this does not impair our investigations. Table 1 gives an overview of the specialization levels for savings banks and cooperative banks.

Table 1: **Summary statistics of specialization measures**

This table presents summary statistics of specialization measures based on average values per bank for the time period 1995-2006.

	savings banks				cooperative banks			
	mean	median	5% quantile	95% quantile	mean	median	5% quantile	95% quantile
HHI	0.107	0.105	0.084	0.135	0.143	0.123	0.091	0.265
HHI^w	0.127	0.122	0.096	0.174	0.163	0.148	0.107	0.258
D^{nation}	0.294	0.288	0.204	0.407	0.432	0.419	0.288	0.619
D^{region}	0.202	0.190	0.099	0.345	0.321	0.306	0.164	0.549

Obviously, savings banks are more diversified than cooperative banks. For each specialization measure, the mean values of the cooperative banks are about 1.5 times higher than the mean values of the savings banks. It is also noteworthy that the 95th percentiles of the savings banks are about as high as the means of the cooperative banks.

[13] For the calculation of $X^{region_b}_{(i,t)}$ we merely include cooperative, savings, and regional banks.

[14] The benchmarks based on the regional lending differ depending on the region to which a bank belongs. Because of this, the benchmark carries the index b.

As the business of cooperative banks and savings banks is mostly regionally constrained, deviations from the national benchmark may stem from deviations of the corresponding regional industry composition from the national benchmark. To analyze the impact of specific regional structures, we use the variable

$$SM\_region_{(b,t)} := \frac{1}{2}\sum_{i=1}^{23} |x_{(i,t)}^{nation} - x_{(i,t)}^{region_b}|. \qquad (4)$$

2.1.2 Measurement of the monitoring quality

In order to examine the relationship between specialization level and monitoring quality, we need to define a proxy for the monitoring quality. The proxy consists of two components, the expected and the actual (loan) loss rates, which we introduce now. The term *expected loss rate* refers to the loss rate given default, but for the unconditional loss rate, which depends on the probability of default (PD) and the LGD. In order to determine the expected losses, we use the borrower statistics and the insolvency statistics. Strictly speaking, we calculate the losses (EL) and the loss rates (ELR), respectively, which can be expected on average based on the industry allocation of each bank. We set

$$EL_{(b,t)} := \sum_{i=1}^{23} X_{(b,i,t)} \cdot IR_{(i,t)} \cdot f_t^{state_b} \qquad (5)$$

as the expected losses of bank b at time t, where $f_t^{state_b}$ is an adjustment factor for the state in which bank b operates. It is calculated as the ratio of the average insolvency rate in the corresponding state at time t to the average insolvency rate in Germany at time t. This refinement seems to be reasonable as savings and cooperative banks have a regional business district. Because of a lack of information the LGD is assumed as 45%.[15] We shall correct for inaccuracies due to this rough assumption later.[16] The expected loss rate of the corporate loans (ELR) is computed as the ratio of the expected loss to the total corporate loan amount. The term expected loss rate has to be used carefully. As the industry is considered as the key risk factor for the PD and the insolvency rates indicate the defaulted proportion of each industry, ELR is a reasonable measure of the loss rate which a bank

[15] The expected loss of each industry is therefore calculated as 0.45·EAD·PD, where EAD corresponds to the loan amount and the PD corresponds to the insolvency rate.

[16] According to Grossman et al. (1997), Bartlett (2000), and Kabance (2001), the industry affiliation has an influence on the recovery rate.

with corresponding industry allocation should show on average. We interpret the *ex post* knowledge of the insolvency rate of an industry as the *ex ante* expected default rate of an industry, i. e. in so far perfect prediction is assumed.

To approximate the actual loss rates which will be related to the expected loss rates we use the following two proxies:[17]

- Rate of distressed loans (LR^{dis})[18]:=

$$\frac{\text{Nominal amount of audited distressed loans}}{\text{Loan amount}} \tag{6}$$

- Failure rate (LR^{fai}):=

$$\frac{(\text{Consumption of specific loan provisions} + \text{Net direct write-offs on loans})}{\text{Loan amount}} \tag{7}$$

The rate of distressed loans LR^{dis} does not consider the loss rate given default unlike LR^{fai}. This is advantageous for our analysis because results based on this variable are robust against any assumption about the LGD. It is, however, based on stock variables and a distressed loan is considered several times. Furthermore, LR^{dis} heavily depends on the point in time a loan is designated as a distressed loan.

The failure rate LR^{fai} has a numerator which is a flow variable and it refers to loan losses which – in contrast to LR^{dis} – are quite certain. It is used by many banks in their annual reports to reveal the actual losses.[19]

Our measure of the monitoring quality is defined by dividing the observed loss rate by the expected loss rate:

$$MON_{(b,t)}^{(dis \text{ or } fai)} := \frac{LR_{(b,t)}^{(dis \text{ or } fai)}}{ELR_{(b,t)}}. \tag{8}$$

This means that $MON_{(b,t)}^{dis}$ denotes the ratio of LR^{dis} to the expected loss rate and $MON_{(b,t)}^{fai}$ denotes the ratio of LR^{fai} to the expected loss rate for bank b at time t. A comparatively

[17] In order to simplify the notation, we do not display subscripts for time and bank.

[18] The audited distressed loans comprise specific doubtful loans and loans with increased latent risk. An alternative would be to use the audited loans as the denominator. However, the risk-orientated audit implies that the portfolio of audited loans particularly contains the critical loan engagements.

[19] Further reasonable variables used in additional examinations are the appropriation rate (ratio of net loan loss provisions appropriation to net write-offs over loan amount) or the loan loss provisions ratio. However, for both variables the same critical points as for the used proxies are valid.

low value of *MON* implies that a bank selects and monitors borrowers in their customer industries in a comparatively better way. Therefore, *MON* is used as a proxy for the monitoring quality of a bank. The lower *MON*, the higher the monitoring quality is.[20]

2.2 Empirical design

The analysis of the relationship between specialization level and monitoring quality is based on the following linear regression model:

$$\begin{aligned}\log(\overline{MON})_b &= \alpha + \beta_1 \cdot \overline{SM}_b + \beta_2 \cdot \overline{loan}_b + \beta_3 \cdot \overline{retail}_b + \beta_4 \cdot \overline{local\_authority}_b \\ &\quad +\beta_5 \cdot \overline{mortgage}_b + +\beta_6 \cdot \overline{unsecured}_b + \beta_7 \cdot \overline{personnel}_b \\ &\quad +\beta_8 \cdot \overline{market}_b + \beta_9 \cdot \overline{size}_b + \beta_{10} \cdot \overline{agglom1}_b + \beta_{11} \cdot \overline{agglom2}_b \\ &\quad +\beta_{12} \cdot \overline{east}_b + \beta_{13} \cdot \overline{merge1}_b + \beta_{14} \cdot \overline{merge2}_b + \epsilon_b,\end{aligned} \tag{9}$$

where the variables represent average values over the observed time period (basically, 1995 to 2006) for each bank. *SM* stands for the four specialization measures introduced in section 2.1.1 and *MON* is short for MON^{dis} and MON^{fai}. The main idea of this investigation is to evaluate the relationship between the specialization level and the ratio (MON) of actual and expected loss rates. This ratio reflects the relation between the actual loan losses and the losses, which are expected based on the industry allocation in corporate lending. The higher *MON* is, the worse is the implied monitoring ability of a bank. We use the natural logarithm of the quotient as relative − and not absolute − variations of *MON* are considered.[21]

The main reason for reducing the panel structure to a pure cross-sectional data structure by averaging for each bank is the objective to use a reasonable and reliable actual loan loss rate. Forming provisions for specific doubtful loans does not usually coincide with the insolvency of a borrower, but it already signals that a timely redemption of interest and amortization payments has become doubtful. Direct write-offs and the consumption of provisions are normally conducted at a later date, when the default is certain. Since

[20] We assume that there is no systematic difference between the risk preference of specialized and diversified banks. Investigations concerning the interest rates in lending confirm this assumption. Corresponding results will be provided by the authors on request.

[21] This means that, for example, a bisection of *MON* is always connected with the same improvement of the monitoring quality not depending on the level of *MON*. To ease reading, we keep the term *MON* instead of $\log(MON)$ below.

the practices differ enormously between banks and banks have intertemporal leeway, it seems to be useful to refer to a longer time period than just one year for the calculation of a reasonable loss variable. These aspects cannot be considered by a panel analysis, for example, a fixed-effects estimation with time lags. Additionally, we prefer to examine the differences between banks rather than different SM values within a bank over time as about 90% (80%) of the whole SM variance of cooperative (savings) banks is explained by variation of the average SM values between banks and just 10% (20%) stems from SM variation over time. The between groups estimation also gives us the opportunity to integrate time fixed variables into the equation, for instance, for being located in former west German or east German territory.

In particular because of the error term correction, we use the number of observed years for each bank as a weighting factor in the regression. Additionally, we conduct a White adjustment for the standard errors. We also perform Ramsey tests to examine whether omitted variables or endogeneities may cause problems and calculate variance inflation factors to check for multi-collinearity. Regressions with modified variable compositions are also conducted. In the case of mergers, we identify the merged bank with the bigger bank or the bank that has taken over another bank. The smaller bank or bank that has been taken over is considered as an independent observation entity until the year of the merger.[22] We exclude banks with less than seven years of observations from the data set as we want to calculate a reliable proxy for the monitoring quality. Incorporating retail banks with just a few corporate loans would provoke biased results if the aim is to examine corporate lending business. Therefore, we exclude banks with a retail share of more than 90%. Furthermore, we perform various robustness checks, which are presented in section 2.4.2.

The main hypothesis is that specialization improves the monitoring quality, which implies $\beta_1 < 0$. A negative β_1 means that specialized banks have, on average, lower actual losses relative to their expected losses than diversified banks. This would mean that specialized banks show monitoring advantages, i.e. superior screening abilities to identify better borrowers in an industry or superior monitoring abilities to influence an ongoing contract positively, which leads to comparatively low losses from lending. This conclusion would be

[22] There are alternative ways of merger treatments, for example, the merged bank is treated as a new entity. Additional examinations have shown no major impact of different merger treatments on the results.

valid because we do not rely solely on loan loss rates, but adjust for each bank's industry allocation. In the case of the MON^{dis} and in contrast to the MON^{fai}, the influence of different LGD values is omitted so that the examination just considers different PD values.

Additionally, further variables which might influence the monitoring quality and the loan losses, respectively, are considered.[23] The share of loans (*loan*) might have an impact, as, for a bank with a high loan share, the relevance of lending could induce a more diligent monitoring activity, or a deeper industry knowledge is achieved. In contrast to this, a higher loan share could also be related to riskier lending which aspires to maintain the high loan share. This means both negative and positive signs could be explained for the coefficient. As the actual loss rate is calculated solely on the basis of the corporate loans, it is implicitly assumed that the loss rate in retail lending equals the loss rate in corporate lending. In order to control for differences, we consider the share of retail loans (*retail*). It might also be plausible that banks with a high retail share pursue safe engagements in corporate lending which merely represents an extension of their credit portfolio. Negative coefficients are expected for the share of local authority loans (*local_authority*) and the share of mortgage loans (*mortgage*) as we could assume a loss rate of 0% for local authority loans[24] and relatively low loss rates for mortgage loans (due to specifics of the German mortgage market).[25] We revert to the unsecured portion in the case of audited specific doubtful loans (*unsecured*) in order to reflect different LGDs across banks[26] and to mitigate the problem of lacking LGD data for industries. The higher *unsecured*, the higher should be MON^{fai}. As MON^{dis} does not depend on the LGD, a significantly positive relation between *unsecured* and MON^{dis} would be a surprise.[27] The proxy for personnel expenses assigned to corporate lending (*personnel*) is used as a proxy for monitoring efforts by Coleman et al. (2006). Thus, we expect that a higher *personnel* value is accompanied by lower *MON* values.[28] A higher market share (*market*) of a bank in its business district could

[23] The exact definitions of the control variables are given in the appendices (section 5.1).

