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Do banks diversify loan portfolios? A tentative answer based on individual bank loan portfolios

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Abstract

Theory of financial intermediation gives contradicting answers to the question whether banks should diversify or focus their loan portfolios. Our aim is to find out which of the two strategies is predominant in the German banking market. To this end we measure diversification for all German banks in the period from 1993 to 2002. As measures we use a broad set of heuristic approaches which capture the deviation of a bank's portfolio from a specified benchmark. Conceivable benchmarks are naive diversification across all industries or, alternatively, the economy's industry structure. With this framework our analysis comprises the widespread measures of concentration, like the Hirschman-Herfindahl index, but also the less known and in this context innovative group of distance measures. We find that different statistical measures of diversification may indicate contradicting results on the individual bank level. Since distance measures are more appealing from a theoretical point of view, the common practice to rely on measures of concentration only in the debate about diversification and focus, may be misleading. We further find that, despite these differences on the individual bank level, both approaches reveal that the majority of banks significantly increased loan portfolio diversification over the last decade. This tendency is especially driven by the large number of credit cooperatives and savings banks. However, some banks (especially regional banks and subsidiaries of foreign banks) reveal a strategy that seems to be more focused on certain industries.

Keywords:
bank lending, loan portfolio, portfolio theory, diversification, concentration measures, distance measures, focus

JEL classification:
G11, G21, C43

Non-technical Summary

Should banks diversify their loan portfolios, or should they focus on homogenous lenders? From a theoretical point of view there is no clear answer to this question. Diversification may reduce risk in the sense of the classical portfolio theory (Markowitz (1952)). Focus, on the other hand, may improve the bank's knowledge of a specific segment and therefore enhance the profitability of the loan portfolio. In our study we analyse how German banks have actually operated in the period between 1993 and 2002. To this end we calculate different statistical measures of the banks' industrial diversification. The data are taken from the Deutsche Bundesbank's borrowers statistics, which contain a panel of all German banks' loans to various industries.

The most customary benchmarks of diversification measure concentration, examples being the Hirschman-Herfindahl index and the Gini coefficient. The common feature of these measures is that they capture the extent to which a portfolio differs from naive diversification. If markets are concentrated, however, naive diversification may not be an appropriate benchmark. We therefore additionally draw on distance measures (Pfingsten and Rudolph (2002)). Distance measures capture the difference to any user-defined benchmark portfolio.

The results are:

1. In the period between 1993 and 2002 German banks showed a trend towards increasing diversification.

2. The general trend towards increasing diversification is mainly driven by the large number of savings banks and cooperative banks. Regional banks and subsidiaries of foreign banks, by contrast, have tended to focus their loan portfolios. Big banks, in the aggregate, seem to have neither focused nor diversified. However, at the beginning of the sample their loan portfolios were more diversified than those of the other banking groups.

3. Measures of concentration and measures of distance often produce contradictory results when applied to individual banks. Since distance measures are theoretically more convincing, they should be used more often as measures of diversification.

Nichttechnische Zusammenfassung

Sollten Banken ihre Kreditportfolien diversifizieren, oder sollten sie sich auf bestimmte Marktsegmente spezialisieren? Vom theoretischen Standpunkt her lässt sich die Frage nicht eindeutig beantworten. Diversifikation kann zu einer Risikoreduktion im Sinne der klassischen Portfoliotheorie (Markowitz (1952)) führen. Spezialisierung hingegen kann die Marktkenntnisse einer Bank und damit die Profitabilität der Kreditbücher verbessern. In der vorliegenden Studie wird untersucht, wie sich deutsche Banken im Zeitraum von 1993 bis 2002 tatsächlich verhalten haben. Zu diesem Zweck werden die Branchenportfolien der Banken mit verschiedenen Diversifikationsmaßen untersucht. Datenbasis ist die Kreditnehmerstatistik der Deutschen Bundesbank, die die Kreditvergabe der einzelnen deutschen Banken an verschiedene Branchen im Zeitablauf enthält.

Die gebräuchlichsten Diversifikationsmaße sind Konzentrationsmaße, wie z. B. der Hirschman-Herfindahl-Index oder der Gini Koeffizient. Konzentrationsmaße verbindet die Eigenschaft, dass sie den Unterschied zur naiven Diversifikation messen. In konzentrierten Märkten ist naive Diversifikation aber möglicherweise keine geeignete Benchmark. Daher setzen wir darüber hinaus auch Distanzmaße (Pfingsten und Rudolph (2002)) ein. Distanzmaße messen die Abweichung zu beliebig festlegbaren Benchmarkportfolios.

Die Ergebnisse der Untersuchung sind:

1. Deutsche Banken haben im Zeitraum zwischen 1993 bis 2002 tendenziell ihre nationalen Kreditportfolien fortwährend stärker diversifiziert.

2. Der allgemeine Trend zur Diversifikation ist in erster Linie auf den Sparkassen- und Kreditgenossenschaftssektor zurückzuführen. Regionalbanken und Zweigstellen ausländischer Kreditinstitute haben sich eher spezialisiert. Großbanken zeigen weder einen Trend zur Diversifikation noch zur Spezialisierung, weisen aber schon zum Untersuchungsbeginn einen höheren Grad an Diversifikation auf als alle anderen Bankengruppen.

3. Auf individueller Ebene kommen Konzentrations- und Distanzmaße oft zu entgegengesetzten Ergebnissen. Aufgrund der theoretischen Vorzüge sollten daher Distanzmaße verstärkt zur Messung von Diversifikation herangezogen werden.

Contents

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1 Introduction

Theoretical and empirical studies in corporate finance yield differing observations regarding *diversification*. While it is performance-improving in the classical theory following Markowitz (1952), it reduces firm value at least for large conglomerates (cf Lang and Stulz (1994) or Berger and Ofek (1995)). A loan portfolio is an investment in risky assets, to which none of these observations necessarily directly applies, since banks are intermediaries. In financial intermediation theory we find recommendations that banks should *diversify* to reduce risk as well as suggestions to *focus* in their loan origination on industries about which they have superior knowledge, as their superior monitoring abilities will then increase risk-adjusted returns.

Those who believe that banks are quite naturally diversified should note that the area a bank covers may have an unbalanced industry structure, or the bank may willingly focus on, or at least build up special knowledge in, particular industries. Some examples that have a flavour of both aspects may suffice for the moment to make this point: HSH Nordbank, a regional state bank active especially along Germany's North Sea and Baltic Sea coasts, is *the world's* largest ship financier.[1] Stadtsparkasse Köln, a regional savings bank in one of Germany's media centres, claims to have superior knowledge of the media business and to be among the leading loan originators for the German media industry.[2] Deutsche Apotheker- und Ärztebank, Germany's largest primary cooperative bank, only originates loans to the medical professions.[3]

The question of diversification versus focus is a question within the very nature of banks as delegated monitors in the sense of Diamond (1984). Diamond (1984) argues that diversification reduces the threat of financial distress as returns of projects are assumed to be imperfectly correlated. This reasoning is in line with classical portfolio theory (Markowitz (1952)). However, monitoring costs are considered to be constant in the Diamond model. Moreover, the quality of monitoring cannot be influenced by a bank. A group of theoretical models challenges these points. Stomper (2004) analyses a bank's incentive to build up sector expertise. In the equilibrium of his model we observe a coexistence of specialized and diversified banks. The more banks invest in hiring sector or industry experts, the less benefit can be derived from building up sector or industry expertise. Winton (1999) points out that banks' chances of failure are endogenously affected by the choice of loan portfolio structures. In his theoretical framework, the risks and costs of poor diversification

We are indebted to the discussants and participants at conferences including a Research Seminar at Deutsche Bundesbank (Frankfurt, Germany, March 2004), a Banking Workshop at the University of Münster (Münster, Germany, May 2004), the 66th Annual Conference of the Association of University Professors of Management (Graz, Austria, June 2004), the 19th Annual Meeting of the European Economic Association (Madrid, Spain, August 2004) and the 11th Annual Meeting of the German Finance Association (Tübingen, Germany, October 2004) for helpful comments on an earlier version of the paper. All remaining errors are, of course, ours. The first author is indebted to the Verein für Socialpolitik and Deutsche Bundesbank for a travel grant in order to attend the European Economic Association conference.
Some additional material concerning our statistical analysis is available upon request.

[1] See HSH Nordbank (2003).
[2] See Stadtsparkasse Köln (2003).
[3] See Deutsche Apotheker- und Ärztebank (2004).

versus benefits in monitoring due to specialisation affect a bank's choice of loan portfolio structure. Diversification across industries appears to be the superior strategy when the downside risks of loans are moderate. If loans are characterised by high downside risks, banks should focus on their monitoring abilities and limit loan origination to industries about which they have superior knowledge. The work of Winton shows that credit risk is endogenously affected by a bank's monitoring decisions. The credit risk of an individual loan or a homogenous group of borrowers is not, as assumed by loan portfolio models as CreditMetrics, CreditRisk$^+$ or CreditPortfolioView, exogenous. Banks can influence the credit risk of a loan investment by building up expertise and strengthening monitoring quality. Winton (1999) also hints at the "winner's curse" problem when banks expand their loan origination into new industries, especially when they face strong competition in that new industry. That may make diversification into new sectors very costly. The theoretical work of Gehrig (1998), Dell'Ariccia et al. (1999), Dell'Ariccia (2001) and Marquez (2002) explicitly shows that there is a winner's curse problem when banks expand their loan origination into new sectors or geographic regions. Shaffer (1998) provides empirical evidence for the winner's curse effect. Newly founded banks experience substantially higher loan chargeoff rates during their third through ninth years than their longer-existing competitors.

Considering these contradicting suggestions on how to optimize a loan portfolio, it is surprising that there is hardly any empirical work (for the few exceptions see the next section) on the composition of banks' loan portfolios.[4] Which lending strategy is actually used by banks ? Do banks diversify their loan portfolios or do they focus on certain industries? We will shed light on this question by analysing the loan portfolio compositions of all German banks. To this end we suggest a set of several measures of statistical diversification in order to quantify banks' loan portfolio diversification. A second aim of our paper is to analyse possible differences between measures of diversification.

The paper is organised as follows. Section 2 provides a brief overview of the scarce empirical literature related to our own work. In Section 3 our data and methodology will be described in some detail. In particular different concepts of diversification and their related measures will be discussed. Section 4 collects our empirical results for various measures of diversification and analyses the relationship between them. Finally, conclusions are drawn and extensions suggested in Section 5.

2 Related empirical literature

An overview of the existing empirical work on loan portfolios will illustrate that it is entirely unclear how loan portfolio diversification should be measured. There are three empirical papers that are closely linked to our research question, but each having a different focus.

Acharya et al. (2004) analyse the effects of loan portfolio diversification on risk and return figures. They examine 105 Italian banks over the period from 1993 to 1999. As a measure of diversification, they use the Hirschman-Herfindahl Index (HHI), which they compute for industrial and sectoral diversification. The industrial HHI (I-HHI) is the sum of the squares of relative exposures under the given classification of industries. The sectoral HHI is calculated analogously. The boundaries of the HHI are given by

[4] One possible explanation for this gap in the literature may be the lack of suitable data.

$$\frac{1}{n} \leq \text{HHI} \leq 1 \ , \qquad (1)$$

where n stands for the number of segments. Note that the index reaches its minimum when the exposures to all segments (industries, sectors) are equal. It is 1 when all loans are originated in one segment.

The effect of diversification on different return and risk figures is analysed using panel regressions. The results show that industrial diversification is linked to a decrease in performance, expressed as declining returns and even an increase in risk. The sectoral diversification has an unclear effect on banks with moderate risk but decreases the performance of banks characterised by a high level of risk. Acharya et al. (2004) conclude that "diversification, per se, is no guarantee of superior performance or greater bank safety" (p 36).

A study on the effects of diversification for financial services firms in the Unites States is performed by Elyasiani and Deng (2004). However, bank supervisors in the United States do not collect data on the loan portfolio composition by industry. Therefore, the analysis comprises sectoral, geographical and activity diversification. Sectoral diversification means the diversification of loans over six sectors: Commercial and industrial, depository institutions, real estate, agriculture, individual, and other loans. Geographical diversification captures the composition of loan portfolios by loans originated by domestic and foreign offices of a bank. Activity diversification stands for the composition of non-interest income by activity lines as eg trading income or service charges.[5] Similar to Acharya et al. (2004) all dimensions of diversification are quantified by using the HHI. Elyasiani and Deng (2004) find that all dimensions of diversification lead to decreasing returns as well as decreasing income. They therefore conclude that the question of diversification is a very typical question of a risk and return tradeoff.[6]

One can derive from Acharya et al. (2004) and Elyasiani and Deng (2004) the tentative recommendation that loan portfolio policy should not be driven by diversification but by a bank's specific monitoring abilities in industries or sectors. Given this statement, it would be interesting to know which strategy banks actually follow in managing their loan portfolios. The work of Acharya et al. (2004) and Elyasiani and Deng (2004) lacks a time series analysis in order to identify trends towards diversification or specialisation.