[24] See Lux (2001).

[25] See Eichwald and Pehle (2000).

[26] See, for example, Grunert and Weber (2007) for the strong dependency between collateralization and LGD.

[27] We remark that the incorporation of the variable *unsecured* counteracts the possibly prevalent effect of specialization on the LGD.

[28] A detailed description of the estimation of the variable *personnel* is given in the appendices (section 5.1).

imply higher bargaining power, which could positively affect the selection of borrowers or the request of collaterals. However, a larger market share could also be the result of an undifferentiated lending policy and market power could also be used to charge higher interest rates instead of reducing the risk. We consider the natural logarithm of total assets (*size*) as a proxy for the size of a bank. We expect that bigger banks have lower *MON* values. Bigger banks can build up deeper industry knowledge more easily than other banks (given a fixed specialization level) because they can allocate the fixed costs related to monitoring activities over a larger volume. Bigger banks, however, are more prone to a bloated organization and communication deficits.[29] This argument suggests a positive relationship between *MON* and *size*. To control for regional specifics, we assign degrees of agglomeration to the business districts. Based on the information of the *Bundesamt für Bauwesen und Raumordnung*, we differentiate between an urban agglomeration, an urban area, and a rural area. We introduce the two dummy variables *agglom1* and *agglom2* where *agglom1*=1 if and only if the business district is an urban agglomeration and *agglom2*=1 if and only if the business district is an urban area.[30] Additionally, we use the dummy variable *east* to indicate whether the business district belongs to eastern Germany (*east*=1) or to western Germany (*east*=0). East German banks might face a different business condition. As mergers could have an effect on banks' business, we introduce the two dummy variables *merge1* and *merge2*, where *merge1*=1 if and only if the bank has taken over another bank during the observation period and *merge2*=1 if and only if the bank has been taken over during the observation period. Banks that have been taken over might postpone write-offs in credit business in order to euphemize their economic condition. As audits should be independent, we assume a negative relation merely for MON^{fai} and not for MON^{dis} with *merge2*. Banks which have taken over another bank might have to make up for the risk provisioning implying a positive coefficient for *merge1* in case of MON^{fai}. Table 11 in the appendices (section 5.2) shows some summary statistics of the introduced variables, and correlations between the variables are given in Tables 12 to 14 of section 5.3.

We run our regressions for savings banks and cooperative banks separately and also perform the joint regression

[29]See Tröger (2003) and Cerasi and Daltung (2000).

[30]See Bundesamt für Bauwesen und Raumordnung (2005).

$$\log(\frac{\overline{LR}_b}{\overline{ELR}_b^C}) = \alpha + \alpha^\star \cdot savings_b + \beta_1 \cdot \overline{SM}_b + \beta_1^\star \cdot \overline{SM}_b \cdot savings_b + \sum_{j=2}^{14} \beta_j \cdot \overline{z}_{(j,b)} + \epsilon_b \quad (10)$$

in order to clarify whether there are significant differences between savings banks and cooperative banks concerning the influence of the specialization level on the monitoring quality. The dummy variable $savings_b$ takes the value 1 if the bank is a savings bank and the value 0 if the bank is a cooperative bank. $z_{(i,b)}$ for $j = 2, \ldots, 14$ stands for the explanatory variables used in equation 9.

2.3 Data

As mentioned above, we restrict our analysis to savings banks and the primary institutions of the category of cooperative banks. These banks are predominantly engaged in traditional lending business and show the highest level of homogeneity among themselves.[31] Furthermore, data constraints, as can be seen below, are not problematic for these banks, which have regional business districts in most cases. Savings banks and cooperative banks constituted 84% (89%) of all German banks in 2006 (1995), their share of aggregated total assets was 24% on average during the period from 1995 to 2006, and their share of domestic loans was 35% on average. From 1995 to 2006, the number of cooperative banks (savings banks) fell – mainly due to mergers – from 2,589 (624) to 1,255 (457). Our analysis is based on annual data from 1995 until 2006, i.e. the investigation period is 12 years. All in all, 80% (90%) of the cooperative banks (savings banks) are, on average, included in the standard data set per year.[32]

In the quarter-annual German borrower statistics, Deutsche Bundesbank records the loan exposures of each German bank in corporate banking differentiated by 23 industries. The classification resembles the industry classification of the Federal Statistical Office and the NACE Code, respectively. Foreign loans are not considered, nor are off-balance-sheet credit transactions and credit derivatives. The impact of these restrictions, however, should be rather low as we restrain on the primary institutions of the cooperative sector and on

[31] See Hackethal (2004).

[32] As mentioned in the previous section, we exclude retail banks and banks with less than seven years of data.

savings banks, which are generally not active players in these business segments. Amongst others, these data are fundamental for the calculation of the specialization level.

The second relevant data source is the *Bankaufsichtliches Informationssystem* (BAKIS). The data which is collected by Deutsche Bundesbank and the German Federal Financial Supervisory Authority (BaFin) includes annual balance sheet, profit and loss data of all German banks, and annual quantitative reports by auditors. Amongst others, we use these data to approximate the actual loan losses.

For the calculation of the expected loan losses, we also resort to the Federal Statistical Office's statistics on insolvencies and numbers of firms liable to sales taxes. The classification by industry is at least as detailed as the one in the borrower statistics. This allows mapping among the 23 industries. The insolvency ratio in each industry is calculated as the number of insolvencies divided by the number of firms liable to sales taxes in this industry.[33]

2.4 Empirical results

2.4.1 Base case

In this section, we present the results of the regressions which will clarify whether specialized banks have a lower ratio of actual to expected loss rates than diversified banks. Table 2 contains the results for the cooperative banks, Table 3 contains the results for the savings banks. In Table 4 we present the results of the joint regressions run for both banking groups for completeness. Since most banks in the sample belong to the cooperative banking category, the results of the joint regressions are closely related to the results of the separate regressions for cooperative banks. Therefore, we focus in our analysis on the regressions for the two separate groups rather than on the joint regressions.

The variables have been $\mu - \sigma -$ standardized to possess mean zero and unit variance. In all cases, the heteroscedasticity-robust F-tests indicate the statistical significance of the regressions. Concerning the Ramsey tests, the hypothesis is rejected at least for the 5%-(10%-)level in the case of the cooperative banks (savings banks). The variance inflation

[33] Although there are inaccuracies for certain industries, for example, agriculture and forestry, the lack of an exhaustive German business register means that using the number of firms liable to sales taxes is a common way of approximating the number of companies in Germany.

factors for the separated regressions are all below 5 and, on average, below 2, signalling no distortion of our results due to near multi-collinearity.

Table 2: **Regression results on specialization benefits of cooperative banks**

This table presents results of the regressions with MON^{fai} and MON^{dis}, respectively, as the dependent variable according to equation 9 for cooperative banks after $\mu - \sigma -$ standardization of the variables. ***, **, * indicate statistical significance at a 0.1%, 1%, 5% significance level. The values in brackets are the corresponding t-values.

	MON^{fai}				MON^{dis}			
	HHI	HHI^w	D^{nation}	D^{region}	HHI	HHI^w	D^{nation}	D^{region}
SM	-0.229***	-0.204***	-0.301***	-0.183***	-0.141***	-0.196***	-0.204***	-0.126***
	(-5.43)	(-5.76)	(-6.65)	(-5.13)	(-3.32)	(-5.21)	(-4.30)	(-3.45)
loan	0.122***	0.143***	0.102**	0.139***	0.205***	0.207***	0.187***	0.212***
	(3.98)	(4.74)	(3.18)	(4.51)	(5.18)	(5.43)	(4.70)	(5.54)
retail	-0.167***	-0.128***	-0.134***	-0.118***	-0.153***	-0.137***	-0.134***	-0.124***
	(-5.31)	(-4.33)	(-4.63)	(-4.13)	(-4.36)	(-4.20)	(-4.09)	(-3.81)
local_authority	-0.056	-0.058	-0.050	-0.066*	-0.065*	-0.049	-0.058	-0.068*
	(-1.76)	(-1.92)	(-1.49)	(-1.97)	(-2.07)	(-1.71)	(-1.75)	(-2.07)
mortgage	-0.111***	-0.099***	-0.109***	-0.104***	-0.099***	-0.090***	-0.098***	-0.094***
	(-3.90)	(-3.38)	(-3.82)	(-3.52)	(-3.58)	(-3.30)	(-3.55)	(-3.39)
unsecured	0.192***	0.179***	0.187***	0.186***	-0.004	-0.013	-0.006	-0.007
	(4.88)	(4.50)	(4.80)	(4.66)	(-0.10)	(-0.33)	(-0.17)	(-0.19)
personnel	-0.061	-0.068	-0.055	-0.045	-0.095**	-0.111***	-0.093**	-0.086**
	(-1.78)	(-1.93)	(-1.57)	(-1.25)	(-2.92)	(-3.45)	(-2.81)	(-2.60)
market	-0.024	-0.027	-0.019	-0.082**	-0.023	-0.017	-0.018	-0.061*
	(-1.14)	(-1.28)	(-0.92)	(-3.20)	(-0.91)	(-0.74)	(-0.73)	(-2.00)
size	0.174***	0.207***	0.060	0.165***	0.023	0.026	-0.060	0.010
	(4.81)	(5.94)	(1.33)	(4.14)	(0.54)	(0.68)	(-1.19)	(0.23)
agglom1	-0.027	-0.008	-0.072*	-0.015	-0.046	-0.027	-0.077*	-0.038
	(-0.90)	(-0.25)	(-2.30)	(-0.51)	(-1.44)	(-0.82)	(-2.35)	(-1.17)
agglom2	0.005	0.010	-0.014	-0.010	0.038	0.043	0.025	0.027
	(0.16)	(0.34)	(-0.48)	(-0.34)	(1.27)	(1.47)	(0.83)	(0.93)
east	0.084**	0.132***	0.093***	0.107***	-0.053	-0.029	-0.051	-0.042
	(3.23)	(5.28)	(3.54)	(4.11)	(-1.67)	(-0.99)	(-1.63)	(-1.37)
merge1	0.112***	0.106***	0.119***	0.115***	0.051	0.041	0.055	0.052
	(4.50)	(4.24)	(4.78)	(4.47)	(1.68)	(1.37)	(1.82)	(1.68)
merge2	-0.055*	-0.038	-0.058*	-0.050*	0.016	0.030	0.014	0.019
	(-2.45)	(-1.65)	(-2.56)	(-2.19)	(0.68)	(1.28)	(0.58)	(0.79)
observations	1575	1575	1575	1575	1575	1575	1575	1575
R^2	0.277	0.273	0.280	0.260	0.129	0.144	0.133	0.124

Table 3: **Regression results on specialization benefits of savings banks**

This table presents results of the regressions with MON^{fai} and MON^{dis}, respectively, as the dependent variable according to equation 9 for savings banks after $\mu-\sigma-$standardization of the variables. ***, **, * indicate statistical significance at a 0.1%, 1%, 5% significance level. The values in brackets are the corresponding t-values.