The work of Pfingsten and Rudolph (2002) partially fills this gap for Germany. Their analysis is based on aggregate data of German bank groups covering the period from 1970 to 2001. The authors measure diversification by distance measures, quantifying the distance between a bank group's loan portfolio and the market's loan portfolio. The diversification by industry is considered for up to 16 industries. The data comprise the lending to businesses and only involve national loan origination.

In running a time series analysis, Pfingsten and Rudolph (2002) find that bank groups increased their loan portfolio diversification over time. However, this result might be driven by the aggregation of data. Aggregating data of banks that specialise in different industries may still lead to an increasingly diversified loan portfolio at bank group level. Thus, an analysis of individual banks is necessary to confirm or reject the result that portfolio diversification is the leading strategy in the recent lending practice of German banks.

[5] See Elyasiani and Deng (2004), pp 19-20.
[6] See Elyasiani and Deng (2004), pp 40-41.

Our work combines aspects from the studies cited above. Like Acharya et al. (2004) and Elyasiani and Deng (2004), we work with individual bank data and use the HHI as one, but in our case not the only measure of diversification. We add several other measures including distance measures as suggested by Pfingsten and Rudolph (2002) and perform both a panel analysis and a time series analysis. This enables us not only to examine which of the two strategies - diversification or focus - individual German banks follow, but also how their behaviour seems to have changed over time.

3 Data and empirical methods

3.1 Data

We use individual bank-level data, which, in our case, are provided by the Deutsche Bundesbank and are part of the borrowers statistics. All banks with a banking licence for the German market have to report their exposures to corporate borrowers, private borrowers, and non-profit organisations. Exposures to private borrowers are subdivided into loans for housing, consumer loans, and other private loans like credit card loans. Exposures to corporate clients are reported for 23 industries. An overview of the lending towards the 23 industries is provided in Table 1. The data set only comprises national loan origination. As most banks in the data set are small regional institutions without any international business, this limitation does not appear to be crucial. However, we cannot measure geographical diversification outside Germany.

The segmentation of private borrowing is rather heterogeneous. Loans to one individual customer might, for instance, occur in all three segments, limiting an analysis of a bank's loan portfolio strategy considerably. A bank's loan portfolio strategy might therefore best be analysed by focusing on loan origination to corporate clients, as diversification across industries does best represent our understanding of diversification. Therefore, we restrict our analysis to the origination of loans to corporate clients in 23 industries. Our data set consists of semi-annual data for the period from 1993 to 2002, ie 20 observations for each bank.

Additional attention must be given to the handling of mergers. Especially within the group of savings banks and credit cooperatives, we have observed much consolidation over the last decade. To isolate our analysis from effects of mergers, we include only banks existing in December 2002 and treat all banks that merged during the period of our analysis as if they had been merged over the whole period. As a consequence, the banks in our data set will probably be more diversified in the beginning than they actually were.[7]

The data set comprises *all* banks that have a license for the German banking market. At the end of 2002 this number amounted to 2, 231 banks. Our analysis covers 2, 218 banks, as 13 banks have no exposures to corporate customers at all. The banks are grouped in 10 different bank groups, which can be assigned to 4 categories. These groups are (in brackets the number of banks within a group):

1. Commercial banks
    (a) Big banks (4)

[7] Analysing the effects of mergers on loan portfolio diversification will be an issue for our future research.

    (b) Regional banks (134)
    (c) Subsidiaries of foreign banks (33)

2. Banks under public law
    (a) Savings banks (520)
    (b) State banks (13)

3. Cooperative banks
    (a) Credit cooperatives (1485)
    (b) Regional cooperative institutions (2)

4. Other banks
    (a) Special-purpose banks (8)
    (b) Private mortgage banks (16)
    (c) State mortgage banks (3)

Credit cooperatives and savings banks are by numbers the biggest bank groups in the German banking market. Savings banks (Sparkassen) are publicly owned by communities, cities, counties or other (groups of) jurisdictions. Credit cooperatives (Kreditgenossenschaften) aim to provide support to their members and have their very origin in rural communities as well as craft communities. Credit cooperatives as well as savings banks offer similar services to commercial banks. Banks of these groups only operate in a local market which should not overlap with markets of other banks within the same group. The group of regional commercial banks mainly comprises private bankers. Results for the category of other banks are, due to their minor importance, not displayed separately. In order to avoid identification of single banks, results for the two regional cooperative banks are not presented separately, either.

3.2 Different concepts of diversification

Following Markowitz (1952) a portfolio is efficient if there is no other portfolio with lower risk and an (at least) equal expected return and no portfolio with a higher expected return and (at most) equal risk. In this context diversification is a means to change the risk of the portfolio. For liquid assets the portfolio's risk can be measured as the standard deviation from expected returns. This setting can hardly be applied to loan portfolios. For one thing, the distribution of returns from loans is highly skewed, making the standard deviation inappropriate. For another, the distribution depends on the correlations between returns. In contrast to liquid assets, the correlation between returns from loans cannot easily be observed. One must also remember that the figures needed would be specific to each bank as credit risk is endogenously affected by a bank's expertise and monitoring abilities. We presume that, for these reasons, most banks of our sample apply heuristics to determine the diversification of their loan portfolios.

Acharya et al. (2004) apply a measure of the HHI in order to quantify loan portfolio diversification. In addition to the HHI we will introduce several other measures of concentration and (in-)equality as statistical measures of loan portfolio diversification. Concentration measures refer to diversification in a *naive* form: one may remember, for example, from

Equation 1 that the HHI reaches its minimum when all exposures to different classes are equal, ie the HHI quantifies naive diversification with a $1/n$-diversification strategy as the benchmark. Generally concentration measures come with the drawback that they ignore the size difference of an economy's industries. An example may illustrate the relevance of this problem: From Table 1, we can see that "manufacturing of non-metallic mineral products is one of the smallest industries within the set of 23 industries, whereas "wholesale and retail trade" belongs to the biggest industries.[8] Having the same exposure to a highly specialised and very small industry as to a major industry of an economy might already be regarded as specialisation in the first industry. Thus, industry weights should matter when measuring diversification. Therefore, we suggest applying a benchmark which reflects the industry composition of an economy when measuring portfolio diversification. We follow Pfingsten and Rudolph (2002) and use distance measures to quantify statistical diversification. The distance from a benchmark can be measured by describing a loan portfolio composition as the (normalised) vector of relative industry shares. In this setting, diversification is at its maximum when a bank's loan portfolio composition reflects the industry shares of the benchmark under review. Distance measures are better heuristics for portfolio management since they use the market as a benchmark.

In the following, we will test whether the bias which occurs when using naive diversification as a benchmark is empirically relevant. To this end we compute a set of concentration measures (which incude the HHI, Gini coefficient and Shannon entropy measures) and a set of distance measures and then compare the results.

To formalise, loans are partitioned into n segments. Let $X_i^{b,t}$ be the nominal exposure of bank b at time t to loan segment i. Then $X^{b,t} = (X_1^{b,t}, ..., X_n^{b,t})$ is the vector of nominal loan exposures of bank b at time t to all loan segments $i = 1, ..., n$. By $x_i^{b,t}$ we denote the corresponding relative exposure,

$$x_i^{b,t} = \frac{X_i^{b,t}}{\sum_{j=1}^{n} X_j^{b,t}} \ , \tag{2}$$

and $x^{b,t} = (x_1^{b,t}, ..., x_n^{b,t})$ is the vector of these shares in the portfolio of bank b at time t.[9] By $y^t = (y_1^t, ..., y_n^t)$ we denote the shares of the loan segments in a benchmark's loan portfolio.

We distinguish between two groups of measures. The first group of measures quantifies *naive* diversification. We will use the HHI, the Gini coefficient and the Shannon entropy measures in order to quantify naive diversification. The second group of measures takes into account the fact that an economy's industries differ in size. These measures relate to benchmarks that reflect the industry composition of the economy. Given the tradeoff between diversification of loan portfolios and focus on homogenous lenders as depicted in the introduction, measuring diversification of loan portfolios does not imply quantifying the risk of a loan portfolio.

[8] At the end of 2002 manufacturing of non-metallic mineral products accounted for 0.65% of Germany's loan market, trade for 12.69%.

[9] When later defining diversification measures, we suppress the superscripts b, t for simplicity.

3.3 Diversification measures

3.3.1 Measures of naive diversification

The *Hirschman-Herfindahl Index* (HHI) is a commonly accepted measure of market concentration. In our study we use the HHI of bank b at time t,

$$\mathrm{HHI}(x) = \sum_{i=1}^{n} (x_i)^2 \ , \tag{3}$$

as a measure of diversification, where small values mean high diversification. Note that the lower limit for the HHI is 1/23 and is attained when exposures to all loan segments are equal. The HHI is equal to 1 when all loans are granted to one segment.

The *Gini coefficient* (G) is often used as a measure of inequality. However, it can also be used to quantify the concentration of a loan portfolio. If one considers the Lorenz curve of an individual bank's loan portfolio, the Gini index is the ratio of the area between the diagonal and the Lorenz curve of a bank and the area of the whole triangle below the diagonal. The Gini coefficient of an individual bank b at time t is calculated as:

$$\mathrm{G}(x) = 1 - \frac{2}{n} \cdot \sum_{j=1}^{n} v_j - \frac{1}{2} \ , \tag{4}$$

with

$$v_j = \sum_{i=1}^{j} \hat{x}_i \ , \tag{5}$$

where $\hat{x}_i$ represents the relative industry shares of a loan portfolio, sorted by size in ascending order. Thus, v_j is the cumulated share of the j smallest industries in a loan portfolio.

Maximum diversification is reached when we observe equal exposures to all industries. That is, the Lorenz curve is diagonal. The Gini coefficient is zero. Maximum focus will lead to a Gini coefficient of 22/23.

Entropy measures are also powerful instruments to indicate variety in distributions at a given point in time. Their potential applications include measuring industrial concentration or corporate diversification.[10] We apply the Shannon entropy[11] (S) in order to measure loan portfolio diversification:

$$S(x) = \sum_{i=1}^{n} x_i \cdot ln(\frac{1}{x_i}) \tag{6}$$

It is standard practice to define $x_i \cdot ln(\frac{1}{x_i}) = 0$ if $x_i = 0$.[12] For the HHI and the Gini coefficient, large values of these measures stand for focus whereas small values stand for diversification. In order to maintain this idea we define $\hat{S} = -S$. If all loans are to one industry $\hat{S}$ is 0, representing maximum focus. Perfect *naive* diversification is expressed as a value of $-ln(23)$.

[10] See Frenken (2004).
[11] See Shannon (1948).
[12] See Theil (1972).

3.3.2 Benchmark measures

As was pointed out earlier, measures of naive diversification apply an equal distribution of loans across all industries as their benchmark, incorporating the unpleasant feature of not being independent of the definition and aggregation of industries. Therefore Pfingsten and Rudolph (2002) have suggested measuring diversification with respect to more general benchmarks.

As suggested by Pfingsten and Rudolph (2002) the industry composition of the economy's loan market portfolio can be used as a benchmark for *statistical* diversification. However, this benchmark neglects regional business structures. If the loan portfolio of a bank reflects the industry structure of its region, than a decline in distance of an individual bank to the national market loan portfolio might be due to a change in regional industry structures. Therefore, our analysis also comprises the distance of an individual bank's loan portfolio to regional benchmarks. These benchmarks are the composition of a state's loan portfolio and the composition of a county's loan portfolio. Another possible nationwide benchmark is to use the industries' contributions to *GNP* as reference point for loan portfolio diversification.[13] Thus, we apply 4 benchmarks as reference points for statistical diversification:

1. composition by industry of the whole German loan market portfolio (D_j^{Nation}),
2. composition by industry of a state's loan market portfolio (D_j^{State}),
3. composition by industries of a county's loan market portfolio (D_j^{County}),
4. composition of industries' contributions to *GNP* (D_j^{GNP}).

When setting *distance measures*, diversification is measured by quantifying the distance between a bank's loan portfolio and the benchmark's loan portfolio. Larger values mean less diversification.[14]

Following Pfingsten and Rudolph (2002), we use several measures:

Measure 1 *Maximum Absolute Difference*

$$D_1(x, y) = \max_i\{|x_i - y_i|\} \ . \tag{7}$$

Measure 2 *Normalised Sum of Absolute Differences*

$$D_2(x, y) = \frac{1}{2}\sum_{i=1}^{n} |x_i - y_i| \ . \tag{8}$$

Measure 3 *Normalised Sum of Squared Differences*

$$D_3(x, y) = \frac{1}{2}\sum_{i=1}^{n} (x_i - y_i)^2 \ . \tag{9}$$

[13] An overview of the contribution to GNP by industries is given by Table 1. The classification of industries does not perfectly reflect the classification of industries used in the loan statistics. Thus, when referring to the GNP as a benchmark, we only take those 21 industries in consideration where the same classification of industries applies for both data sets.

[14] For some basic properties of distance measures see Pfingsten and Rudolph (2002).