	MON^{fai}				MON^{dis}			
	HHI	HHI^{w}	D^{nation}	D^{region}	HHI	HHI^{w}	D^{nation}	D^{region}
SM	-0.034	-0.190***	-0.216***	-0.038	-0.010	-0.119*	-0.132*	-0.036
	(-0.68)	(-3.93)	(-4.08)	(-1.00)	(-0.22)	(-2.46)	(-2.27)	(-0.84)
loan	0.022	-0.005	-0.027	0.022	-0.025	-0.042	-0.055	-0.025
	(0.35)	(-0.07)	(-0.42)	(0.35)	(-0.36)	(-0.61)	(-0.78)	(-0.36)
retail	-0.142**	-0.138**	-0.138**	-0.142**	-0.262***	-0.260***	-0.260***	-0.264***
	(-2.98)	(-2.94)	(-2.97)	(-2.97)	(-5.42)	(-5.45)	(-5.47)	(-5.52)
local_authority	-0.067	-0.083*	-0.079	-0.066	-0.046	-0.056	-0.053	-0.045
	(-1.58)	(-2.00)	(-1.81)	(-1.56)	(-1.02)	(-1.24)	(-1.14)	(-0.99)
mortgage	-0.121**	-0.104*	-0.138**	-0.122**	-0.270***	-0.258***	-0.279***	-0.269***
	(-2.76)	(-2.41)	(-3.23)	(-2.79)	(-5.22)	(-5.02)	(-5.50)	(-5.23)
unsecured	0.339***	0.321***	0.333***	0.339***	0.102	0.091	0.098	0.102
	(6.82)	(6.42)	(6.69)	(6.82)	(1.90)	(1.68)	(1.82)	(1.90)
personnel	0.145**	0.128*	0.141**	0.144**	0.023	0.011	0.019	0.020
	(2.75)	(2.41)	(2.67)	(2.69)	(0.37)	(0.18)	(0.31)	(0.32)
market	-0.064	-0.057	-0.064	-0.081	-0.048	-0.043	-0.047	-0.063
	(-1.46)	(-1.36)	(-1.52)	(-1.78)	(-0.97)	(-0.89)	(-0.97)	(-1.23)
size	0.234***	0.161**	0.095	0.236***	-0.158*	-0.207**	-0.246***	-0.164*
	(4.03)	(2.68)	(1.43)	(4.06)	(-2.41)	(-3.09)	(-3.38)	(-2.58)
agglom1	-0.084	-0.068	-0.127*	-0.087	-0.006	0.006	-0.030	-0.005
	(-1.42)	(-1.17)	(-2.18)	(-1.47)	(-0.10)	(0.10)	(-0.50)	(-0.08)
agglom2	0.041	0.046	0.029	0.040	0.163**	0.165**	0.155**	0.161**
	(0.79)	(0.88)	(0.55)	(0.76)	(2.94)	(2.98)	(2.82)	(2.91)
east	0.235**	0.277***	0.172*	0.223**	-0.069	-0.041	-0.106	-0.077
	(3.02)	(3.60)	(2.18)	(2.85)	(-0.85)	(-0.51)	(-1.31)	(-0.96)
merge1	-0.005	0.009	-0.002	-0.004	-0.050	-0.043	-0.050	-0.052
	(-0.11)	(0.22)	(-0.06)	(-0.11)	(-1.08)	(-0.93)	(-1.09)	(-1.13)
merge2	0.001	0.017	-0.007	0.002	0.015	0.025	0.010	0.016
	(0.03)	(0.44)	(-0.18)	(0.06)	(0.38)	(0.64)	(0.25)	(0.42)
observations	534	534	534	534	534	534	534	534
R^2	0.316	0.337	0.338	0.316	0.195	0.204	0.204	0.196

Table 4: **Regression results on specialization benefits of a pooled sample of cooperative banks and savings banks**

This table presents results of the regressions with MON^{fai} and MON^{dis}, respectively, as the dependent variable according to equation 9 for savings banks after $\mu-\sigma-$standardization of the variables. ***, **, * indicate statistical significance at a 0.1%, 1%, 5% significance level. The values in brackets are the corresponding t-values.

	MON^{fai}				MON^{dis}			
	HHI	HHI^{w}	D^{nation}	D^{region}	HHI	HHI^{w}	D^{nation}	D^{region}
SM	-0.237***	-0.216***	-0.379***	-0.215***	-0.162***	-0.207***	-0.279***	-0.159***
	(-6.23)	(-6.56)	(-8.11)	(-6.11)	(-4.40)	(-6.29)	(-5.84)	(-4.63)
SM·savings	2.701	-0.024	0.203**	0.115**	1.859	0.059	0.192*	0.064
	(1.53)	(-0.33)	(2.89)	(3.02)	(1.44)	(0.66)	(2.19)	(1.39)
loan	0.121***	0.143***	0.093**	0.139***	0.171***	0.176***	0.148***	0.182***
	(4.19)	(5.03)	(3.10)	(4.85)	(4.98)	(5.30)	(4.23)	(5.49)
retail	-0.174***	-0.142***	-0.142***	-0.124***	-0.169***	-0.154***	-0.148***	-0.136***
	(-6.53)	(-5.53)	(-5.70)	(-5.01)	(-6.01)	(-5.77)	(-5.52)	(-5.13)
local_authority	-0.050	-0.053*	-0.053	-0.058*	-0.032	-0.024	-0.032	-0.036
	(-1.88)	(-2.10)	(-1.93)	(-2.08)	(-1.20)	(-0.95)	(-1.15)	(-1.26)
mortgage	-0.115***	-0.098***	-0.121***	-0.109***	-0.108***	-0.097***	-0.113***	-0.103***
	(-4.37)	(-3.62)	(-4.59)	(-4.00)	(-4.47)	(-4.02)	(-4.65)	(-4.22)
unsecured	0.210***	0.195***	0.205***	0.208***	0.023	0.012	0.021	0.022
	(6.08)	(5.54)	(5.96)	(5.93)	(0.76)	(0.37)	(0.67)	(0.69)
personnel	-0.036	-0.043	-0.029	-0.021	-0.094***	-0.108***	-0.091**	-0.085**
	(-1.17)	(-1.37)	(-0.93)	(-0.64)	(-3.38)	(-3.92)	(-3.21)	(-2.96)
market	-0.037*	-0.043*	-0.030	-0.084***	-0.025	-0.024	-0.017	-0.062*
	(-2.00)	(-2.36)	(-1.61)	(-3.81)	(-1.11)	(-1.10)	(-0.76)	(-2.38)
size	0.220***	0.248***	0.074	0.211***	-0.010	-0.007	-0.120*	-0.026
	(5.94)	(6.67)	(1.63)	(5.28)	(-0.25)	(-0.18)	(-2.35)	(-0.59)
agglom1	-0.032	-0.011	-0.076**	-0.023	-0.034	-0.014	-0.066*	-0.026
	(-1.21)	(-0.43)	(-2.79)	(-0.87)	(-1.25)	(-0.53)	(-2.39)	(-0.96)
agglom2	0.018	0.025	-0.000	0.004	0.070**	0.077**	0.057*	0.059*
	(0.69)	(0.96)	(-0.01)	(0.14)	(2.77)	(3.03)	(2.23)	(2.33)
east	0.109***	0.165***	0.104***	0.134***	-0.055	-0.026	-0.061*	-0.040
	(3.97)	(6.17)	(3.77)	(4.85)	(-1.82)	(-0.92)	(-2.04)	(-1.34)
merge1	0.093***	0.090***	0.095***	0.095***	0.037	0.028	0.037	0.037
	(4.41)	(4.27)	(4.50)	(4.38)	(1.50)	(1.16)	(1.51)	(1.49)
merge2	-0.049*	-0.030	-0.054**	-0.045*	0.017	0.031	0.013	0.019
	(-2.48)	(-1.52)	(-2.73)	(-2.27)	(0.84)	(1.57)	(0.64)	(0.97)
savings	-0.180	-0.035	-0.288***	-0.154**	-0.364***	-0.306**	-0.450***	-0.287***
	(-1.82)	(-0.43)	(-3.41)	(-3.00)	(-3.41)	(-3.10)	(-4.43)	(-4.81)
observations	2109	2109	2109	2109	2109	2109	2109	2109
R^2	0.278	0.274	0.284	0.260	0.188	0.201	0.194	0.181

We shall concentrate on the main results, which refer to the relation between specialization level and monitoring quality. Both for cooperative banks and savings banks, negative coefficients β_1 are prevalent for both loss rates. Furthermore, the coefficients are negative for the joint estimations. In the case of the cooperative banks, statistically and economically significant negative relationships between the specialization level and the ratio of actual loss rate over expected loss rate can be observed. In all cases, there is statistical significance at the 0.1% level. This means that specialized cooperative banks, on average, show a higher monitoring quality than other cooperative banks. The strongest negative relation can be detected in the case of the distance measure D^{nation}, but the differences between the results for different specialization measures are rather low. Naive specialization measures as well as distance measures seem to be appropriate for capturing specialization benefits in lending. Using MON^{dis} or MON^{fai} as a proxy for monitoring quality does not make a big difference. We notice a slightly stronger relation in the case of MON^{fai}. Compared to the cooperative banks, the relationship is somewhat weaker for the savings banks, as is indicated by the positive coefficients for the interaction term in Table 4.[34] We observe statistically significant negative relations between the specialization level and the proxies for monitoring quality in four out of eight cases. The differences between the results for the specialization measures are quite large. For HHI^{w} and D^{nation} we can state statistical significance in contrast to the measures HHI and D^{region} with insignificant relations. The discrepancy between the results for HHI and HHI^{w} might indicate that savings banks gear their monitoring efforts more to the related risk than to the volume of a loan exposure. Thus, higher HHI^{w} values would tend to suggest deeper industry knowledge than higher HHI values in the case of the savings banks. The results for D^{nation} and D^{region} indicate that deviations from regional benchmarks, which could be regarded as actively chosen specialization, are inferior to deviations from the national benchmark, which might be seen as passive specialization, in explaining superior monitoring abilities. However, it should be considered that these results may also be driven by neglecting supraregional banks within the calculation of D^{region}. Furthermore, the negative relationship is stronger for MON^{fai} than for MON^{dis}. As MON^{dis} does not consider − as mentioned above − the impact of different LGDs, we could conclude that the LGD, in particular, is influenced by the specialization level and that the effect of specializing in certain industries on the PD is rather small. Overall, we can conclude that monitoring benefits are prevalent for both specialized cooperative banks and specialized savings banks.

[34]An exception has to be noted for the specialization measure HHI^{w} in the case of MON^{fai}. The results concerning the significance of the interaction coefficients have to be interpreted carefully because, in most cases, the corresponding variance inflation factors are higher than 10.