Measure 4 *Average Relative Difference*

$$D_4(x,y) = \frac{1}{n}\sum_{i=1}^{n} \frac{|x_i - y_i|}{x_i + y_i} \ . \tag{10}$$

Measure 5 *Average Squared Relative Difference*

$$D_5(x,y) = \frac{1}{n}\sum_{i=1}^{n} \left(\frac{x_i - y_i}{x_i + y_i}\right)^2 \ . \tag{11}$$

Before we start analysing the data, it is important to understand some characteristics of these measures. Note that all are normalised to the interval $[0,1]$. D_1 just gives the maximum absolute difference across all loan segments, $|x_i - y_i|$, between a bank's portfolio x and the benchmark portfolio y. Thus, it is only sensitive to the segment with the biggest absolute difference. D_2 is a normalised version of the arithmetic mean of the absolute differences across all segments. It can be interpreted as the proportion of a bank's portfolio x which would have to be rearranged in order to achieve the composition of the benchmark portfolio. D_3 assigns higher weights to large deviations from the benchmark.[15]

Measures D_4 and D_5 represent measures based on relative differences $\frac{|x_i-y_i|}{x_i+y_i}$.[16] The relative measures D_4 and D_5 have the property that the deviation in each segment is seen relative to the size of this segment. However, these measures come with a disadvantage when some of the segments are not relevant (that is $x_i = 0$). Each segment i with $x_i = 0$ contributes $1/n$ towards the distance measure, irrespective of the related y_i. Measures D_4 and D_5 correspond to measures D_2 (average deviations) and D_3 (squared deviations) respectively.[17]

A further set of indices is given by calculating the *ratio of an individual bank's Gini coefficient and a benchmark's Gini coefficient.* All benchmarks presented before can be used for this set of indices. We will refer to these indices as:[18]

$$BG^{\text{Benchmark}} = \frac{\text{G}}{\text{G}^{\text{Benchmark}}} \tag{12}$$

Figure 1 illustrates the idea of these indices.[19] A ratio that is greater than 1 means that the individual bank is more concentrated than the benchmark portfolio, whereas an index smaller than 1 indicates that a bank is more diversified than the benchmark portfolio. In contrast to our distance measures these measures do not use the whole industry structure as a benchmark but only the industry concentration. A ratio of 1 indicates equal concentration yet concentration may still occur on different industries.

[15] It should be noted that a large difference in one segment implies another large difference or a number of smaller differences in other segments.

[16] More precisely the relative differences should be called relative *absolute* differences as they are, in turn, calculated from absolute values.

[17] The measure corresponding to D_1 would be the *Maximum Relative Difference*. See Pfingsten and Rudolph (2002). It equals 1 as soon as at least one x_i equals zero. Due to the fine division of loan segments, the measure indeed becomes 1 for most banks and is therefore not taken into further consideration.

[18] The superscripts b, t are again suppressed for simplicity,

[19] In this example with North Rhine-Westfalia as the state and Düsseldorf as the county, we do not see much deviation in industry concentration. One would expect greater deviation for more rural counties.

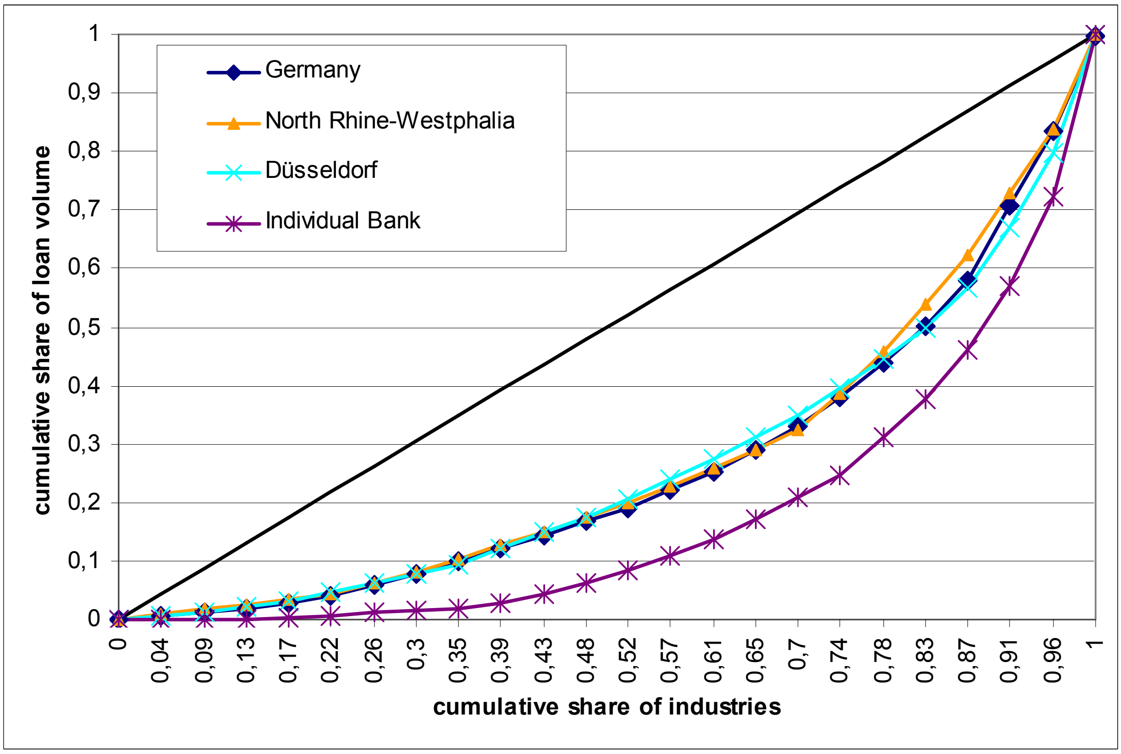

Figure 1: Gini coefficient

Finally we apply *Spearman's rank correlation coefficient* (RC; see, for instance, Zar (1972)) in order to quantify loan portfolio diversification. The basic idea is to compute the rank correlation coefficient between the industry structure of an individual bank's loan portfolio and one of our benchmarks as described above. The rank correlation coefficient is standardised between -1 and 1. A rank correlation of 1 indicates that the structure of a bank's loan portfolio is perfectly rank correlated with the structure of the benchmark's portfolio. That is to say, all industries sorted by size have the same rank in the bank's loan portfolios as in the benchmark's loan portfolio. Within this setting a RC of 1 therefore stands for perfect diversification. Since for all other measures described before, large values stand for focus whereas small values stand for diversification, we define $\hat{RC} = -RC$. That is to say, a $\hat{RC}$ of -1 stands for perfect diversification, whereas 1 represents perfect focus.

3.4 Statistical analysis

Using the set of data with 2,218 banks, all measures of statistical diversification are calculated for 20 observations per bank.[20]

For all of these measures, a fixed-effect *panel estimation* is performed in order to check for trends towards diversification or focus over time. We regress the measures of diversification on a linear trend variable:

[20] One exception applies: The analysis based on the industries' contribution to the GNP is based on annual data, as semiannual data of the industries' contribution is not available. Moreover, industries' GNP data for 2002 was not yet available at the time of our analysis. Our analysis therefore only covers 9 points of observation from 1993 to 2001 when the composition of the GNP is used as a benchmark.

$$DM_b^t = \alpha + \beta \cdot \text{time} + \epsilon_b^t \tag{13}$$

DM_b^t stands for the diversification measure of bank b at time t. We perform fixed effects panel estimations on the whole banking sector as well as on bank groups for savings banks, credit cooperatives, state banks, big banks, regional banks, and subsidiaries of foreign banks. The panel estimator reflects the average behaviour of the whole banking sector/group, because the coefficient of the trend variable is restricted to be equal for all banks considered in the regression.

To assess the behaviour of individual banks we perform *bank- level estimations*. All measures of diversification are regressed on a linear trend variable for each individual bank:

$$DM_b^t = \alpha_b + \beta_b \cdot \text{time} + \epsilon_b^t \tag{14}$$

Thus, the distribution of the trend coefficients of the bank-level regressions allows us to assess the deviation from the average behaviour given by the panel estimator.

However, trends need not necessarily be linear. We therefore also calculate the Spearman *rank correlation coefficient* (RC) of a diversification measure with time on the bank level. The distribution of RC gives us a descriptive answer to the question of whether banks' behaviour follows a monotonic trend that is not restricted to be linear. A rank correlation of 1 indicates that a measure increased with every step in time. A rank correlation of -1 shows that a measure decreased with every step in time. Note that we use the RC coefficient as a measure of diversification (RC of the industry structure of an individual bank's loan portfolio with a benchmark) as well as a statistical tool in order to analyse changes in a diversification measure over time (RC of a diversification measure with time).

4 Empirical results

4.1 Statistical analysis of diversification

Table 2[21] gives a first impression of the time paths of a selection of our diversification measures by listing their means over all banks. These figures indicate that banks have moved towards diversification and therefore support, at the individual bank level, the results obtained by Pfingsten and Rudolph (2002) on a highly aggregated level. Note that, for all measures, a trend towards diversification is expressed as a decrease in the measure.

As we aim merely at an overview, we will not present a detailed analysis of *all* diversification measures suggested in section 3.3.[22] We start our more thorough inspection of some measures with a closer inspection of the HHI as a measure of diversification.

[21] All Tables are displayed in the Appendix.
[22] Tables with some key statistics for all measures are provided upon request.

Hirschman-Herfindahl index

Table 3 shows key statistics of the HHI for different banking groups. Looking at the *absolute magnitude* of the HHI, we see that big banks have the lowest average HHI, followed by savings banks. That means these banks have, on average, the strongest naive diversification. Subsidiaries of foreign banks and regional banks have on average the weakest diversification.

Let us now turn to *changes over time*. For all banks, the panel estimator shows a highly significant negative trend of the HHI over time. Note that a decline in the HHI stands for an increase in diversification. The individual trend estimations reveal that 50.72% of all banks significantly (at a 5% significance level) increased naive diversification over the last decade. Furthermore, we use the rank correlation coefficient (RC) of a diversification measure with time in order to identify monotone but not necessarily linear trends over time. A negative RC indicates that the HHI is declining over time while diversification increases. The mean (median) of the RC coefficient over all banks is -0.2543 (-0.4015). 67.63% of all banks have a negative RC, hinting at an increase in diversification.

When analysing the different banking groups, we see that these results are mainly driven by credit cooperatives (CC) and savings banks (SB). Both groups show strong tendencies towards diversification in terms of highly significant panel trends, of majorities of individual banks with significant trends, as well as of majorities of individual banks with a negative rank correlation of the HHI over time. For the group of state banks (StB), the panel estimation reveals a significant trend towards diversification. However, at the individual bank level, 5 out of 13 state banks show a significant trend towards diversification, whereas 5 other state banks show a significant trend towards specialisation. Results are also mixed for the groups of big banks (BB) and regional banks (RB). Subsidiaries of foreign banks (SFB) reveal a trend towards specialisation, indicated by the panel estimator and by a slight majority of individual banks for whom this trend is significant. Such a specialisation of subsidiaries of foreign banks is not surprising because often these banks accompany the foreign business activities of firms from their home market. For these banks, then, a specialisation in one country can still be consistent with a diversified portfolio at the international level.

Figure 2 further illustrates our results. It shows histograms of the Spearman rank correlation coefficients of the HHI over time. The upper left-hand panel shows the histogram for all banks. It can easily be seen that a majority of banks increased their loan portfolio diversification. The upper right-hand panel shows the corresponding histogram for credit cooperatives whereas the lower left-hand panel shows the histogram for savings banks. Corresponding to the figures from Table 3, one can see the strong tendencies towards naive diversification within these two groups. The less pronounced histogram in the lower right hand panel is based on commercial banks, combining big banks, regional banks and subsidiaries of foreign banks.

Gini coefficient

The results for the Gini coefficient in Table 4 are apparently quite similar to the results for the HHI. Note that a Gini coefficient of 0 represents perfect naive diversification. Considering the absolute magnitude of this diversification measure, we see that again big banks followed by savings banks have the strongest diversification whereas regional banks and subsidiaries of foreign banks are more focused. Moroever, changes in the measure over time are also in line with our results from the HHI.

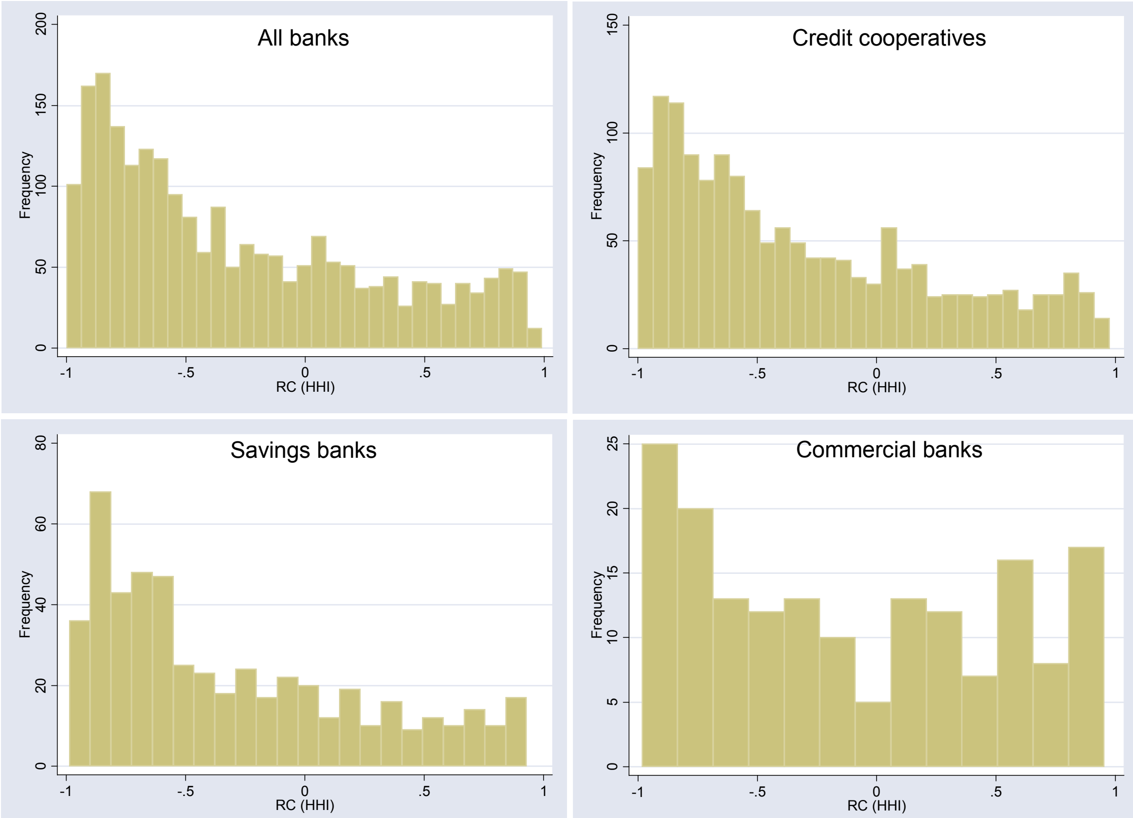

Figure 2: Histogram of RC between HHI and time for all banks, CC, SB, and CB

Shannon entropy

The results for the Shannon entropy ($\hat{S}$) in Table 5 are basically in line with our results for the HHI and the Gini coefficient. Remember that maximum naive diversification is expressed as an entropy value of $-ln(23) \approx -3.14$ whereas maximum focus equals an entropy value of 0. Among others, we again see the remarkably clear trend towards diversification for the groups of credit cooperatives and savings banks.

Distance Measures

All measures applied so far quantify naive diversification, ie diversification is maximised when a bank has equal exposures towards all industries. This understanding of diversification makes little sense when industries differ dramatically in size. Let us suppose that the industries' total loan volumes are used as the benchmark for distance measures.[23] Then, firstly, not all banks can achieve perfect naive diversification if industries' loan volumes differ, but they all can diversify perfectly with respect to distance measures. This also shows, secondly, that measures of naive diversification, unlike distance measures, are sensitive with respect to the definition of industries, which we think is a somewhat unpleasant feature for empirical research. We therefore turn now to distance measures.

[23] Contributions to GNP and total assets are other conceivable indices of size.

Distance measure D_2

We start with D_2 as an example of an absolute distance measure. As a first benchmark we apply the composition of the national loan market by industry. Our results are displayed in Table 6.

Big banks and savings banks appear to be closest to the market, whereas regional banks and subsidiaries of foreign banks reveal the biggest distance from the national loan market portfolio.[24] Recall that the mean of D_2, as of December 2002, of 29.45% for savings banks means that they would have to rearrange, on average, 29.45% of their loan portfolio in order to achieve the industry composition of the national loan market portfolio. Considering the distance to the market, it can be concluded that regional banks and subsidiaries of foreign banks are rather specialised in their loan origination.

Again, the panel estimation reveals a highly significant trend towards diversification. It is underpinned by the bank-level regressions, showing that at a 5% significance level 48.33% of all banks reveal a significant decline in distance to the national loan market portfolio. According to the rank correlation, 70.47% of all banks reduced their distance to the loan market portfolio.

Again, this trend towards diversification is best viewed for credit cooperatives and savings banks. Both groups reveal highly significant trends towards diversification based on the panel estimator. This trend is strongest for credit cooperatives whereas for the bank-level regressions the group with the highest percentage of banks with a significant trend towards diversification is that of savings banks. Results for state banks, big banks, and regional banks are, as almost always, rather mixed. Subsidiaries of foreign banks increased their distance to the national loan market; this is indicated by the panel estimator and by a majority of individual banks showing a trend towards specialisation.

Once more we use histograms to illustrate our results. Figure 3 shows histograms of the rank correlation coefficients of D_2^{Nation} over time. It can easily be seen from the different panels that large majorities of credit cooperatives and savings banks decreased their distance to the national loan portfolio and therefore increased diversification over the past decade. The histogram of commercial banks (big banks, regional banks, and subsidiaries of foreign banks) underlines the fact that a majority of commercial banks increased specialisation according to D_2^{Nation}.

A comparison between the lower right-hand panel of Figure 3 and the lower right-hand panel of Figure 2 shows that measuring diversification according to a concentration measure such as the HHI and according to distance measures such as D_2^{Nation} can provide contradicting results. This can also be seen when comparing the results of the individual bank regressions for the four big banks. The HHI indicates that two big banks significantly increased naive diversification and one of the big banks has an insignificant trend towards diversification. Applying D_2^{Nation} as measure of diversification, we see that only one bank has a significant trend towards diversification. Three out of four big banks show a positive slope of the coefficient on the time variable. We will examine the relationship between the various distance measures in more detail in Section 4.2.

[24] Note that the short-hand expression "market portfolio", used for the set of all loans considered here, does not intend to suggest that this benchmark portfolio is efficient in the sense of Markowitz.

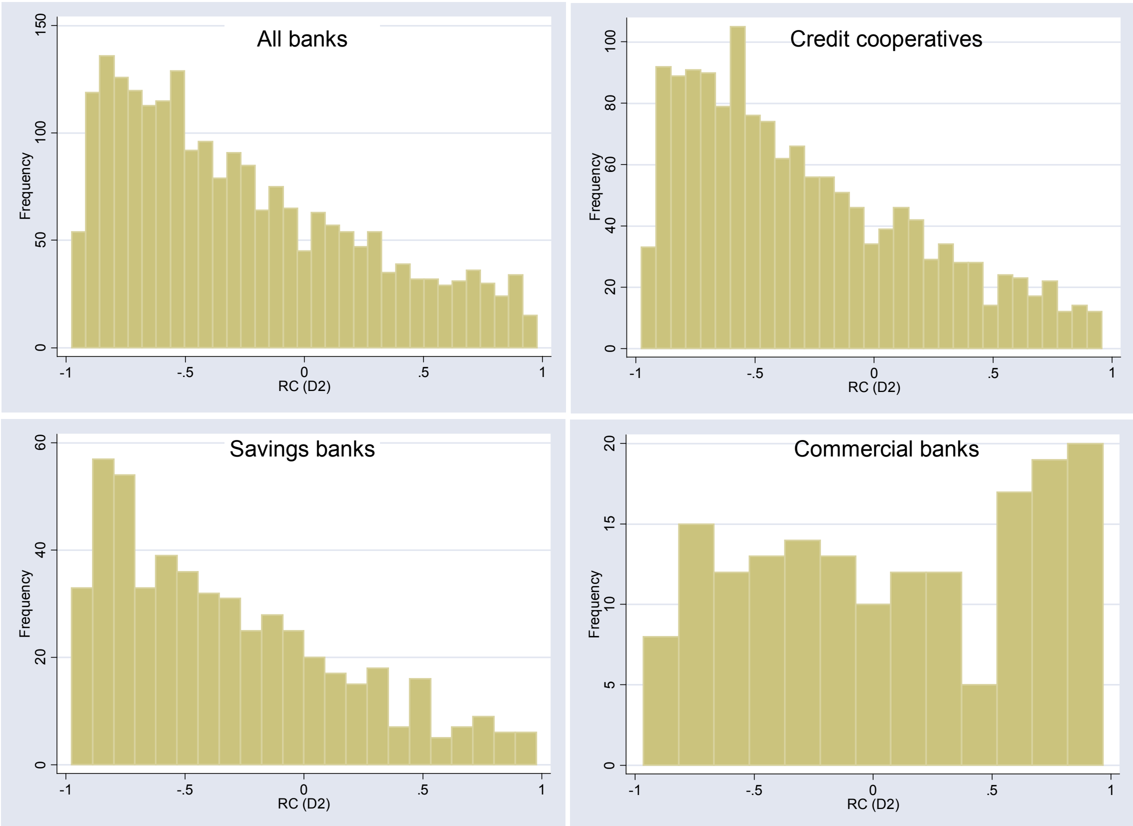

Figure 3: Histogram of RC between D_2^{Nation} and time for all banks, CC, SB, and CB

Distance measure D_4

After having analysed the results for the group of absolute distance measures, we will now focus on the group of relative distance measures.[25] As D_4 corresponds to D_2, we will analyse it in some detail. Table 7 gives an overview of our findings based on D_4^{Nation}.

The results for D_4^{Nation} support the findings based on D_2^{Nation}. Credit cooperatives and savings banks show a highly significant trend towards diversification whereas big banks, regional banks, and subsidiaries of foreign banks show a tendency towards specialisation as indicated by the panel estimator. The regressions on the bank level show majorities of individual banks with a significant trend towards focus for state banks, regional banks and subsidiaries of foreign banks. Big banks reveal a slight tendency towards an increase in distance to the national loan market, but it must be taken into account that these banks are on average still closest to the market.

Distance measure D_2 with regional benchmarks

We have found a movement towards the nation's loan market portfolio especially for the groups of credit cooperatives and savings banks. However, the individual banks within these groups operate in regional markets. Hence the observed tendency towards diversification is economically not fully convincing and may be merely the result of changes in

[25] By and large our results for measure D_2 are supported by the other absolute distance measures.

regional industry structures. Thus, it seems preferable to consider regional benchmarks such as the compositions of a state's loan portfolio or a county's loan portfolio. We will substantiate our findings using distance measure D_2. Tables 8 and 9 report the results for D_2^{State} and D_2^{County} respectively. Note that regional benchmarks do not make sense for big banks and subsidiaries of foreign banks as they generally operate nationwide. Furthermore, the composition of a county's loan portfolio is not an appropriate benchmark for state banks.

The composition of a state's loan portfolio must be considered the appropriate benchmark for state banks. Applying D_2^{State} indeed reveals a significant trend towards diversification for this group of banks, indicated by the panel trend coefficient as well as by a majority of banks with such behaviour. D_2^{State} also still shows highly significant trends towards diversification for credit cooperatives and savings banks. For these banks, the results continue to hold even if the benchmark is broken down to county level.

For both benchmarks, however, D_2 reveals a tendency towards focus for the group of regional banks, as indicated by the panel estimator, and a majority of individual banks with a significant trend towards focus. Moreover, this group of banks is characterised by having, on average, the greatest deviation from the two local benchmarks. This supports our earlier impression that regional banks seem to be more specialised in their loan origination.

Distance measure D_2 with contribution to GNP as benchmark

As a fourth benchmark to be applied with distance measures, we analyse the composition of the industries' contribution to GNP. This time we must refer to annual data, as semiannual data of the industries' contribution to GNP were not readily available. Again we use D_2 as the example to illustrate our results. The key statistics of D_2^{GNP} are provided in Table 10.

Despite significance levels many other studies would be happy about, the results for D_2^{GNP} are not as clear as for other measures. For most groups of banks we see mixed results. Only credit cooperatives still display a tendency towards diversification and, to a lesser extent, subsidiaries of foreign banks towards specialisation. As a tentative explanation for the much lesser significance, we offer the thesis that contribution to the GNP and loan financing may not necessarily be highly correlated, eg due to variations in equity ratios, and hence banks do not use GNP figures as a guideline for limits on their exposure to industries.

Benchmark Gini

We wind up our analysis with BG^{Nation} and RC^{Nation}. Let us recall that BG^{Nation} stands for the ratio of an individual bank's Gini coefficient and the national loan market's Gini coefficient. Remember that a ratio bigger than 1 means that the individual bank is more focused than the national loan portfolio. Thus, a decrease in this measure stands for an increase in diversification. Results for BG^{Nation} are displayed in Table 11.

It is striking to see that *all* bank groups have a highly significant panel trend towards diversification as measured by BG^{Nation}. Moreover, for all bank groups we see clear absolute majorities of individual banks with such a trend being significant and even vast majorities, from about 70% to almost 90%, of banks with rank correlation indicating this trend.