We shall now highlight some of the results for the control variables. A larger loan share is accompanied by higher *MON* values in the case of the cooperative banks. Cooperative banks with larger loan shares possibly neglect risk aspects to maintain the large loan shares.[35] There is a statistically significant negative relationship between the retail share and *MON*. This could stem from lower loss rates in retail business compared to corporate business, or banks with a larger share of retail activities might concentrate purely on apparently low-risk borrowers in corporate lending. As assumed, we see negative relationships in the case of *local_authority*, *mortgage* and *unsecured*. A larger unsecured portion is accompanied by a higher MON^{fai}-value as the LGD is increasing. In the case of the savings banks, there is slight evidence that a higher collateralization rate related to audited specific doubtful loans, which includes subsequent collateralization, is connected with a better monitoring quality as we can also observe negative relations for MON^{dis}. The results for the personnel expenses are rather heterogenous. All in all, personnel expenses show just a marginal and not a uniform impact on *MON*. For savings banks, positive relationships can be observed. Higher personnel expenses for the credit business tend − contrary to our expectations − to worsen the monitoring quality in the case of savings banks. Regressions which omit the specialization measure as an explanatory variable show a slightly negative relationship for the *personnel* variable.[36] It is obvious that the specialization level has higher explanatory power for the monitoring quality than the personnel expenses in lending. The market share which specifies the loan share a bank possesses in its customers' industries in relation to the whole regional lending exhibits an insignificant negative relationship with *MON*. Considerations which equate a higher market share with higher market power and conclude that there are benefits for the selection of the borrowers and the collateralization cannot be verified here. In addition, there is no indication that a larger market share is the result of an unrestrained and imprudent lending policy. We do not examine whether both effects coexist and cancel each other. Both for cooperative banks and savings banks, MON^{dis} decreases and MON^{fai} increases in the case of increasing bank size. To some extent, we can observe that the agglomeration level of the business district has an impact on *MON*. In agglomeration areas, the *MON* values tend to be lower, possibly due to lower insolvency rates. MON^{fai} values are significantly lower in western Germany than in eastern Germany, but MON^{dis} values are insignificantly higher

[35] Negative correlations between loan share and loan growth over the observation period indicate, however, that banks with larger loan shares do not aggressively expand their credit business.

[36] The results will be provided by the authors on request.

in western Germany. This might be explained by higher LGD values in eastern Germany. Cooperative banks that have been taken over in a merger seem to postpone loan write-offs as indicated by a negative relation between *merge2* and MON^{fai} and a positive relation between *merge2* and MON^{dis}. Cooperative banks that have taken over have to make up for loan loss adjustments signaled by a positive *merge2*-coefficient if using MON^{fai} as proxy for monitoring quality.

2.4.2 Robustness checks

To check whether the results are robust to variations, we conduct additional regressions based on a modified data set or a modified model. We restrict the presentation of the results on the relationship between specialization level and monitoring quality as we are mainly interested in the existence of specialization benefits, but not on effects of control variables.

Firstly, we check whether variations in the data base have a crucial impact on the results. In detail, we proceed as follows:

- We exclude banks which have values lower than the 1%-quantile or above the 99%-quantile in one of the variables. By doing so, we wish to clarify whether any results are driven mainly by banks with extreme variable specifications.
- We change the threshold for the retail share from 90% to 60%. Banks with a retail share larger than 60% are excluded. As the 90% threshold was chosen rather arbitrarily, we wish to ascertain that this specific choice was not a crucial factor for the presented results.
- We use an insolvency rate of 0% for agriculture and forestry. As the evaluation of a correct insolvency rate in this industry is rather difficult owing to the fact that many firms of this industry are not liable to sales taxes, we check whether specialization benefits would still be valid under an extreme assumption. Specialized cooperative banks, in particular, are engaged in agriculture and forestry.[37] Therefore,

[37]For the quarter of the cooperative banks with the highest *HHI* values, this industry accounts, on average, for 25% of the lending volume. For the quarter with the lowest *HHI* values, this industry accounts for 6.8%. For other specialization measures, we observe similar figures.

if a negative relation between specialization level and MON is disclosed under the assumption of no default, it should be valid under all other assumptions concerning the insolvency rate of agriculture and forestry.

- We include all savings banks and cooperative banks with at least one year of observation. As the exclusion of banks with less than seven years of observation predominantly relates to banks that have been taken over, we check whether the regression results might be biased because of that.

- We restrict the data set to banks with 12 years of observations. As different observation periods might have specific characteristics not captured by our variables, for example, the introduction of the new insolvency law in 1999,[38] we use a balanced data set and

- integrate dummies for different observation periods.

In order to analyze the stability of the relationship between specialization level and monitoring quality over time,

- we divide the data set into two parts. The first part comprises the time period from 1995 to 2000 and the second part covers the period from 2001 to 2006 after a new insolvency law had come into effect. Based on the average values of these time periods, we run the regressions according to equation (9).[39]

- Furthermore, we conducted fixed-effects estimations in order to exhaust the panel data structure, though we stress that panel regressions are unfavorable in this special case (see section 2.2).

The results of these analyses confirm the negative relationship between specialization level and MON^{fai} or MON^{dis}.[40] The results are not driven – at least not in an essential way – by the specific data set and specialization benefits prove to be stable over time.

[38] See, for example, Ehricke (2007).

[39] For these regressions, we exclude banks with less than four years of observation in the corresponding time period in order to ensure a reliable calculation of the monitoring quality proxy. Alternatively, we based the regressions on banks with 12 years of observation, which implies an equal set of banks for the first and second time period, and on banks with at least one year of observation. We note that the results just vary marginally.

[40] The results will be provided by the authors on request.

The model given by equation (9) is motivated mainly by economic factors. We are aware that other variables may also have an influence on the monitoring quality. The problem of omitted variables cannot be solved entirely in an empirical analysis with real observations. We checked whether the results concerning the specialization benefits would change if we introduced variables such as the share of customer deposits, the share of interbank loans, a variable for the market structure, quadratic terms for the specialization level and size, and a different measure of the market share. We also exchanged the *personnel* variable for a variable which comprises all personnel expenses as endogeneity problems might be suspected.[41] We observe a stable negative relation between specialization level and monitoring quality proxies. The same is true if variables are eliminated. Negative linear correlations and rank correlations between the specialization level and the monitoring quality proxies may be seen as a useful indication. We now present two slight modifications of equation (9):

- We skip the *unsecured* variable. As mentioned above, the specialization level might also influence the (subsequent) collateralization policy. Using *unsecured* as a control variable does not allow us to see this possible effect.[42]
- We use the deviation of the banks' business district lending structure from the national lending benchmark (*SM_region*) as a proxy for the banks' specialization level. We want to examine whether specialization benefits are bank-driven or depend just on the loan structure of its business district.

Table 5 shows the results of the regressions without the *unsecured* variable as a control variable and Table 6 shows the results of the regressions with *SM_region* as the specialization measure.[43]

[41] Some of the explanatory variables in equation (29) (see appendix) are also used together with the *personnel* variable to explain the monitoring quality.

[42] We have to note, that we do not control for differences in collateralization rates between industries in this case.

[43] We merely present the results for the most relevant variables. The complete results will be provided by the authors on request.

Table 5: **Robustness checks of regression results (part one)**

This table presents results (extract) of the regressions with MON^{fai} and MON^{dis}, respectively, as the dependent variable according to equation (9) without the variable *unsecured* as control variable after $\mu - \sigma-$standardization of the variables. ***, **, * indicate statistical significance at a 0.1%, 1%, 5% significance level. The values in brackets are the corresponding t-values.

	MON^{fai} as endogenous variable				MON^{dis} as endogenous variable			
	HHI	HHI^{w}	D^{nation}	D^{region}	HHI	HHI^{w}	D^{nation}	D^{region}
cooperative banks								
SM	-0.217***	-0.207***	-0.293***	-0.175***	-0.141**	-0.195***	-0.204***	-0.127***
	(-5.34)	(-6.37)	(-6.60)	(-4.97)	(-3.29)	(-5.18)	(-4.26)	(-3.42)
observations	1575	1575	1575	1575	1575	1575	1575	1575
R^2	0.242	0.241	0.245	0.226	0.129	0.144	0.133	0.124
savings banks								
SM	-0.037	-0.226***	-0.230***	-0.038	-0.011	-0.129**	-0.136*	-0.036
	(-0.67)	(-4.56)	(-3.95)	(-0.93)	(-0.24)	(-2.69)	(-2.31)	(-0.84)
mortgage	-0.148**	-0.126**	-0.166***	-0.150**	-0.278***	-0.265***	-0.288***	-0.277***
	(-3.18)	(-2.76)	(-3.68)	(-3.25)	(-5.44)	(-5.20)	(-5.75)	(-5.47)
observations	534	534	534	534	534	534	534	534
R^2	0.230	0.262	0.255	0.230	0.188	0.198	0.197	0.188

Table 6: **Robustness checks of regression results (part two)**

This table presents results (extract) of the regressions with MON^{fai} and MON^{dis}, respectively, as the dependent variable and *SM_region* as the specialization measure according to equation 9 after $\mu - \sigma-$standardization of the variables. ***, **, * indicate statistical significance at a 0.1%, 1%, 5% significance level. The values in brackets are the corresponding t-values.

	cooperative banks		savings banks	
	MON^{fai}	MON^{dis}	MON^{fai}	MON^{dis}
SM_region	-0.008	-0.040	-0.019	0.022
	(-0.32)	(-1.27)	(-0.53)	(0.60)
observations	1575	1575	534	534
R^2	0.242	0.117	0.316	0.196

We cannot observe any major changes if we omit the variable *unsecured* compared to the results of the regression based on equation (9). In the case of the savings banks, the negative relationship between *SM* and MON^{fai} is slightly stronger. It may be seen as a weak indication that specialized savings banks are able to reduce their LGDs by higher (subsequent) collateralization. For the savings banks, we also note a more pronounced relationship between mortgage loan share and monitoring quality as the high collateralization rate in the case of mortgage loans is no longer represented by a further variable. The results shown in Table 6 reveal that higher monitoring quality cannot be explained solely by the regional industry composition. Specialization measurement should not rely on business district figures even if we examine regionally restrained banks such as cooperative and savings banks, but relate to bank-specific industry compositions.

All in all, we can conclude that specialization benefits are stable over time and also prove robust against data set and model variation.

3 Specialization benefits vs. concentration risk

Below-average default probabilities due to a better monitoring do not necessarily imply a lower portfolio risk. The reason is that monitoring is accompanied by a higher sectoral concentration. In this section, we apply a commonly used credit risk model in order to measure portfolio risk by the economic capital (EC) or unexpected loss. We define EC as the difference between the value at risk given a 99.9% solvency probability and the expected loss of the portfolio. Since this risk measure focuses on the adverse tail of the loss distribution, the risk of sectoral concentrations is automatically taken into account.

3.1 Methodology

In order to measure the EC, we apply the one-period default-mode version of the widely used multi-factor Gaussian copula model. It is a stylized version of an asset value model that belongs to the class of *conditionally independent factor models* (see Schönbucher (2001)). Credit risk materializes only in default events after a one-year period. Defaults are triggered in this static model if the ability-to-pay variable Y_n of the $n-$th borrower falls below a default threshold γ_n.

$$Y_n = r \cdot X_{s(n)} + \sqrt{1-r^2} \cdot U_n. \tag{11}$$

Y_n depends on a single systematic risk factor $X_{s(n)}$ and an idiosyncratic risk factor U_n. Y_n is standard normal since both risk factors are pairwise independent and standard normally distributed by assumption. The mapping $s : \{1, ..., N\} \to \{1, ..., S\}$ uniquely assigns every borrower to an industry sector. The systematic risk factors are jointly standard normal distributed with correlation matrix Ω. The asset correlation between any pair of firms in the same sector is given by r^2.