Considering Figure 1, this finding means that the Lorenz curve for most individual banks has approached the diagonal, and hence naive diversification, more (or moved away from it less) than the Lorenz curve of the national loan portfolio has over the last decade. As long as a bank's individual loan portfolio started out more concentrated than the nation's, which seems to be the dominant case according to the initial group-wise means of BG^{Nation}, this implies that the former has come closer to the latter.

Interestingly, at the end of 2002 the four big banks had, on average, the same Gini coefficient as the national market loan portfolio BG^{Nation}. The Gini coefficient of the national loan portfolio had a significant positive trend over this period. That is to say, the concentration of the national loan portfolio significantly increased over time. For the big banks, this means that their slightly higher loan portfolio concentration compared to the national loan portfolio increased less than the latter.

Rank correlation

The key statistics for the $\hat{RC} = -RC$ as a measure of diversification are displayed in Table 12. Remember that a RC ($\hat{RC}$) of 1 (-1) represents perfect rank correlation of individual bank's loan portfolio structure with the structure of the benchmark portfolio. Economically, the largest industry in both portfolios is the same, as is the second largest, and so on. Thus, within this setting a RC ($\hat{RC}$) of 1 (-1) represents perfect diversification.[26]

As the readers will by now expect, the results for credit cooperatives and savings banks indicate a trend towards diversification. Surprisingly, we see a trend towards diversification within the group of regional banks. The panel estimator reflects a significant trend towards diversification. Moreover, we observe a majority of individual regional banks with a trend towards diversification. State banks and subsidiaries of foreign banks show a trend towards focus, whereas the results for the big banks are not conclusive.

Brief summary

We can sum up by saying that for all measures (concentration measures as well as distance measures) most banks show a significant trend towards diversifying their loan portfolios. A comparison of the analysed measures of diversification for the group of all banks is provided in Table 13. The trend towards diversification is especially driven by the large number of credit cooperatives and savings banks. However, we also see that regional banks and subsidiaries of foreign banks are and becoming even more specialised in their loan origination. Their concentration measures are, on average, higher than those of other banking groups, and distance measures of these banks deviate rather widely from the benchmark loan portfolios. Moreover, time series analyses, by and large, reveal no trend towards diversification for these groups. For the state banks and the big banks, the latter being closest to the market, the results are rather mixed.[27]

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[26] Admittedly, this is a rather weak property here, in particular when there are noticeable size differences between industries.

[27] Results for the groups of big banks and state banks must be interpreted very carefully. First of all, these banks are involved in the market for credit derivatives. Thus, the data of the loan statistics might not perfectly reflect the exposures of these banks. Secondly, these banks (especially the big banks) have the strongest influence of all banks on the benchmarks. It is therefore not surprising that they are closest to the benchmarks.

4.2 Relationship between different measures of diversification

The previous section has shown that different measures of diversification may lead to different results. We therefore now turn to a more detailed analysis of the relationship between different measures of diversification.

We start our analysis with a correlation matrix of a selection of our diversification measures (Table 14). The correlations between the measures of diversification are calculated with 20 observations for each bank.[28] RC^{Nation}, only taking into account the rankings of industry shares but not the actual industry shares within a portfolio, has the lowest correlation (in absolute value) with all other diversification measures. HHI is next. Although we have obtained some differences in significance in our previous results when using the composition of GNP as a benchmark in comparison to other benchmarks, the correlations of D_2^{GNP} and D_4^{GNP} with other measures do not indicate a major divergence.

Comparing the HHI with distance measures

In a next step, we condense each time series for a bank into one observation. More specifically, we compare the relationship of the rank correlations of various measures over time. The corresponding differences that appear in the bank trend in diversification when measured, for example, by the HHI and a distance measures are emphasised by Figure 4. Its four panels display the relationship between the rank correlation over time of the HHI and the distance measures D_1^{Nation}, D_2^{Nation}, D_3^{Nation}, and D_4^{Nation}. Each dot in a scatter plot represents a single one of our total set of 2218 banks.

An example should help to understand the bottom line of these scatter plots: Let us consider an individual bank located close to the upper left-hand corner of one of these panels. Such an individual bank has a negative rank correlation of the HHI over time, in fact, of just a little above the minimum of -1, and at the same time a positive rank correlation, close to the maximum of 1, of the distance measure used in this panel over time. This tells us that this individual bank simultaneously increased the naive diversification of its loan portfolio and increased its distance towards the national loan market portfolio. We have already seen this phenomenon for the big banks before. A bank close to the lower right corner of a panel in one of these scatter plots represents the opposite effect: It has increased its specialisation over time as measured by the HHI but decreased the distance towards the national loan market portfolio at the same time.

Contradicting results for the HHI and a distance measure can be caused, for instance, by increasing the share of loans towards small industries at the expense of the share of loans towards larger industries. As mentioned before, glass and ceramics, for example, only accounted for 0.6% of Germany's loan market at end-2002 but trade for 12.7%. Thus, if a bank increases its share in glass and ceramics from 0.7% to 1.0%, say, and reduces its share in trade from 12.6% to 12.3%, it would increase its naive diversification but at the same time increase its separation from the national loan market.

[28] One exception applies: When calculating the correlation with a measure that uses GNP as a benchmark, only 9 observations for each bank are used.

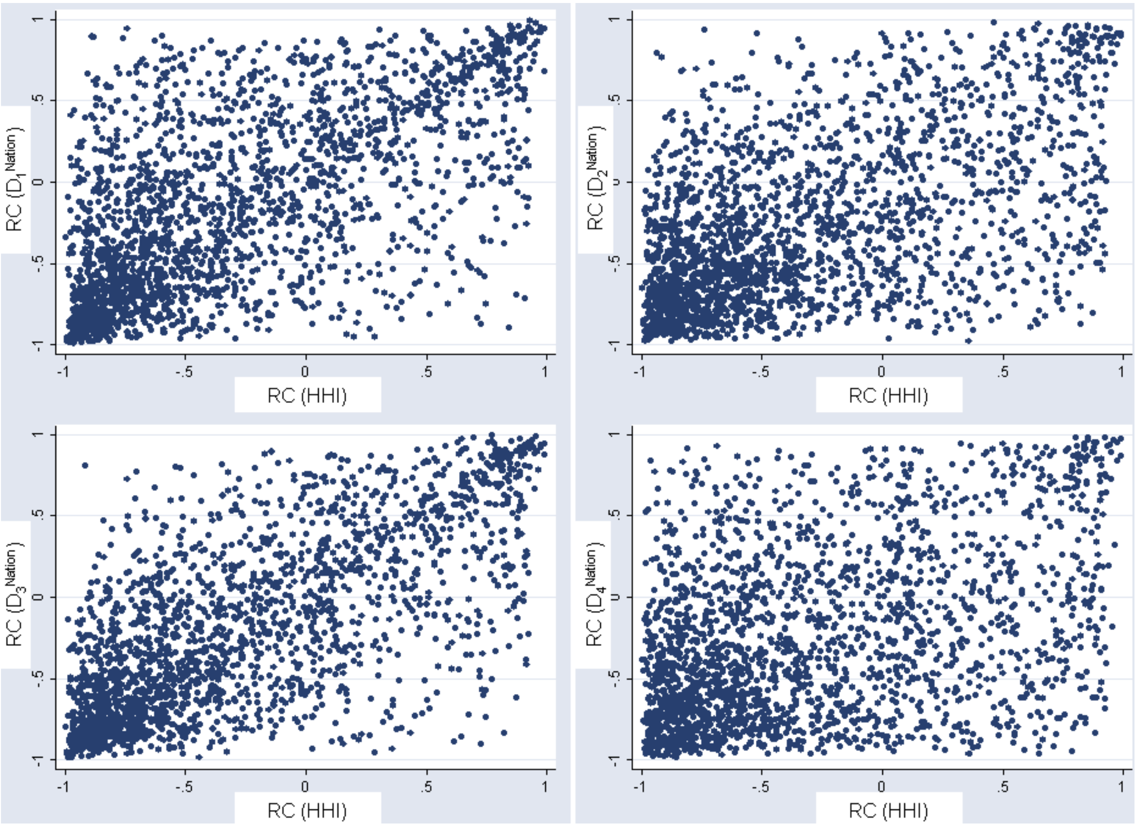

Figure 4: Relationship between RC of HHI over time and RC of D_1^{Nation}, D_2^{Nation}, D_3^{Nation}, and D_4^{Nation} with time

There are plausible arguments for using the HHI as well as distance measures as statistical measures of diversification. If both were just different numerical representations of the same concept, the scatter plots would have all dots on an upward sloping, but not necessarily straight, line. Alas, this is not what we see. Instead, we find that diversification according to the HHI is not very closely correlated with diversification according to distance measures. In many cases the HHI shows a strong increase in focus, whereas distance measures indicate that the bank's loan portfolio distance towards the market decreased and vice versa.

The scatterplots reveal that for individual banks different diversification measures may lead to contradicting results. However, the aggregate results for Germany presented so far were robust to the choice of the diversification measure and revealed trends towards diversification for virtually all measures. This is reflected in the high frequency of banks in the south-western quadrant of the scatterplots. These banks show a trend towards naive diversification and a decline in distance to the market at the same time. Moreover, readers may also wonder why we observe similar levels of significance for different measures, although these measures may lead to contradicting results on an individual bank level. We offer the following explanation: In basically all scatter plots shown so far and later on, we find similar numbers of banks above and below a line that might serve as an approximate monotonic relation between the measures being compared. Therefore, even when the trends found for bank groups were about the same for different measures and had similar levels of significance, it is still possible that the banks with such a trend and those with opposite behaviour were not the same for both measures. Put differently, a lack of striking differences between measures at the aggregate level does not imply that their assessment for individual banks will be very similar.

It is interesting to note that, among the group of distance measures, the results for D_1^{Nation} and D_3^{Nation} seem to be most consistent with the results from the HHI (cf the scatter plots on the left-hand side of Figure 4). This is not much of a surprise since the HHI is an absolute measure (with the $1/n$ benchmark), and one would certainly expect the most similar results to show up with the absolute and not the relative distance measures. Not quite in line with this, and unfortunately for no obvious reason, the results for the normalised sum of absolute differences (D_2^{Nation}; cf upper right-hand panel) differ considerably from the results for the HHI. The lack of agreement of the measures for individual banks is less surprising and even more obvious when comparing the relative distance measure D_4^{Nation} (lower right-hand panel of Figure 4) with the HHI.

Comparing different distance measures

These findings urge us to take a closer look at the relationships between different distance measures. Figure 5 illustrates the divergences in results between the rank correlation of D_2^{Nation} over time and the rank correlation over time of other distance measures using the same benchmark. Similar scatter plots for the relationship of D_4^{Nation} with the other distance measures using the national loan portfolio as the benchmark are illustrated in Figure 6.

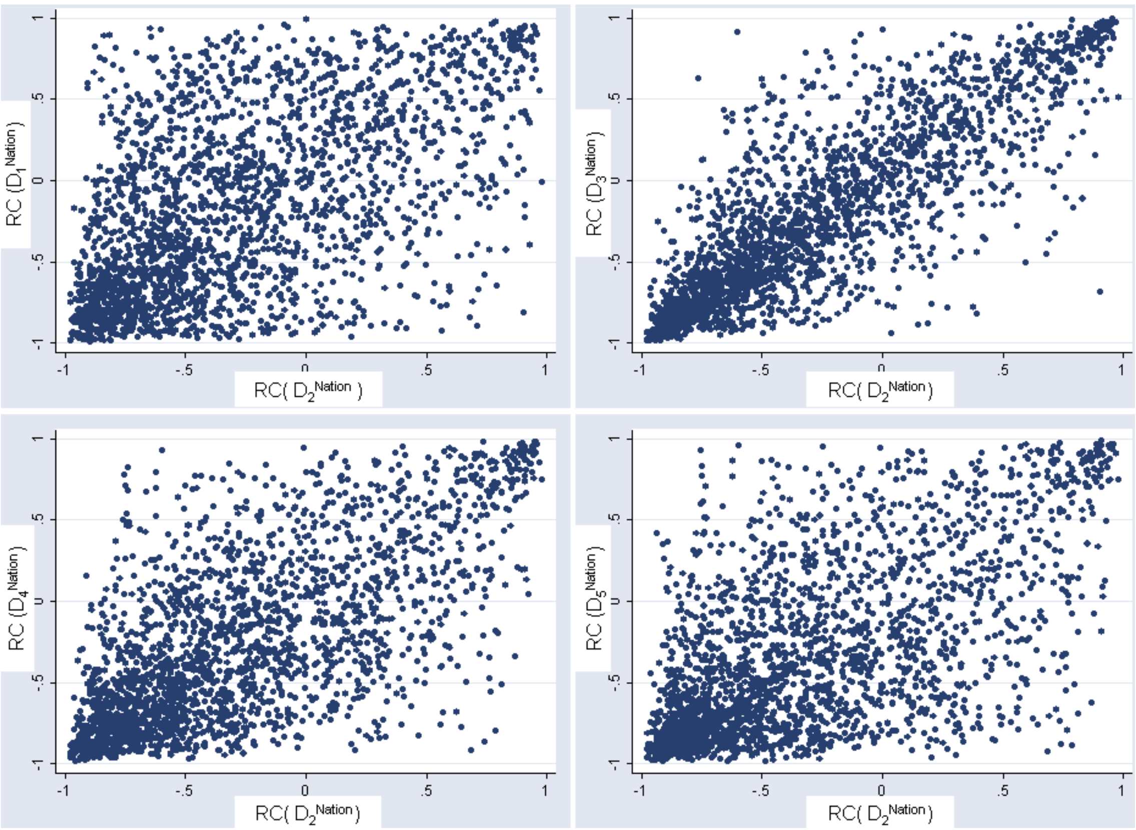

Figure 5: Relationship between RC of D_2^{Nation} over time and RC of D_1^{Nation}, D_3^{Nation}, D_4^{Nation}, D_5^{Nation} over time