Since Y_n is standard normally distributed, the default barrier γ_n can be inferred from the probability of default (PD) $p_n(t)$,

$$\gamma_n = \Phi^{-1}(p_n), \tag{12}$$

where $\Phi()^{-1}$ denotes the inverse of the cumulative standard normal distribution function.

Since we have neither information on the loan sizes nor the PDs of individual borrowers, we employ a slightly more restricted version of the model which allows us to compute the VaR very efficiently by a numerical approximation developed in Cespedes et al. (2006). They assume that the portfolio is infinitely fine-grained in every industry sector, i.e. idiosyncratic risk is eliminated through diversification across single borrowers. In this case, EC can be approximated by multiplying the economic capital of the bank in a single risk factor model (EC_b^{sf}) by a calibration factor ($CF(DI_b, \overline{\beta}_b)$) which, in turn, depends on two variables: the diversification index DI and an average inter-sector correlation $\overline{\beta}$. We define

$$EC_b = CF(DI_b, \overline{\beta}_b)\, EC_b^{sf} \tag{13}$$

with

$$EC_b^{sf} = \sum_j EC_{b,j} \tag{14}$$

and

$$EC_{b,j} = w_{b,j}\, \psi \left[\Phi\left(\frac{\Phi^{-1}(\hat{p}_j) - r\, \Phi^{-1}(0.999)}{\sqrt{1-r^2}} \right) - \hat{p}_j \right]. \tag{15}$$

The weight $w_{b,j}$ of each sector is the relative weight of all loans in that sector relative to the total loan volume of the bank's portfolio. The parameter ψ denotes the expected loss given default which we assume to be constant in the cross-section and also over time. Since the application of the EC formula requires inputs on sector level, we use the expected default rate $\hat{p}_j$ instead of p_n.

The diversification index DI_b in (13) is defined as a Herfindahl-Hirschman-Index over sectors but with the relative exposure weight replaced by the relative economic capital of every sector:

$$DI_b = \sum_j \left(\frac{EC_{b,j}}{EC_b^{sf}} \right)^2. \tag{16}$$

The average inter-sector correlation $\overline{\beta}_b$ in (13) requires the inter-sector correlation matrix Ω:

$$\overline{\beta}_b = \frac{\sum_j \sum_{k\neq j} EC_{b,j}\, EC_{b,k}\, \Omega_{j,k}}{\sum_j \sum_{k\neq j} EC_{b,j}\, EC_{b,k}}. \tag{17}$$

The calibration factor in (13) is defined as a second-order polynomial. Its coefficients are calibrated in Cespedes et al. (2006) by Monte-Carlo simulations:

$$CF_b(DI_b, \overline{\beta}_b) = 1-0.852\,(1-\overline{\beta}_b)\,(1-DI_b)+0.426\,(1-\overline{\beta}_b)^2\,(1-DI_b)-0.481\,(1-\overline{\beta}_b)^2\,(1-DI_b)^2. \tag{18}$$

In order to measure the impact of the monitoring effect we differentiate between the PD without monitoring p_n and the PD $p_{b,n}^{mon}$ after monitoring. The latter is defined by

$$p_{b,n}^{mon} = a_{\overline{SM}}\, p_n\, e^{\beta_1\, \overline{SM}_b - \overline{SM}_1}. \tag{19}$$

β_1 stands for the regression coefficients of the specialization level which stem from the the monitoring quality regressions in section 2.4. We revert to the regressions which are based on the failure rate as the rate of distressed loans has several shortcomings and use regression results without $\mu - \sigma-$standardization of the variables. $\overline{SM}_1$ represents the lowest specialization level. The scaling factor $a_{\overline{SM}}$ ensures that the exposure-weighted average PD of all cooperative banks and savings banks, respectively, after monitoring is the same as without monitoring:

$$a_{\overline{SM}} = \frac{\sum_b \overline{X}_b}{\sum_b \overline{X}_b\, e^{\beta_1\, \overline{SM}_b - \overline{SM}_1}}, \tag{20}$$

where $\overline{X}_b$ denotes the average loan exposure of bank b and $a_{\overline{SM}}$ is calculated separately for cooperative banks and savings banks.

3.2 Data

As in section 2 of the paper, the sector weights are based on the loan exposure data of the German borrower statistics. The expected loss given default ψ is set to 0.45, which is in line with the value in the foundation version of the internal ratings based approach in Basel II. The sector-dependent expected default rate $\hat{p}_j$ is approximated by the sector's observed default rate, taken from the Federal Statistical Office (Destatis).

The inter-sector correlations collected in the correlation matrix Ω are estimated from the sample correlations of stock index returns of the respective industrial sectors. We use the

ICB sector scheme of 16 sectors which allows us to use the Eurostoxx stock indices.[44] The sample correlations are estimated from weekly stock index returns over two years. As a robustness check, we use also an average correlation matrix. The correlation r^2 with the systematic risk factor in (11) is determined through the following calibration argument. We assume an average pairwise asset correlation $\bar{\rho}$ of 9%, based on empirical findings in Hahnenstein (2004). Then, the value of r is calculated as $\sqrt{\frac{\bar{\rho}}{\bar{\omega}}}$ with $\bar{\omega}$ the average of the non-diagonal elements Ω over time.

3.3 Empirical results

Firstly, we present the results for the relationship between specialization level and economic capital, where we do not adjust for monitoring. Table 7 shows the corresponding linear correlations between specialization level and the average EC over the observation period.[45]

Table 7: **Correlations between specialization level and economic capital**

This table presents correlations between specialization level and economic capital, where the PDs are not adjusted for monitoring quality and the economic capital is averaged over the observation period. $\overline{EC}^{av}$ is based on the correlations, averaged over the observation period, between the systematic risk factors and $\overline{EC}^{an}$ on the two-year correlation matrices. * indicates statistical significance at the 1% significance level.

	HHI	HHI^w	D^{nation}	D^{region}
	cooperative banks			
$\overline{EC}^{an}$	0.126*	0.320*	0.097*	-0.004
$\overline{EC}^{av}$	0.134*	0.331*	0.109*	-0.001
	savings banks			
$\overline{EC}^{an}$	0.200*	0.455*	0.063	-0.045
$\overline{EC}^{av}$	0.202*	0.462*	0.063	-0.050

In most cases, we can observe the expected result: A higher specialization level is accompanied by a higher economic capital. Significantly positive correlations in the case of *HHI* and HHI^w and insignificantly positive correlations for D^{nation} can be stated for both cooperative banks and savings banks. However, in the case of D^{region}, a insignificant negative relation with *EC* is detected. This result can be explained by the fact that banks

[44] The sector classification of the borrower statistic is mapped to this ICB sector scheme.

[45] Using Spearman rank correlations instead of linear correlations does not make a big difference in this case.

with larger deviations from their regional benchmark lend mainly to low-risk industry sectors, indicated by a negative correlation between EC^{sf} and D^{region}. We further note that using the average correlations between the systematic risk factors instead of the two-year correlation matrices does not seem to have a major impact on the results.

Henceforth, we consider different monitoring quality levels. In Table 8 we present – by analogy with Table 7 – the correlations between specialization level and economic capital, this time adjusted for monitoring according to equations (19) and (20).

Table 8: **Correlations between specialization level and economic capital with monitoring-adjusted probabilities of default**

This table presents correlations between specialization level and economic capital, where the PDs are adjusted for monitoring quality and the economic capital is averaged over the observation period. $\overline{EC}^{av}$ is based on the correlations, averaged over the observation period, between the systematic risk factors and $\overline{EC}^{an}$ on the two-year correlation matrices. * indicates statistical significance at the 1% significance level.

	HHI	HHI^{w}	D^{nation}	D^{region}
	cooperative banks			
$\overline{EC}^{(an,SM)}$	-0.388*	-0.216*	-0.564*	-0,435*
$\overline{EC}^{(av,SM)}$	-0.382*	-0.207*	-0.559*	-0.432*
	savings banks			
$\overline{EC}^{(an,SM)}$	0.147*	0.164*	-0.255*	-0.102
$\overline{EC}^{(av,SM)}$	0.150*	0.174*	-0.252*	-0.106

Considering monitoring advantages for specialized banks is accompanied by significantly negative relationships between specialization level and EC for all specialization measures in the case of the cooperative banks. The higher the specialization level is – measured either by Hirschman Herfindahl indices or by distance measures – the lower the portfolio risk is on average. That tells us that specialization benefits overcompensate the concentration disadvantages. For the distance measures, we see a stronger negative dependency than for the naive specialization measures. Distance measures show a comparatively weak linkage to the diversification index DI and, at the same time, a strong linkage to monitoring quality, as we observed in Table 9. All in all, specialized cooperative banks tend to have a lower portfolio risk than diversified cooperative banks.

In the case of the savings banks, the results are more heterogeneous. We have to differentiate between specialization based on Hirschman Herfindahl indices and specialization in terms of deviations from national or regional benchmarks. For the HHI and HHI^w, we see significantly positive correlations between specialization level and economic capital. A higher naive diversification is accompanied by a lower portfolio risk. Particularly for the HHI^w with its high specialization benefits, this might be somewhat surprising. The result can be explained by the fact that high HHI^w values are achieved especially if a large portion of the credit portfolio is assigned to a risky industry sector which implies a positive relationship between HHI^w and average PD (before considering monitoring effects) of the portfolio. For the distance measures, we can observe negative correlations between specialization level and EC, which are statistically significant in the case of D^{nation}. Savings banks characterized by large deviations from the national loan portfolio benchmark exploit specialization benefits and tend to have lower portfolio risks.

Why do cooperative banks show similar results for HHI measures and distance measures in contrast to savings banks where opposing results have been detected for HHI and distance measures? In Table 12 of section 5.3, the correlations between the different specialization measures are depicted. We can see high correlations between HHI measures and distance measures for cooperative banks indicating a strong positive dependence whereas low values for savings banks reveal different assessment of specialization by HHI and distance measures. Cooperative banks are on average exposed to a high specialization level, demonstrated both by high HHI values and high deviations from regional and national benchmarks as can be seen in Table 1. To gain relatively high HHI values compared to other cooperative banks, a cooperative bank has to be extremely exposed to certain industry sectors. As regional and national benchmarks are relatively balanced with respect to the industry sector composition, comparably high HHI values are accompanied by comparably high deviations from the benchmarks. For savings banks, more moderate specialization levels have been presented by Table 1, which means that a relatively high naive concentration can be achieved without an extreme focus on certain industry sectors. Thus, high HHI values do not have to be accompanied by high deviations from regional and national benchmarks which explains the lower dependence between naive specialization measures and distance measures for savings banks compared to cooperative banks.

So far, we have considered the average EC over the observation period. However, there might be huge differences between the economic capital values over time, and it is possible to doubt whether the predominantly negative relation between specialization level and economic capital still holds in a recession when concentration risks materialize. Therefore, we calculate the correlation coefficients for the annual portfolio risk values, too. In Table 9, the results are summarized by presenting the median, minimum and maximum value of the correlations.