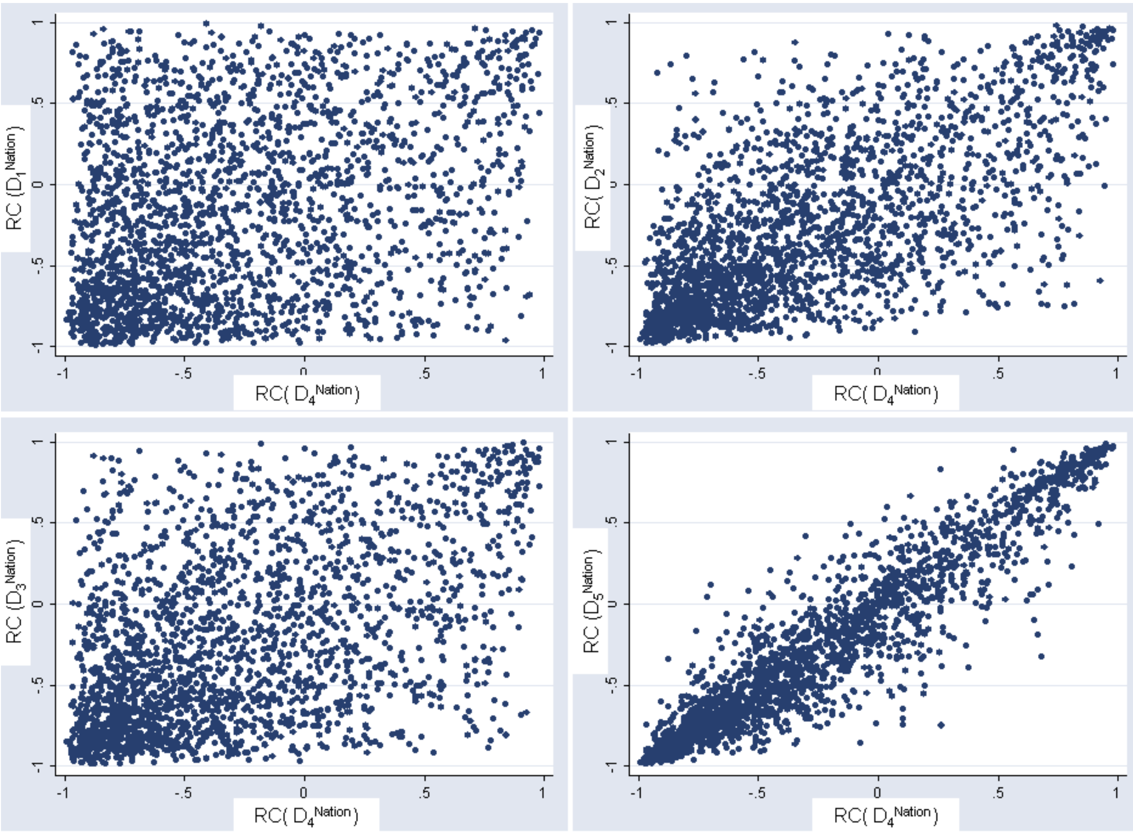

Figure 6: Relationship between RC of D_4^{Nation} over time and RC of D_1^{Nation}, D_2^{Nation}, D_3^{Nation}, D_5^{Nation} over time

Applying the two absolute measures D_2 and D_3 apparently leads to very similar results (upper right-hand panel of Figure 5). The same holds for a pair of relative distance measures, D_4 and D_5 (lower right-hand panel of Figure 6). In contrast, we see major divergences in results when calculating diversification according to an absolute distance measure, on the one hand, and a relative distance measure, on the other. In many cases these measures indicate movements in opposite directions. And even within the group of absolute distance measures we see a pair of measures with a clear disagreement, D_2 and D_1 (upper left-hand panel of Figure 5).

Relevance of benchmarks

Finally, we examine the outcome when one diversification measure is applied with various benchmarks. Figure 7 shows scatter plots of the RC of D_2 over time, where the three panels differ in the benchmarks being used. It is not surprising that results for the national loan portfolio and the states' loan portfolios (panel on the upper left-hand side) are more consistent with each other than the results for the national loan portfolio and the counties' loan portfolios (panel on the upper right-hand side).

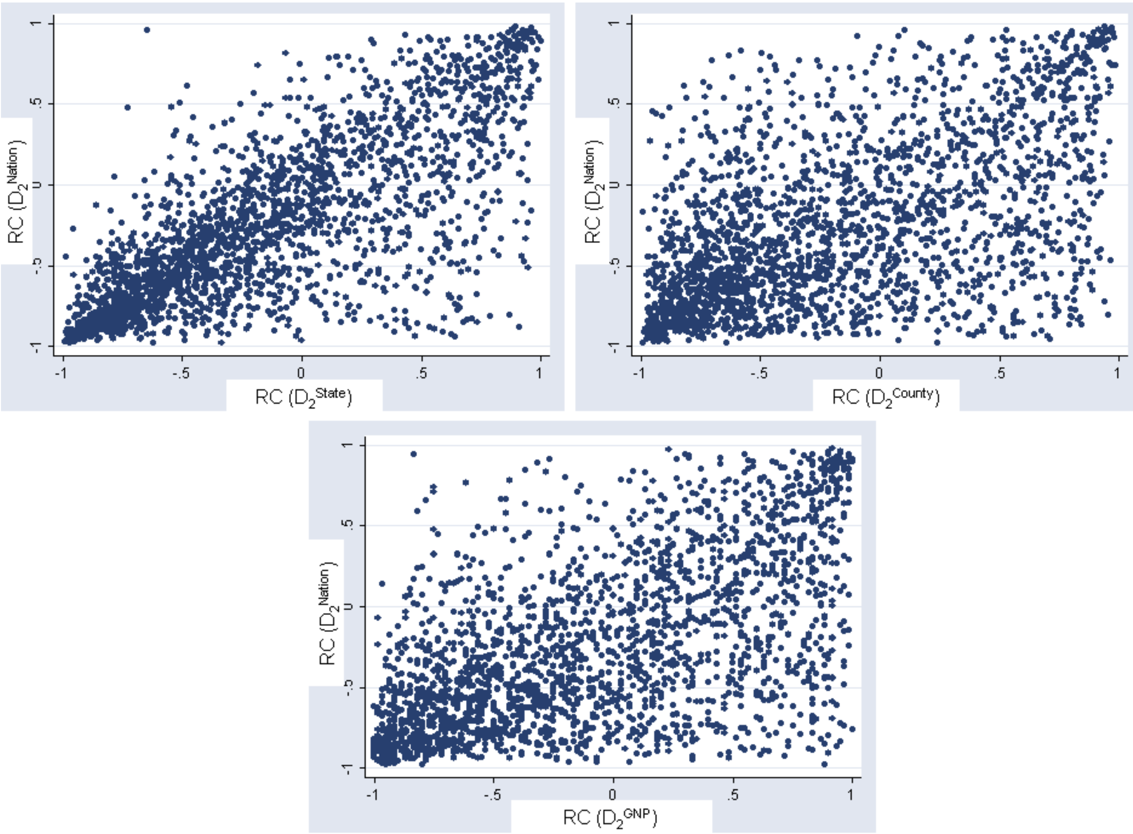

Figure 7: Relationship between RC of D_2^{Nation}, RC of D_2^{State}, RC of D_2^{County}, and of RC D_2^{GNP} over time

The bottom panel of Figure 7 illustrates the fairly large differences when the national loan portfolio and the industries' contribution to the GNP are used as benchmarks with distance measure D_2. Readers may recall that the results for GNP as a benchmark were less clear-cut (cf Table 10). This is also visible here because, unlike in the other panels, the entries above and below a virtual line for an approximate monotonic relationship between the measures seem to be very different in numbers and also biased to the bottom right-hand corner.

At any rate, we can infer that results regarding diversification versus focus in general do not only depend on the choice of a particular distance measure but also vary with the benchmark used when a distance measure is applied.

In the absence of reliable risk and return data on loan segments, it is common practice to use the HHI as a measure of statistical diversification. Our findings show that this practice can be misleading, at least at the individual bank level. The results illustrate the informational power of distance measures as measures of statistical diversification. It would therefore be interesting to test the robustness of the results of Acharya et al. (2004) when applying other measures of diversification, eg the distance measures advocated here. However, even different distance measures can sometimes indicate contradicting trends on the individual bank level. Thus, we have to be very careful when working with necessarily simplifying measures of statistical diversification. To date, no single measure seems to be unanimously superior, and hence more research is needed to discriminate between different alternatives. In order to do so, more reference to initial principles or very specific purposes for applications may be required.

5 Conclusion

We have applied a broad set of diversification measures to the national loan portfolios of German banks for the period from 1993 to 2002. The measures used in this paper are concentration measures and distance measures. Concentration measures capture the difference between a portfolio and naive diversification. Distance measures allow the use of benchmarks that reflect the industry structure of an economy. For all measures we find that the majority of banks exhibit a significant trend towards increasing diversification.

We find a strong trend towards diversification within the group of credit cooperatives and savings banks, a phenomenon indicated by highly significant trend coefficients of the panel estimations and the majority of single bank estimations. The results for state banks and big banks are mixed. However, concerning the absolute magnitude of our diversification measures, big banks show the highest level of diversification across all measures. Given the level of diversification, it is therefore not surprising that they do not show any further trends towards diversification. However, it must be mentioned that results for big banks and state banks are probably influenced by the usage of credit derivatives. Regional banks and subsidiaries of foreign banks have, on average, the highest concentration measures and are found to have the biggest distance to the benchmark loan portfolios. Moreover, by and large they reveal no tendency towards diversification. Therefore, the overall result of an increasing diversification of German banks' loan portfolios seems to be driven by the large number of credit cooperatives and savings banks.

Our findings are independent of the large number of mergers over the last decade, since in our analysis all banks that have merged during the period of observation have been treated as being merged over the whole period. A possible explanation for our results might be that bank managers have become more aware of loan portfolio diversification and that, in the same period, sophisticated techniques of managing loan portfolios have become more and more available to small banks, too. The tendency toward diversification might have been enforced by the broad debate on credit risk in the context of Basel II and some defaults and problems of German banks due to the poor quality of their loan portfolios in recent years.

The specialisation observed for subsidiaries of foreign banks is not surprising, since these banks typically accompany their national enterprises abroad. Therefore, specialisation of the national loan portfolio does not imply international specialisation. For the group of regional banks (which according to the Deutsche Bundesbank's classification mainly includes private bankers) the observed specialisation may be explained as a strategy of seeking niches in the competitive German banking market.

Although the trends described so far are revealed by virtually all measures, we find that, at an individual level, the diversification measures may differ significantly. It is notable that concentration measures and distance measures often produce contradicting results. The difference is relevant for banks, which, in the absence of reliable loan portfolio risk measurement tools, rely on diversification measures for portfolio management. We believe that distance measures are generally superior to concentration measures, since by their very definition they are well-suited to incorporate the structure of the market a bank serves as the natural reference point.

Appendix

Table 1: Lending to industries and contribution to GNP by industries

	Lending to industries		Contribution to GNP by industries	
	June 1993	Dec 2002	1993	2001
Agriculture, hunting and forestry, fishing and fish farming	2.95%	2.44%	0.77%	0.72%
Electricity, gas and water supply; mining and quarrying	2.80%	2.92%	1.74%	1.26%
Manufacture of				
chemical products, coke, refined petroleum products and nuclear fuel	1.20%	0.93%	1.48%	1.55%
rubber and plastic products	0.88%	0.62%	0.70%	0.64%
non-metallic mineral products	1.05%	0.65%	0.63%	0.46%
basic metals and fabricated metal products	1.71%	1.97%	1.83%	1.69%
machinery and equipment; manufacture of vehicles	4.34%	2.26%	3.74%	4.10%
electrical and optical equipment	3.16%	1.39%	2.19%	1.76%
wood, paper wood and paper products, furniture etc.; printing and publishing; recycling	2.57%	2.38%	1.90%	1.59%
textiles and textile products; leather and leather products	1.32%	0.57%	0.52%	0.29%
food products, beverage and tobacco	2.66%	1.82%	1.38%	1.20%
Construction	5.24%	5.04%	4.10%	2.85%
Wholesale and retail trade, repair of motorvehicles and personal household goods	15.72%	12.69%	6.29%	6.32%
Transport, storage and communication	6.48%	4.01%	3.53%	3.69%
Financial institutions (excluding MFIs)* and insurance	2.81%	3.08%	0.89%	0.75%
Services Sector (including the professions)				
Housing Enterprises	11.67%	12.87%	6.42%	7.36%
Holding companies	1.82%	3.92%	not available	
Other real estate companies	11.40%	16.17%	not available	
Hotels and restaurants	2.73%	2.20%	0.84%	0.78%
Computer and related activities, research and development	5.38%	7.92%	5.73%	7.07%
Health, veterinary and social work (enterprises and the professions)	4.45%	5.88%	3.49%	3.70%
Letting of movables	0.58%	1.91%	0.91%	1.02%
Other services	7.09%	6.04%	9.59%	9.00%

* MFI = Monetary Financial Institution. Thus, interbank lending is not included.

Table 2: Means of selected diversification measures over time

Date	HHI	G	$\hat{S}$	D_2^{Nation}	D_4^{Nation}	D_2^{State}	D_4^{State}	D_2^{County}	D_4^{County}	D_2^{GNP}	D_4^{GNP}	BG^{Nation}	$\hat{RC}^{Nation}$
Jun-93	0.1706	0.6527	-2.2477	0.4390	0.5197	0.3936	0.5003	0.3517	0.4769	0.4306	0.5116	1.4907	-0.4773
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Dec-97	0.1603	0.6446	-2.2894	0.4077	0.4905	0.3769	0.4755	0.3344	0.4503	0.4253	0.5035	1.3813	-0.5269
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Dec-02	0.1518	0.6331	-2.3252	0.4119	0.4869	0.3859	0.4719	0.3315	0.4406	0.4187	0.4973	1.3236	-0.5182

Table 3: Key statistics of HHI

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
HHI							
Mean of HHI (June 1993)	0.1706	0.1707	0.1148	0.1936	0.0851	0.2916	0.4056
Mean of HHI (Dec 2002)	0.1529	0.1468	0.1046	0.1356	0.0867	0.3015	0.4717
Panel estimation							
Panel trend	-0.000935	-0.001227	-0.000562	-0.001550	-0.000124	-0.000364	0.004451
t-statistic	-25.23***	-34.83***	-30.96***	-2.72***	-1.65	-1.00	4.17***
Bank-level regression							
Percentage of banks with trend[1]							
significantly< 0 (5% level)	50.72%	51.63%	52.50%	38.46%	50.00%	41.18%	30.30%
significantly< 0 (10% level but not 5% level)	3.25%	3.77%	2.12%	0.00%	0.00%	3.00%	3.03%
insignificantly< 0	14.65%	14.20%	17.31%	7.69%	25.00%	14.23%	3.03%
insignificantly> 0	12.26%	12.66%	10.96%	7.69%	0.00%	11.98%	24.24%
significantly> 0 (10% level but not 5% level)	1.89%	1.55%	1.73%	7.69%	0.00%	5.24%	3.03%
significantly> 0 (5% level)	17.22%	16.19%	15.38%	38.46%	25.00%	24.37%	36.36%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.2543	-0.2746	-0.2773	0.0584	-0.2662	-0.1181	0.1195
Median of RC	-0.4015	-0.4135	-0.4338	0.1639	-0.4368	-0.2368	0.2030
Percentage of banks with RC< 0	67.63%	68.96%	69.62%	38.46%	75.00%	55.97%	39.39%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 4: Key statistics of Gini coefficient (G)

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
G							
Mean of G (June 1993)	0.6527	0.6648	0.5853	0.6073	0.4503	0.7325	0.7995
Mean of G (Dec 2002)	0.6331	0.6399	0.5691	0.6074	0.4769	0.7435	0.8183
Panel estimation							
Panel trend	-0.001189	-0.001437	-0.001027	-0.000882	0.000561	0.000247	0.000859
t-statistic	-48.06***	-52.20***	-23.57***	-2.14**	1.39	1.57	2.15**
Bank-level regression							
Percentage of banks with trend[1]							
significantly <0 (5% level)	46.93%	49.21%	44.81%	38.46%	50.00%	35.19%	33.33%
significantly <0 (10% level but not 5% level)	3.56%	3.37%	4.04%	0.00%	0.00%	3.00%	9.09%
insignificantly <0	15.55%	16.56%	14.23%	0.00%	0.00%	17.97%	3.03%
insignificantly >0	12.40%	12.99%	11.54%	23.08%	0.00%	10.48%	12.12%
significantly >0 (10% level but not 5% level)	2.75%	2.69%	3.08%	0.00%	0.00%	1.50%	6.06%
significantly >0 (5% level)	18.8%	15.18%	22.31%	38.46%	50.00%	31.86%	36.36%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.2199	-0.2684	-0.1715	0.0316	0.0658	-0.0393	0.0667
Median of RC	-0.3549	-0.3842	-0.3023	0.2481	0.0421	-0.1203	0.1970
Percentage of banks with RC <0	65.33%	68.75%	61.54%	61.54%	50.00%	53.73%	45.45%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 5: Key statistics of the negative of Shannon entropy ($\hat{S}$)

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
Shannon Entropy ($\hat{S}$)							
Mean of $\hat{S}$ (Dec 1993)	-2.25	-2.22	-2.50	-2.31	-2.77	-1.83	-1.46
Mean of $\hat{S}$ (Dec 2002)	-2.33	-2.32	-2.55	-2.43	-2.74	-1.79	-1.31
Panel estimation							
Panel trend	-0.004242	-0.005341	-0.002942	-0.005061	0.000650	-0.000298	0.008795
t-statistic	-41.78***	-52.94***	-28.61***	-2.92***	1.05	-0.32	3.38***
Bank-level regression							
Percentage of banks with trend[1]							
significantly<0 (5% level)	49.95%	52.17%	48.46%	38.46%	50.00%	37.44%	36.36%
significantly<0 (10% level but not 5% level)	3.61%	3.84%	3.46%	0.00%	0.00%	2.25%	3.03%
insignificantly<0	14.97%	15.15%	15.58%	0.00%	0.00%	17.97%	6.06%
insignificantly>0	12.35%	12.93%	11.35%	23.08%	0.00%	9.73%	12.12%
significantly>0 (10% level but not 5% level)	1.49%	1.41%	1.35%	0.00%	0.00%	2.25%	6.06%
significantly>0 (5% level)	17.63%	14.5%	19.81%	38.46%	50.00%	30.36%	36.36%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.2528	-0.2962	-0.2213	0.0816	0.0015	-0.0832	0.0662
Median of RC	-0.3985	-0.4346	-0.3729	0.3714	-0.0248	-0.1936	0.2376
Percentage of banks with RC<0	67.94%	70.91%	65.96%	38.46%	50.00%	55.97%	49.00%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 6: Key statistics of D_2^{Nation}

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
D_2^{Nation}							
Mean of D_2^{Nation} (June 1993)	0.4389	0.4631	0.3292	0.3576	0.2117	0.5377	0.6319
Mean of D_2^{Nation} (Dec 2002)	0.4128	0.4350	0.2945	0.3194	0.2164	0.5452	0.7249
Panel estimation							
Panel trend	-0.001961	-0.002224	-0.002235	-0.001186	0.001069	0.000347	0.005063
t-statistic	-59.93***	-60.28***	-41.07***	-2.11**	2.42**	1.58	10.63***
Bank-level regression							
Percentage of banks with trend[1]							
significantly< 0 (5% level)	48.33%	49.88%	52.88%	23.08%	25.00%	27.70%	6.06%
significantly< 0 (10% level but not 5% level)	3.88%	3.97%	4.04%	0.00%	0.00%	2.25%	3.03%
insignificantly< 0	18.08%	18.38%	17.50%	7.69%	0.00%	18.72%	27.27%
insignificantly> 0	13.62%	13.80%	12.31%	30.77%	50.00%	14.98%	12.12%
significantly> 0 (10% level but not 5% level)	1.76%	1.68%	1.92%	0.00%	0.00%	2.25%	3.03%
significantly> 0 (5% level)	14.34%	12.28%	11.35%	38.46%	25.00%	34.11%	48.48%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.2520	-0.2792	-0.3107	0.1215	0.0733	0.0555	0.3075
Median of RC	-0.3579	-0.3820	-0.4083	0.3053	0.2158	0.0489	0.4662
Percentage of banks with RC< 0	70.47%	72.66%	74.23%	30.77%	25.00%	48.51%	36.36%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 7: Key statistics of D_4^{Nation}

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
D_4^{Nation}							
Mean of D_4^{Nation} (June 1993)	0.5196	0.5434	0.4091	0.3938	0.2392	0.6232	0.7420
Mean of D_4^{Nation} (Dec 2002)	0.4869	0.5081	0.3688	0.3764	0.2490	0.6283	0.7761
Panel estimation							
Panel trend	-0.001969	-0.002206	-0.002219	-0.000126	0.000705	0.000438	0.001633
t-statistic	-62.17***	-62.70***	-38.97***	-0.21	2.16**	2.05**	3.45***
Bank-level regression							
Percentage of banks with trend[1]							
significantly< 0 (5% level)	48.69%	50.39%	51.92%	23.08%	0.00%	28.12%	30.30%
significantly< 0 (10% level but not 5% level)	4.87%	5.32%	3.85%	7.69%	0.00%	3.74%	6.06%
insignificantly< 0	17.31%	17.84%	17.88%	0.00%	25.00%	14.23%	15.15%
insignificantly> 0	13.48%	13.87%	11.54%	0.00%	50.00%	16.47%	12.12%
significantly> 0 (10% level but not 5% level)	1.44%	1.41%	1.54%	7.69%	0.00%	1.50%	0.00%
significantly> 0 (5% level)	14.20%	11.18%	13.27%	61.54%	25.00%	35.94%	36.36%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.2618	-0.2983	-0.2966	0.2502	0.2767	0.0633	0.0775
Median of RC	-0.3759	-0.4030	-0.4233	0.5489	0.2233	0.0722	-0.1233
Percentage of banks with RC< 0	70.56%	73.13%	73.65%	30.77%	25.00%	45.52%	51.51%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 8: Key statistics of D_2^{State}

	All	CC	SB	StB	RB
Number of banks	2218	1485	520	13	134
D_2^{State}					
Mean of D_2^{State} (June 1993)	0.3936	0.4156	0.2776	0.3490	0.5233
Mean of D_2^{State} (Dec 2002)	0.3859	0.4072	0.2631	0.2658	0.5421
Panel estimation					
Panel trend	-0.001100	-0.001377	-0.001058	-0.003201	0.000723
t-statistic	-32.09***	-35.00***	-18.56***	-5.65***	3.29***
Bank-level regression					
Percentage of banks with trend[1]					
significantly< 0 (5% level)	40.40%	41.74%	41.92%	46.15%	26.96%
significantly< 0 (10% level but not 5% level)	3.61%	3.97%	3.46%	0.00%	1.50%
insignificantly< 0	18.21%	17.97%	19.04%	15.38%	16.47%
insignificantly> 0	14.07%	14.34%	12.31%	15.38%	17.97%
significantly> 0 (10% level but not 5% level)	2.39%	2.63%	1.92%	0.00%	1.50%
significantly> 0 (5% level)	21.33%	19.35%	21.35%	23.08%	35.60%
Spearman rank correlation coefficient (RC)					
Mean of RC	-0.1377	-0.1616	-0.1549	-0.2223	0.0705
Median of RC	-0.2241	-0.2556	-0.2195	-0.2556	0.0902
Percentage of banks with RC< 0	62.26%	64.38%	58.08%	69.23%	43.28%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, RB = Regional Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 9: Key statistics of D_2^{County}

	All	CC	SB	RB
Number of banks	2218	1485	520	134
D_2^{County}				
Mean of D_2^{County} (June 1993)	0.3517	0.3701	0.2380	0.5013
Mean of D_2^{County} (Dec 2002)	0.3315	0.3438	0.2216	0.5200
Panel estimation				
Panel trend	-0.001370	-0.0018272	-0.000904	0.000752
t-statistic	-37.33***	-42.53***	-15.27***	3.32***
Bank-level regression				
Percentage of banks with trend[1]				
significantly<0 (5% level)	42.56	45.37	40.58	28.45
significantly<0 (10% level but not 5% level)	3.65	3.77	3.85	2.25
insignificantly<0	15.60	14.94	17.31	14.98
insignificantly>0	14.16	14.2	13.27	15.72
significantly>0 (10% level but not 5% level)	1.80	1.88	1.73	1.50
significantly>0 (5% level)	22.23	19.82	23.27	37.10
Spearman rank correlation coefficient (RC)				
Mean of RC	-0.1463	-0.1886	-0.1211	-0.1467
Median of RC	-0.2383	-0.3083	-0.2060	-0.2383
Percentage of banks with RC<0	61.27%	63.57%	61.54%	44.03%

CC = Credit Cooperatives, SB = Savings Banks, RB = Regional Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 10: Key statistics of D_2^{GNP}

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
D_2^{GNP}							
Mean of D_2^{GNP} (Dec 1993)	0.4306	0.4487	0.3371	0.4210	0.2424	0.5185	0.6374
Mean of D_2^{GNP} (Dec 2001)	0.4187	0.4311	0.3369	0.4429	0.2552	0.5103	0.6706
Panel estimation							
Panel trend	-0.000690	-0.001020	-0.000200	0.000630	0.000975	0.000129	0.001925
t-statistic	-13.47***	-17.46***	-2.60**	0.96	1.74*	0.35	2.13**
Bank-level regression							
Percentage of banks with trend[1]							
significantly<0 (5% level)	26.33%	28.81%	20.19%	15.38%	25.00%	23.96%	21.21%
significantly<0 (10% level but not 5% level)	4.55%	4.58%	4.23%	0.00%	0.00%	7.49%	3.03%
insignificantly<0	24.93%	25.31%	26.54%	23.08%	0.00%	19.47%	15.15%
insignificantly>0	21.87%	21.74%	22.5%	23.08%	0.00%	22.46%	24.24%
significantly>0 (10% level but not 5% level)	3.20%	3.03%	3.08%	7.69%	25.00%	4.49%	0.00%
significantly>0 (5% level)	19.12%	16.52%	23.46%	30.77%	50.00%	22.13%	36.36%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.0781	-0.1235	0.0002	0.2500	0.3208	-0.0286	0.1742
Median of RC	-0.1333	-0.1833	-0.0050	0.4667	0.5917	-0.0333	0.3667
Percentage of banks with RC<0	55.46%	58.05%	51.35%	38.46%	0.25%	52.99%	39.39%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

This analysis is based on annual data, as semiannual data of the industries' contribution to the GNP is not available.