Table 9: **Summary statistics of time series of correlations between specialization level and annual economic capital**

This table presents median, minimum, and maximum of the correlations between specialization level and annual economic capital over the observation period, where the PDs are adjusted for monitoring quality. $EC_t^{(an,SM)}$ is based on the two-year correlation matrices. * indicates statistical significance at the 1% significance level.

	median	minimum	maximum
cooperative banks			
$\mathrm{EC}_t^{(an,HHI)}$	-0.369*	-0.410*	-0.242*
$\mathrm{EC}_t^{(an,HHI^w)}$	-0.193*	-0.264*	-0.031
$\mathrm{EC}_t^{(an,D^{nation})}$	-0.533*	-0.570*	-0.420*
$\mathrm{EC}_t^{(an,D^{region})}$	-0.415*	-0.458*	-0.305*
savings banks			
$\mathrm{EC}_t^{(an,HHI)}$	0.137*	0.093	0.207*
$\mathrm{EC}_t^{(an,HHI^w)}$	0.164*	0.041	0.298*
$\mathrm{EC}_t^{(an,D^{nation})}$	-0.229*	-0.317*	-0.171*
$\mathrm{EC}_t^{(an,D^{region})}$	-0.107	-0.141*	-0.041

It is noteworthy that the robustness of the earlier results is largely confirmed. Specialized cooperative banks tend to have a lower portfolio risk than diversified cooperative banks in each year of the observation period as can be derived by the fact that the maximum correlation coefficients are negative. The same is true for the savings banks if the specialization level is measured by one of the distance measures. The minimum correlation coefficients are positive in the case of the Hirschman Herfindahl indices, which means that the positive relationship between naive specialization level and economic capital in the case of the savings banks is robust over time.

At the end of this section, we briefly remark that further robustness checks have been performed:

- We exclude banks which have a specialization level lower than the 1%-quantile or above the 99%-quantile.

- Instead of assuming a multivariate normal distribution for the joint distribution of the systematic risk factors, we assumed that the dependency between the risk factors is given by a t-copula with three degrees of freedom and run simulations to evaluate the economic capital. By doing so, we considered a more realistic distribution of the portfolio losses and detected possible effects of fat tails on the relationship between specialization level and portfolio risk.

- Firstly, we applied a higher correlation $r^2 = 0.25$. Secondly, we performed analyses based on sector-specific r^2s.

- We performed analyses based on sector-specific monitoring adjustments.

We stress that the stability of the earlier results is confirmed by these robustness checks.[46]

4 Conclusions

This paper investigates the cumulative impact of benefits from industry sector specialization and from associated sectoral credit concentrations on the credit risk of banks' loan portfolios. The empirical analysis is based on a comprehensive sample of German cooperative banks and savings banks. It comprises two parts.

In the first part, we apply a linear regression model in order to explore whether banks specializing in industry sectors can reap significant screening and monitoring benefits. The monitoring quality is measured by the ratio of the observed actual loss rate to the expected loss rate. The expected loss rate is calculated as the average of default rates of industry sectors, weighted by the nominal credit volume per sector. We use four different specialization measures, i.e. two Hirschman-Herfindahl indices (HHI and HHI^w) and two distance measures (D^{nation} and D^{region}). The HHI is based on loan exposures per sector, whereas the HHI^w is based on loan exposures per industry sector, weighted by the default rates of the sector. D^{nation} refers to deviations from a national lending benchmark and D^{region} refers to deviations from the lending benchmark of the region in which the bank operates. Furthermore, we apply two proxies for the actual loss rate, based on the relative share of either distressed loans or new loan loss provisions.

[46] More detailed information will be provided by the authors on request.

In the second part, we analyze the relationship between specialization level and economic capital where differences in monitoring quality between banks with respect to their specialization level are provided by the first part. Credit concentrations are automatically taken into account by using a multi-factor asset value model of credit risk together with the value at risk as risk measure.

The first part of our empirical analyses confirms significant monitoring benefits for both specialized cooperative banks and specialized savings banks. Differences between the results for different specialization measures are small. For savings banks, we find a weaker relationship between specialization level and monitoring quality when compared with cooperative banks. There is statistical significance in four out of eight cases, i.e. there are larger differences between the results for different specialization measures: HHI^w and D^{nation} show significant, and HHI and D^{region} show insignificant results. The discrepancy between the results for HHI and HHI^w might indicate that savings banks gear their monitoring efforts more to the related risk than to the volume of a loan exposure. The relationship between specialization level and monitoring quality is stronger if the actual loss rate is based on new loan loss provisions than on distressed loans. Considering that the actual loss rate based on the distressed loans does not consider the impact of different LGDs, this finding suggests that the LGD, in particular, is influenced by the specialization level and that the PD impact of specializing in certain industries is rather small. Various additional checks confirm that these results are robust against variations of the data set and the model.

The results of the second part are somewhat ambiguous since they differ between cooperative banks and savings banks. Before considering monitoring advantages for specialized banks, a positive relationship between specialization level and economic capital prevails, except for D^{region} because banks with larger deviations from the regional benchmark lend mainly to low-risk industries. After considering monitoring advantages, we find that a higher specialization level reduces portfolio risk measured by economic capital for the sample of cooperative banks. In this case the specialization benefits outweigh the concentration risk. In the case of the savings banks, however, results are mixed and strongly depend on the used specialization measure. For the two specialization measures HHI and HHI^w, economic capital tends to increase for more specialized banks, but this result is not significant. For the two distance measures the relationship is converse as it is for cooperative banks. Only for the distance measure D^{region}, this negative relationship is statistically significant. The robustness checks show that these results are stable over time and prove robust against various model variations. In summary, we find empirical support that it is possible for a substantial number of banks to overcompensate the higher concentration risk implied by a specialized lending strategy through the associated monitoring benefits.

References

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

Akerlof, G. A., 1970. The market for 'lemons': Quality uncertainty and the market mechanism. Quarterly Journal of Economics 84, 488–500.

Allen, F., Santomero, A. M., 1998. The theory of financial intermediation. Journal of Banking and Finance 21, 1461–1485.

Bartlett, F., 2000. Secured loan recovery study: The UK experience, Europe loan products. Fitch IBCA.

Basel Committee on Banking Supervision, 2006. International convergence of capital measurement and capital standards – a revised framework, comprehensive version.

Boot, A. W., Schmeits, A., 2000. Market discipline and incentive problems in conglomerate firms with applications to banking. Journal of Financial Intermediation 9, 240–273.

Böve, R., Pfingsten, A., 2008. Why do specialized banks succeed? An empirical investigation of the credit business of cooperative and savings banks. Tech. rep., Westfälische Wilhelms-Universität, Münster.

Bundesamt für Bauwesen und Raumordnung, 2005. Raumordnungsbericht 2005, Band 21, Bonn.

Bundesanstalt für Finanzdienstleistungsaufsicht, 2009. Mindestanforderungen an das Risikomangament, Rundschreiben 15/2009.

Cerasi, V., Daltung, S., October 2000. The optimal size of a bank: Costs and benefits of diversification. European Economic Review 44, 1701–1726.

Cespedes, J. C., Herrero, J. A., Kreinin, A., Rosen, D., 2006. A simple multi-factor 'factor adjustment' for the treatment of credit capital diversification. Journal of Credit Risk 2, 57–85.

Coleman, A. D. F., Esho, N., Sharpe, I. G., 2006. Does bank monitoring influence loan contract terms? Journal of Financial Services Research 30, 177–198.

Craigwell, R., Maxwell, C., Terrelonge, S., Moore, W., 2006. The impact of diversification on the banking industry: A non-stationary panel approach in the presence of cross section dependence. Tech. rep., Central Bank of Barbados, Barbados.

Degryse, H., Ongena, S., 2003. The impact of competition on bank orientation and specialization. Tech. rep., Tilburg University.

Düllmann, K., Masschelein, N., 2007. A tractable model to measure sector concentration risk in credit portfolios. Journal of Financial Services Research 32, 55–79.

Ehricke, U., 2007. Insolvenzrecht. Springer, Berlin.

Eichwald, B., Pehle, H., 2000. Die Kreditarten. In: von Hagen, J., von Stein, J. H. (Eds.), Geld-, Bank- und Börsenwesen, 40th Edition. Schaeffer Poeschel, pp. 742–814.

Franks, J. R., de Sevigny, A., Davydenko, S., 2004. A comparative analysis of the recovery process and recovery rates for private companies in the U.K., France, and Germany. Standard and Poor's Risk Solutions.

Freixas, X., Rochet, J.-C., 2008. Microeconomics of banking, 2nd Edition. MIT Press, Cambridge, Massachusetts.

Greenbaum, S. I., Thakor, A. V., 2007. Contemporary financial intermediation, 2nd Edition. Dryden, Fort Worth et al.

Grossman, R. J., Brennan, W. T., Vento, J., 1997. Syndicated bank loan recovery study. Fitch Research.

Grunert, J., Volk, A., 2005. Die Bedeutung der Ausfalldefinition bei der Berechnung der Recovery Rate von Unternehmenskrediten. Finanzbetrieb 5, 317–326.

Grunert, J., Weber, M., 2007. Recovery rates of commercial lending: Empirical evidence for German companies. Tech. rep., URL: http://ssrn.com/abstract=964453 (15.09.2008).

Hackethal, A., 2004. German banks and banking structure. In: Krahnen, J., Schmidt, R. H. (Eds.), The German financial system. Oxford University Press, pp. 71–105.

Hahnenstein, L., 2004. Calibrating the creditmetrics correlation concept – empirical evidence from Germany. Financial Markets and Portfolio Management 18, 358–381.

Hauswald, R., Marquez, R., 2006. Competition and Strategic Information Acquisition in Credit Markets. Review of Financial Studies 19, 967–1000.

Hayden, E., Porath, D., von Westernhagen, N., 2007. Does diversification improve the performance of German banks? Evidence from individual bank loan portfolios. Journal of Financial Services Research 32, 123–140.

Kabance, G., 2001. Mexican bankruptcy and recovery rate study. Fitch IBCA.

Kamp, A., 2006. Diversifikation versus Spezialisierung von Kreditportfolios – Eine Empirische Analyse. Fritz Knapp Verlag, Frankfurt am Main.

Kötter, M., Wedow, M., 2006. Finance and growth in a bank-based economy: Is it quantity or quality that matters? Tech. Rep. 02/2006, Deutsche Bundesbank, Frankfurt am Main.

Lux, R., 2001. Beleihungswert und Zertifizierung. Der langfristige Kredit 52, 345–351.

Norden, L., Szerencses, M., 2005. Migration and concentration risks in bank lending: New evidence from credit portfolio data. Tech. rep., Universität Mannheim.

Pfingsten, A., Rudolph, K., 2004. Eine Empirische Analyse der Kreditportfoliozusammensetzung deutscher Bankengruppen. Zeitschrift für Betriebswirtschaft, Ergänzungsheft 2/2004, 1–24.

Rossi, P., Schwaiger, M. S., Winkler, G., 2009. How loan portfolio diversification affects risk, efficiency and capitalization: A managerial behaviour model for austrian banks. Journal of Banking and Finance 33, 2218–2226.

Schönbucher, P. J., 2001. Factor models: Portfolio credit risks when defaults are correlated. Journal of Risk Finance 3, 45–56.

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

Tröger, N. H., 2003. Mergers & Acquisitions im deutschen Bankensektor. Eine Analyse der Bestimmungsfaktoren. Gabler, Wiesbaden.

Winton, A., 1999. Don't put all your eggs in one basket? Diversification and specialization in lending. Tech. Rep. 9903, Finance Department, University of Minnesota, Minneapolis.