Table 11: Key statistics of BG^{Nation}

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
BG^{Nation}							
Mean of BG^{Nation} (Dec 1993)	1.49	1.52	1.34	1.39	1.03	1.67	1.83
Mean of BG^{Nation} (Dec 2002)	1.32	1.34	1.19	1.27	1.00	1.55	1.71
Panel estimation							
Panel trend	-0.007372	-0.007964	-0.006537	-0.00651	-0.002314	-0.005065	-0.004235
t-statistic	-136.43***	-130.52***	-68.67***	-6.99***	-2.71***	-14.49***	-4.78***
Bank-level regression							
Percentage of banks with trend[1]							
significantly< 0 (5% level)	73.04%	76.14%	70.77%	53.85%	50.00%	59.15%	54.55%
significantly< 0 (10% level but not 5% level)	2.98%	2.89%	3.27%	7.69%	0.00%	3.74%	0.00%
insignificantly< 0	10.64%	10.23%	11.35%	7.69%	25.00%	9.73%	18.18%
insignificantly> 0	6.54%	6.29%	6.73%	7.69%	0.00%	7.90%	6.06%
significantly> 0 (10% level but not 5% level)	1.35%	1.08%	1.73%	0.00%	0.00%	0.75%	3.03%
significantly> 0 (5% level)	5.46%	3.37%	6.15%	23.08%	25.00%	18.72%	18.18%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.5421	-0.5826	-0.1714	-0.3287	-0.3248	-0.3354	-0.2906
Median of RC	-0.7135	-0.7323	-0.3023	-0.5759	-0.4714	-0.5744	-0.6045
Percentage of banks with RC< 0	86.29%	89.02%	84.81%	69.23%	75.00%	71.64	72.73%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 12: Key statistics of the negative of RC ($\hat{RC}^{Nation}$)

	All	CC	SB	StB	BB	RB	SFB
Number of banks	2218	1485	520	13	4	134	33
$\hat{RC}^{Nation}$							
Mean of $\hat{RC}^{Nation}$ (Dec 1993)	-0.4773	-0.4456	-0.5988	-0.7400	-0.6872	-0.3740	-0.2245
Mean of $\hat{RC}^{Nation}$ (Dec 2002)	-0.5182	-0.4857	-0.6541	-0.7383	-0.7085	-0.4206	-0.0455
Panel estimation							
Panel trend	-0.003121	-0.003702	-0.002609	0.002251	-0.000624	-0.001964	0.008627
t-statistic	-45.91***	-45.00***	-23.38***	3.30***	-0.53	-5.13***	9.11***
Bank level regression							
Percentage of banks with trend[1]							
significantly< 0 (5% level)	39.00%	41.06%	36.73%	7.69%	25.00%	34.44%	15.15%
significantly< 0 (10% level but not 5% level)	4.73%	4.78%	4.42%	0.00%	0.00%	7.49%	0.00%
insignificantly< 0	22.41%	22.08%	26.35%	23.08%	25.00%	15.72%	9.09%
insignificantly> 0	16.01%	15.72%	16.92%	38.46%	50.00%	10.89%	15.15%
significantly> 0 (10% level but not 5% level)	2.03%	2.22%	1.35%	0.00%	0.00%	3.00%	3.03%
significantly> 0(5% level)	15.83%	14.14%	14.23%	30.77%	0.00%	28.45%	57.58%
Spearman rank correlation coefficient (RC)							
Mean of RC	-0.1725	-0.2019	0.5167	0.1551	-0.1485	-0.0465	0.2971
Median of RC	-0.2493	-0.2917	0.6887	0.1865	-0.0910	-0.1275	0.4752
Percentage of banks with RC< 0	65.24%	66.94%	67.12%	30.77%	50.00%	54.48%	24.24%

CC = Credit Cooperatives, SB = Savings Banks, StB = State Banks, BB = Big Banks, RB = Regional Banks, SFB = Subsidiaries of Foreign Banks

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent and 10 percent significance level (two-sided t-test).

Table 13: Comparison of diversification measures (results for all banks)

	HHI	G	$\hat{S}$	D_2^{Nation}	D_4^{Nation}
Number of banks	2218	2218	2218	2218	2218
Mean of Diversification Measure (DM)					
Mean of DM (June 1993)	0.1706	0.6527	-2.25	0.4389	0.5196
Mean of DM (Dec 2002)	0.1529	0.6331	-2.33	0.4128	0.4869
Panel estimation					
Panel trend	-0.000935	-0.001189	-0.004242	-0.001961	-0.001969
t-statistic	-25.23***	-48.06***	-41.78***	-59.93***	-62.17***
Bank level regression					
Percentage of banks with trend[1]					
significantly< 0	50.72%	46.93%	49.95%	48.33%	48.69%
insignificantly	32.05%	34.26%	32.42%	37.34%	37.10%
significantly> 0	17.22%	18.80%	17.63%	14.34%	14.20%
Spearman rank correlation coefficient (RC)					
Mean of RC	-0.2543	-0.2199	-0.2528	-0.2520	-0.2618
Median of RC	-0.4015	-0.3549	-0.3985	-0.3579	-0.3759
Percentage of banks with RC< 0	67.63%	65.33%	67.94%	70.47%	70.56%

	D_2^{State}	D_2^{County}	D_2^{GNP}	BG^{Nation}	$\hat{RC}^{Nation}$
Number of banks	2218	2218	2218	2218	2218
Mean of Diversification Measure (DM)					
Mean of DM (June 1993)	0.3936	0.3517	0.4306	1.49	-0.4773
Mean of DM (Dec 2002)	0.3859	0.3315	0.4187	1.32	-0.5182
Panel estimation					
Panel trend	-0.001100	-0.001370	-0.000690	-0.007372	-0.003121
t-statistic	-32.09***	-37.33***	-13.47***	-136.43***	-45.91***
Bank level regression					
Percentage of banks with trend[1]					
significantly< 0	40.40%	42.56	26.33%	73.04%	39.00%
insignificantly	38.28%	35.21%	54.52%	21.51%	45.18%
significantly> 0	21.33%	22.23%	19.12%	5.46%	15.83%
Spearman rank correlation coefficient (RC)					
Mean of RC	-0.1377	-0.1463	-0.0781	-0.5421	-0.1725
Median of RC	-0.2241	-0.2383	-0.1333	-0.7135	-0.2493
Percentage of banks with RC< 0	62.26%	61.27%	55.46%	86.29%	65.24%

***,**,* indicate statistical significance at the 1, 5, 10 percent level respectively.

[1] Trend tested at 5 percent (two-sided t-test).

Table 14: Correlation matrix of diversification measures

	HHI	G	$\hat{S}$	D_2^{Nation}	D_4^{Nation}	D_2^{State}	D_4^{State}	D_2^{County}	D_4^{County}	D_2^{GNP}	D_4^{GNP}	BG^{Nation}	$\hat{RC}^{Nation}$
HHI	1												
G	0.7941	1											
$\hat{S}$	0.9570	0.9292	1										
D_2^{Nation}	0.7772	0.8771	0.8757	1									
D_4^{Nation}	0.7346	0.8853	0.8638	0.9431	1								
D_2^{State}	0.7460	0.8261	0.8367	0.9356	0.8983	1							
D_4^{State}	0.7185	0.8634	0.8449	0.9194	0.9779	0.9343	1						
D_2^{County}	0.7146	0.7758	0.7927	0.8227	0.8025	0.8456	0.8146	1					
D_4^{County}	0.6996	0.8543	0.8278	0.8778	0.9382	0.8719	0.9455	0.9050	1				
D_2^{GNP}	0.7930	0.8837	0.8828	0.9317	0.8907	0.8653	0.8593	0.7586	0.8208	1			
D_4^{GNP}	0.7548	0.8939	0.8779	0.9089	0.9714	0.8649	0.9458	0.7761	0.9087	0.9230	1		
BG^{Nation}	0.7889	0.9943	0.9238	0.8756	0.8832	0.8222	0.8608	0.7717	0.8517	0.8769	0.8873	1	
$\hat{RC}^{Nation}$	0.3466	0.4275	0.4161	0.6918	0.5953	0.6422	0.5938	0.5110	0.5482	0.5976	0.5231	0.4299	1

References

Acharya, V., Hasan, I., Saunders, A., 2004. Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios. Tech. rep., London Business School, London, forthcoming in: Journal of Business.

Berger, P. G., Ofek, E., 1995. Diversification's Effect on Firm Value. Journal of Financial Economics 37, 39–65.

Dell'Ariccia, G., 2001. Asymmetric Information and the Structure of the Banking Industry. European Economic Review 45, 1957–1980.

Dell'Ariccia, G., Friedman, E., Marquez, R., 1999. Adverse Selection as a Barrier to Entry in the Banking Industry. RAND Journal of Economics 30, 515–534.

Deutsche Apotheker- und Ärztebank, 2004. Corporate Profile. http://www.apobank.de/70partner/20ir/20ir_en/index.html (October 7, 2004).

Diamond, D., 1984. Financial Intermediation and Delegated Monitoring. Review of Economic Studies 51, 393–414.

Elyasiani, E., Deng, S., 2004. Diversification Effects on the Performance of Financial Services Firms. Tech. rep., Temple University, Philadelphia.

Frenken, K., 2004. Entropy Statistics and Information Theory. In: Foster, J., Hölzl, W. (Eds.), The Elgar Companion to Neo-Schumpeterian Economics. Edward Elgar, Cheltenham and Northampton, p. forthcoming.

Gehrig, T., 1998. Screening, Cross-Border Banking, and the Allocation of Credit. Research in Economics 52, 387–407.

HSH Nordbank, 2003. Schifffahrt. http://www.hsh-nordbank.de/home/kunden/ schifffahrt/ schifffahrt.jsp (December 8, 2003).

Lang, L., Stulz, R., 1994. Tobin's q, Corporate Diversification, and Firm Performance. Journal of Political Economy 102, 1248–1280.

Markowitz, H. M., 1952. Portfolio Selection. Journal of Finance 7, 77–91.

Marquez, R., 2002. Competition, Adverse Selection, and Information Dispersion in the Banking Industry. The Review of Financial Studies 15, 901–926.

Pfingsten, A., Rudolph, K., 2002. German Banks' Loan Portfolio Composition: Market-Orientation Vs. Specialisation. Tech. Rep. 02-02, Institut für Kreditwesen, Münster.

Shaffer, S., 1998. The Winner's Curse in Banking. Journal of Financial Intermediation 7, 359–392.

Shannon, C. E., 1948. A Mathematical Theory of Communication. Bell System Technical Journal 27, 623–656.

Stadtsparkasse Köln, 2003. Kurzprofil. http://www.sk-koeln.de/ueber_uns/unter nehmen/kurzprofil (December 8, 2003).

Stomper, A., 2004. A Theory of Banks' Industry Expertise, Market Power, and Credit Risk. Tech. rep., University of Vienna.

Theil, H., 1972. Statistical Decomposition Analysis. North-Holland, Amsterdam.

Winton, A., 1999. Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending. Tech. rep., Finance Department, University of Minnesota, Minneapolis.

Zar, J., 1972. Significance Testing of the Spearman Rank Correlation Coefficient. Journal of the American Statistical Association 67, 578–580.

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