5 Appendix

5.1 Definition of control variables

Share of loans:

$$loan := \frac{\text{loan amount (without interbank loans)}}{\text{total assets}} \tag{21}$$

Share of retail loans:

$$retail := \frac{\text{retail loan amount}}{\text{loan amount (without interbank loans)}} \tag{22}$$

Share of local authority loans:

$$local\_authority := \frac{\text{amount of local authority loans}}{\text{loan amount}} \tag{23}$$

Share of mortgage loans:

$$mortgage := \frac{\text{amount of mortgage loans}}{\text{loan amount (without interbank loans)}} \tag{24}$$

Unsecured portion in case of audited specific doubtful loans:

$$unsecured := \frac{\text{unsecured volume of audited spefific doubtful loans}}{\text{amount of audited specific doubtful loans}} \tag{25}$$

The average market share (*market*) which can be attributed to a savings or cooperative bank in its business district is defined as

$$market_{(b,t)} := \sum_{i=1}^{23} ms_{(b,i,t)} \cdot x_{(b,i,t)} \tag{26}$$

for the bank b at time t with

$$ms_{(b,i,t)} := \frac{X_{(b,i,t)}}{X_{(i,t)}^{region_b}} \tag{27}$$

where $X_{(b,i,t)}$ stands for the loan amount of bank b in industry i at time t. *market* denotes the portion of the bank's loan volume in industry i as a share of the total loan volume in the region in industry i at time t. It therefore considers the market shares of a bank in all the industries, but weights with respect to the portion which each industry contributes to the corporate loan volume of the bank.[47]

To evaluate the personnel expenses which contribute to the corporate lending activities, we follow the methodology of Coleman et al. (2006).[48] By running a fixed-effects estimation, we adjust the ratio of personnel expenses over non-interest rate expenses for specific bank features. In accordance with Coleman et al. (2006), we define the Salary Exposure Rate (*SER*) as

$$SER_{(b,t)} := \frac{\text{personnel expenses}_{(b,t)}}{\text{non interest rate expenses}_{(b,t)}} \tag{28}$$

and perform the following fixed-effects estimation in order to assess the proxy for the personnel expenses assigned to corporate lending (*personnel*):

$$SER_{(b,t)} = personnel_b + \sum_{j=1}^{8} \beta_j \cdot Y_{(j,b,t)} + \epsilon_{(b,t)}. \tag{29}$$

SER is adjusted for different influencing factors so that the time-constant bank-proprietary term (*personnel*) shows the expenses (additionally adjusted for size and efficiency effects) for the corporate loan business of a bank. We use the share of retail loans (*retail*) and the share of interbank loans (*interbank_loan*) as control variables. We assume that the first ratio has a positive influence on *SER* because a higher ratio is probably characterized by lower revenues per employee and, therefore, a higher personnel intensity. The second ratio might tend to be negatively correlated with *SER* because of the more standardized business and higher transaction volumes. The share of loans in total assets (*loan*) and the share of fees in total earnings (*fee*) represent major bank characteristics. Both variables are indicators for the labor-intensity of the bank's business and should influence the *SER* positively.[49] We also consider the share of liabilities against banks in total assets (*interbank_liabilities*) and the share of securitized liabilities in total assets (*securitized_liabilities*). Owing to the expected labor-intensity, we assume a negative relationship with *SER* for the

[47]Therefore, a high *market*-value could stem from just one industry. However, by introducing the specialization measures, we shall control for this circumstance.

[48]Coleman et al. (2006) use the the personnel expenses which contribute to the corporate lending activities as a proxy for the monitoring quality.

[49]Here, and in the remainder of the paper, we have performed robustness tests to check for the relevance of endogeneity. Leaving out certain variables in the regressions, we have so far noted no major changes in the results.

first and a positive relationship for the second variable. In order to measure the efficiency of a bank, we resort to the return on total assets (*return_ratio*). For a more profitable bank we assume a lower *SER*-value. The control variable *size* reflects the fact that bigger banks might benefit from economies of scale.[50]

The results of the estimation based on equation 29 are stated in Table 10.

Table 10: **Regression results for *personnel* as the dependent variable**

This table presents results of the regression for *personnel* as the dependent variable according to equation (29). ***, **, * indicate statistical significance at a 0.1%, 1%, 5% significance level. The values in brackets are the corresponding t-values.

	(1) cooperative banks	(2) savings banks	(3) both banking groups
loan	-0.043***	-0.046***	-0.043***
	(-5.42)	(-3.53)	(-6.42)
retail	-0.028***	0.026	-0.015*
	(-3.70)	(1.90)	(-2.34)
interbank_loan	0.057***	0.028***	0.049***
	(9.25)	(3.32)	(9.57)
fee	0.267***	0.433***	0.295***
	(16.39)	(12.76)	(20.31)
securitized_liability	-0.104***	-0.024	-0.113***
	(-5.64)	(-0.93)	(-7.43)
interbank_liability	-0.005	-0.017	0.002
	(-0.53)	(-1.58)	(0.27)
size	-0.020***	0.005	-0.018***
	(-14.03)	(1.91)	(-13.86)
return_ratio	-3.537***	-0.058	-3.110***
	(-25.02)	(-0.23)	(-25.19)
observations	17454	6059	23513
R^2	0.08	0.08	0.07

For the variables *loan*, *fee*, *securitized_liabilities*, *interbank_liabilities*, and *return_ratio* we can observe the expected relations with the variable *personnel*. For the share of retail loans there is a positive, albeit not statistically significant, link in the case of the savings banks. In the case of the cooperative banks, a significantly negative relationship has to be noted. Servicing retail clients is possibly linked to lower-paid employees. Banks with a larger share of interbank loans on average have − contrary to our assumption − higher *personnel* values. This indicates that a refinancing-focused business model is personnel-intensive. The results for *size* are as expected for the cooperative banks, higher values are

[50]In Coleman et al. (2006), similar control variables are used.

accompanied by lower *personnel* values. The relationship between bank size and *personnel* is insignificantly positive for the savings banks. This could stem from the fact that savings banks are, on average, six times as tall (w.r.t. the asset size) as cooperative banks and fixed costs degression effects are counteracted by extra organizational costs in this size cluster. It is also imaginable that especially the big savings banks look for highly qualified employees working as specialists and are willing to pay more for these.

5.2 Descriptive statistics

Table 11: **Summary statistics of variables based on bank means (1995-2006)**

This table presents summary statistics of variables based on average values per bank for the time period 1995-2006. p5 (p95) stands for the 5th (95th) percentile. The variable *agglom* combines *agglom1* and *agglom2*. *agglom* takes the values 1,2 or 3 if the business district is an urban agglomeration, an urban area or a rural area.

	savings banks		cooperative banks		both banking groups	
	mean	median	mean	median	p5	p95
total assets in mill. €	1,700	1,100	280	160	32	2,400
loan	0.66	0.68	0.72	0.74	0.52	0.83
retail	0.52	0.52	0.53	0.53	0.36	0.0,70
local authority	0.08	0.07	0.02	0.01	0.00	0.13
mortgage	0.41	0.41	0.30	0.30	0.07	0.53
unsecured	0.44	0.44	0.44	0.43	0.28	0.61
market	0.15	0.08	0.04	0.01	0.00	0.33
agglom	1.80	.	1.86	.	.	.
east	0.17	.	0.07	.	.	.

5.3 Correlation matrices

Table 12: **Correlations between specialization measures**

This table presents correlations between specialization measures based on average values per bank for the time period 1995-2006. * indicates statistical significance at the 1% significance level.

	cooperative banks				savings banks			
	HHI	HHI^w	D^{nation}	D^{region}	HHI	HHI^w	D^{nation}	D^{region}
HHI	1				1			
HHI^w	0.745*	1			0.586*	1		
D^{nation}	0.775*	0.626*	1		0.331*	0.447*	1	
D^{region}	0.652*	0.531*	0.761*	1	0.340*	0.139*	0.318*	1

Table 13: **Correlations between control variables**

This table presents correlations between control variables based on average values per bank for the time period 1995-2006. * indicates statistical significance at the 1% significance level.

cooperative banks	loan	retail	local_authority	mortgage	unsecured	personnel	market	size	agglom	east
loan	1									
retail	0.026	1								
local_authority	-0.341*	-0.095*	1							
mortgage	0.153*	0.263*	0.002	1						
unsecured	-0.049	-0.018	0.036	-0.041	1					
personnel	0.197*	0.051	-0.181*	0.134	-0.028	1				
market	-0.023	-0.196*	0.046	-0.078*	-0.011	0.033	1			
size	0.025	-0.254*	0.163*	0.043*	0.090*	0.077*	0.313*	1		
agglom	-0.173*	-0.075*	0.050*	-0.163*	-0.083*	0.043*	-0.026*	-0.127*	1	
east	-0.412*	-0.287*	0.257*	-0.197*	0.020*	-0.312*	0.020	0.011	0.064	1
savings banks	loan	retail	local_authority	mortgage	unsecured	personnel	market	size	agglom	east
loan	1									
retail	0.082	1								
local_authority	-0.488*	-0.202*	1							
mortgage	-0.023	0.129*	0.106*	1						
unsecured	-0.228*	-0.236*	0.256*	-0.049	1					
personnel	0.379*	0.184*	-0.239*	0.118*	-0.282*	1				
market	-0.051	-0.291*	0.110	-0.301*	0.244*	-0.360*	1			
size	0.063	-0.317*	0.089	-0.208*	0.292*	-0.299*	0.558*	1		
agglom	-0.102	-0.204*	0.181*	0.178*	0.058	-0.006	-0.043	-0.156*	1	
east	-0.629*	-0.208*	0.492*	0.156*	0.359*	-0.582*	0.222*	-0.054	0.189*	1

Table 14: **Rank correlations between specialization measures and selected control variables**

This table presents rank correlations (Spearman) between specialization measures and some control variables based on average values per bank for the time period 1995-2006. * indicates statistical significance at the 1% significance level.

	cooperative banks				savings banks			
	HHI	HHI^{w}	D^{nation}	D^{region}	HHI	HHI^{w}	D^{nation}	D^{region}
MON^{fai}	-0.308*	-0.283*	-0.383*	-0.329*	-0.120*	-0.217*	-0.287*	-0.182*
MON^{dis}	-0.197*	-0.237*	-0.187*	-0.161*	-0.065 *	-0.138*	-0.007	-0.022
loan	-0.231*	-0.186*	-0.269*	-0.142*	-0.096	-0.285*	-0.073	0.053
retail	0.046	0.119*	0.221*	0.252*	0.056	0.113*	0.258*	0.147*
mortgage	-0.193*	-0.124*	-0.174*	-0.069*	0.155*	0.191*	0.082	0.188*
unsecured	-0.033	-0.033	-0.066*	-0.029	-0.030	-0.065	-0.228*	-0.146*
market	-0.198*	-0.194*	-0.333*	-0.571*	-0.089	-0.137*	-0.391*	-0.583*
size	-0.556*	-0.486*	-0.726*	-0.607*	-0.283*	-0.440*	-0.653*	-0.447*
east	0.100*	0.219*	0.040	-0.063	0.168*	0.376*	-0.056	-0.117*
agglom	0.141*	0.005	0.279*	0.038	-0.099	0.045	0.217*	-0.021

The following Discussion Papers have been published since 2009:

Series 1: Economic Studies

01	2009	Spillover effects of minimum wages in a two-sector search model	Christoph Moser Nikolai Stähler
02	2009	Who is afraid of political risk? Multinational firms and their choice of capital structure	Iris Kesternich Monika Schnitzer
03	2009	Pooling versus model selection for nowcasting with many predictors: an application to German GDP	Vladimir Kuzin Massimiliano Marcellino Christian Schumacher
04	2009	Fiscal sustainability and policy implications for the euro area	Balassone, Cunha, Langenus Manzke, Pavot, Prammer Tommasino
05	2009	Testing for structural breaks in dynamic factor models	Jörg Breitung Sandra Eickmeier
06	2009	Price convergence in the EMU? Evidence from micro data	Christoph Fischer
07	2009	MIDAS versus mixed-frequency VAR: nowcasting GDP in the euro area	V. Kuzin, M. Marcellino C. Schumacher
08	2009	Time-dependent pricing and New Keynesian Phillips curve	Fang Yao
09	2009	Knowledge sourcing: legitimacy deficits for MNC subsidiaries?	Tobias Schmidt Wolfgang Sofka
10	2009	Factor forecasting using international targeted predictors: the case of German GDP	Christian Schumacher

11	2009	Forecasting national activity using lots of international predictors: an application to New Zealand	Sandra Eickmeier Tim Ng
12	2009	Opting out of the great inflation: German monetary policy after the breakdown of Bretton Woods	Andreas Beyer, Vitor Gaspar Christina Gerberding Otmar Issing
13	2009	Financial intermediation and the role of price discrimination in a two-tier market	Stefan Reitz Markus A. Schmidt, Mark P. Taylor
14	2009	Changes in import pricing behaviour: the case of Germany	Kerstin Stahn
15	2009	Firm-specific productivity risk over the business cycle: facts and aggregate implications	Ruediger Bachmann Christian Bayer
16	2009	The effects of knowledge management on innovative success – an empirical analysis of German firms	Uwe Cantner Kristin Joel Tobias Schmidt
17	2009	The cross-section of firms over the business cycle: new facts and a DSGE exploration	Ruediger Bachmann Christian Bayer
18	2009	Money and monetary policy transmission in the euro area: evidence from FAVAR- and VAR approaches	Barno Blaes
19	2009	Does lowering dividend tax rates increase dividends repatriated? Evidence of intra-firm cross-border dividend repatriation policies by German multinational enterprises	Christian Bellak Markus Leibrecht Michael Wild
20	2009	Export-supporting FDI	Sebastian Krautheim

21	2009	Transmission of nominal exchange rate changes to export prices and trade flows and implications for exchange rate policy	Mathias Hoffmann Oliver Holtemöller
22	2009	Do we really know that flexible exchange rates facilitate current account adjustment? Some new empirical evidence for CEE countries	Sabine Herrmann
23	2009	More or less aggressive? Robust monetary policy in a New Keynesian model with financial distress	Rafael Gerke Felix Hammermann Vivien Lewis
24	2009	The debt brake: business cycle and welfare consequences of Germany's new fiscal policy rule	Eric Mayer Nikolai Stähler
25	2009	Price discovery on traded inflation expectations: Does the financial crisis matter?	Alexander Schulz Jelena Stapf
26	2009	Supply-side effects of strong energy price hikes in German industry and transportation	Thomas A. Knetsch Alexander Molzahn
27	2009	Coin migration within the euro area	Franz Seitz, Dietrich Stoyan Karl-Heinz Tödter
28	2009	Efficient estimation of forecast uncertainty based on recent forecast errors	Malte Knüppel
29	2009	Financial constraints and the margins of FDI	C. M. Buch, I. Kesternich A. Lipponer, M. Schnitzer
30	2009	Unemployment insurance and the business cycle: Prolong benefit entitlements in bad times?	Stéphane Moyen Nikolai Stähler
31	2009	A solution to the problem of too many instruments in dynamic panel data GMM	Jens Mehrhoff

32	2009	Are oil price forecasters finally right? Regressive expectations toward more fundamental values of the oil price	Stefan Reitz Jan C. Rülke Georg Stadtmann
33	2009	Bank capital regulation, the lending channel and business cycles	Longmei Zhang
34	2009	Deciding to peg the exchange rate in developing countries: the role of private-sector debt	Philipp Harms Mathias Hoffmann
35	2009	Analyse der Übertragung US-amerikanischer Schocks auf Deutschland auf Basis eines FAVAR	Sandra Eickmeier
36	2009	Choosing and using payment instruments: evidence from German microdata	Ulf von Kalckreuth Tobias Schmidt, Helmut Stix
01	2010	Optimal monetary policy in a small open economy with financial frictions	Rossana Merola
02	2010	Price, wage and employment response to shocks: evidence from the WDN survey	Bertola, Dabusinskas Hoeberichts, Izquierdo, Kwapil Montornès, Radowski
03	2010	Exports versus FDI revisited: Does finance matter?	C. M. Buch, I. Kesternich A. Lipponer, M. Schnitzer
04	2010	Heterogeneity in money holdings across euro area countries: the role of housing	Ralph Setzer Paul van den Noord Guntram Wolff
05	2010	Loan supply in Germany during the financial crises	U. Busch M. Scharnagl, J. Scheithauer

06	2010	Empirical simultaneous confidence regions for path-forecasts	Òscar Jordà, Malte Knüppel Massimiliano Marcellino
07	2010	Monetary policy, housing booms and financial (im)balances	Sandra Eickmeier Boris Hofmann
08	2010	On the nonlinear influence of Reserve Bank of Australia interventions on exchange rates	Stefan Reitz Jan C. Ruelke Mark P. Taylor
09	2010	Banking and sovereign risk in the euro area	S. Gerlach A. Schulz, G. B. Wolff
10	2010	Trend and cycle features in German residential investment before and after reunification	Thomas A. Knetsch
11	2010	What can EMU countries' sovereign bond spreads tell us about market perceptions of default probabilities during the recent financial crisis?	Niko Dötz Christoph Fischer
12	2010	User costs of housing when households face a credit constraint – evidence for Germany	Tobias Dümmler Stephan Kienle
13	2010	Extraordinary measures in extraordinary times – public measures in support of the financial sector in the EU and the United States	Stéphanie Marie Stolz Michael Wedow
14	2010	The discontinuous integration of Western Europe's heterogeneous market for corporate control from 1995 to 2007	Rainer Frey
15	2010	Bubbles and incentives: a post-mortem of the Neuer Markt in Germany	Ulf von Kalckreuth Leonid Silbermann

16	2010	Rapid demographic change and the allocation of public education resources: evidence from East Germany	Gerhard Kempkes
17	2010	The determinants of cross-border bank flows to emerging markets – new empirical evidence on the spread of financial crisis	Sabine Herrmann Dubravko Mihaljek
18	2010	Government expenditures and unemployment: a DSGE perspective	Eric Mayer, Stéphane Moyen Nikolai Stähler
19	2010	NAIRU estimates for Germany: new evidence on the inflation-unemployment trade-off	Florian Kajuth
20	2010	Macroeconomic factors and micro-level bank risk	Claudia M. Buch Sandra Eickmeier, Esteban Prieto
21	2010	How useful is the carry-over effect for short-term economic forecasting?	Karl-Heinz Tödter
22	2010	Deep habits and the macroeconomic effects of government debt	Rym Aloui

Series 2: Banking and Financial Studies

01	2009	Dominating estimators for the global minimum variance portfolio	Gabriel Frahm Christoph Memmel
02	2009	Stress testing German banks in a downturn in the automobile industry	Klaus Düllmann Martin Erdelmeier
03	2009	The effects of privatization and consolidation on bank productivity: comparative evidence from Italy and Germany	E. Fiorentino A. De Vincenzo, F. Heid A. Karmann, M. Koetter
04	2009	Shocks at large banks and banking sector distress: the Banking Granular Residual	Sven Blank, Claudia M. Buch Katja Neugebauer
05	2009	Why do savings banks transform sight deposits into illiquid assets less intensively than the regulation allows?	Dorothee Holl Andrea Schertler
06	2009	Does banks' size distort market prices? Evidence for too-big-to-fail in the CDS market	Manja Völz Michael Wedow
07	2009	Time dynamic and hierarchical dependence modelling of an aggregated portfolio of trading books – a multivariate nonparametric approach	Sandra Gaisser Christoph Memmel Rafael Schmidt Carsten Wehn
08	2009	Financial markets' appetite for risk – and the challenge of assessing its evolution by risk appetite indicators	Birgit Uhlenbrock
09	2009	Income diversification in the German banking industry	Ramona Busch Thomas Kick
10	2009	The dark and the bright side of liquidity risks: evidence from open-end real estate funds in Germany	Falko Fecht Michael Wedow

11	2009	Determinants for using visible reserves in German banks – an empirical study	Bornemann, Homölle Hubensack, Kick, Pfingsten
12	2009	Margins of international banking: Is there a productivity pecking order in banking, too?	Claudia M. Buch Cathérine Tahmee Koch Michael Koetter
13	2009	Systematic risk of CDOs and CDO arbitrage	Alfred Hamerle, Thilo Liebig Hans-Jochen Schropp
14	2009	The dependency of the banks' assets and liabilities: evidence from Germany	Christoph Memmel Andrea Schertler
15	2009	What macroeconomic shocks affect the German banking system? Analysis in an integrated micro-macro model	Sven Blank Jonas Dovern
01	2010	Deriving the term structure of banking crisis risk with a compound option approach: the case of Kazakhstan	Stefan Eichler Alexander Karmann Dominik Maltritz
02	2010	Recovery determinants of distressed banks: Regulators, market discipline, or the environment?	Thomas Kick Michael Koetter Tigran Poghosyan
03	2010	Purchase and redemption decisions of mutual fund investors and the role of fund families	Stephan Jank Michael Wedow
04	2010	What drives portfolio investments of German banks in emerging capital markets?	Christian Wildmann
05	2010	Bank liquidity creation and risk taking during distress	Berger, Bouwman Kick, Schaeck

06	2010	Performance and regulatory effects of non-compliant loans in German synthetic mortgage-backed securities transactions	Gaby Trinkaus
07	2010	Banks' exposure to interest rate risk, their earnings from term transformation, and the dynamics of the term structure	Christoph Memmel
08	2010	Completeness, interconnectedness and distribution of interbank exposures – a parameterized analysis of the stability of financial networks	Angelika Sachs
09	2010	Do banks benefit from internationalization? Revisiting the market power-risk nexus	C. M. Buch C. Tahmee Koch, M. Koetter
10	2010	Do specialization benefits outweigh concentration risks in credit portfolios of German banks?	Rolf Böve Klaus Düllmann Andreas Pfingsten

Visiting researcher at the Deutsche Bundesbank

The Deutsche Bundesbank in Frankfurt is looking for a visiting researcher. Among others under certain conditions visiting researchers have access to a wide range of data in the Bundesbank. They include micro data on firms and banks not available in the public. Visitors should prepare a research project during their stay at the Bundesbank. Candidates must hold a PhD and be engaged in the field of either macroeconomics and monetary economics, financial markets or international economics. Proposed research projects should be from these fields. The visiting term will be from 3 to 6 months. Salary is commensurate with experience.

Applicants are requested to send a CV, copies of recent papers, letters of reference and a proposal for a research project to:

Deutsche Bundesbank
Personalabteilung
Wilhelm-Epstein-Str. 14

60431 Frankfurt
GERMANY