Does diversification improve the performance of German banks? Evidence from individual bank loan portfolios

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Abstract: Should banks be diversified or focused? Does diversification indeed lead to increased performance and therefore greater safety on the part of banks as traditional portfolio and banking theory would suggest? This paper investigates the link between banks' profitability and their portfolio diversification across different industries, broader economic sectors and geographical regions. To explore this issue, we use a unique data set of the individual bank loan portfolios of 983 German banks for the period from 1996 to 2002. The overall evidence we provide shows that there are no large performance benefits associated with diversification since each type of diversification tends to reduce the banks' returns. Additionally, we find that banks do not use diversification to operate at a constant level of risk-return efficiency, which implies that banks are not risk-return efficient. Moreover, we find that the impact of diversification strongly depends on the risk level. However, only for moderate risk levels and in the case of industrial diversification does diversification significantly improve the banks' returns.

Keywords: focus, diversification, monitoring, bank returns, bank risk

JEL Classification: G21, G28, G32

Should banks diversify their portfolios across different industries or even broader economic sectors and geographical regions, or should they focus on a few related fields? Does diversification indeed lead to increased performance and therefore greater safety on the part of banks as traditional portfolio and banking theory would suggest? In this paper, we try to shed some light on these questions by empirically investigating the situation of German banks.

The focus vs. diversification issue is important in the context of banks as they are affected by several regulations that create incentives either to diversify or to focus their portfolios, ie the imposition of capital requirements tied to the risk of the banks' assets or asset investment restrictions. Hence, policymakers should be especially interested to see whether or not banks benefit from diversification.

Experts on financial institutions generally argue that banks – which are typically highly leveraged – should diversify to reduce their chances of suffering costly financial distress. In addition, several models of intermediation theory suggest that diversification makes it cheaper for institutions to achieve credibility in their role as screeners or monitors of borrowers (see eg Diamond (1984) and Boyd and Prescott (1986)). However, corporate finance theory suggests that firms should focus so as to obtain the greatest possible benefit from management's expertise and to reduce agency problems, leaving investors to diversify on their own (see eg Jensen (1986), Berger and Ofek (1996), or Denis et al. (1997)). Since real world cases can be found to support either view, the question arises as to which circumstances call for one strategy or the other to be applied.

Winton (1999) presents a theoretical framework to investigate the above issue. He argues that the benefit from diversification should be greatest when banks' loans have medium levels of downside risk, ie the banks' probabilities of default are moderate. By way of example, let us assume that the banks' ability to monitor loans is constant across different sectors. Such pure diversification increases the central tendency of the banks' return distribution, which generally reduces their chance of failure. However, if the loans have a low exposure to sector downturns, specialised banks have a low probability of failure anyway and the benefits of diversification are minor. Moreover, diversification can actually increase the banks' default probabilities if their loans have sufficiently high downside risk, as then a downturn in one sector is enough to make a bank fail, and a diversified bank is exposed to more sectors than a specialised one. Furthermore, diversification involves moving into economic sectors or geographical regions that differ from the banks' home base, therefore implying a lower monitoring effectiveness in these areas, at least initially. Some papers also suggest that a bank entering a sector with several established banks faces increased adverse selection in its pool of borrowers (see eg Gehrig (1998) and Shaffer (1998)). Thus, overall, diversification is more likely to be unattractive, particularly when the bank's home sector loans have either low or high downside risk.

Although the issue of focus versus diversification has a long history in corporate finance literature, it has not been addressed thoroughly in an empirical context for financial institutions and banks. The existing literature focuses mainly on geographical diversification and US data, and also provides mixed results. Hughes et al. (1996) and Berger and DeYoung (2001), for example, use more aggregated measures of bank diversification to examine geographical diversification for US banks, while Caprio and Wilson (1997) consider cross-country evidence of a relationship between on-balance-sheet concentration and bank insolvency. In addition, Dahl and Logan (2003) and Buch at al (2004) suggest that international diversification offers benefits while, according to Klein and Saidenberg (1998) and Morgan and Samolyk (2003), the geographical diversification of US banks is not necessarily associated with an increase in profitability. DeLong (2001) finds that geographically-focused bank mergers in the US result in superior performance, while Stiroh and Rumble (2003) and Stiroh (2004) show that a shift towards non-interest income does not offer large diversification benefits.

Therefore, there is clearly a need for more empirical evidence on the effects of diversification on banks' performance based on individual bank-level data from European countries. The leading study in this respect is probably the one by Acharya et al (2004), which examines the effect of sectoral and industrial loan diversification on the performance of Italian banks. The results of this study are consistent with Winton's theory of a deterioration in the effectiveness of banks' monitoring activities at high levels of risk. In addition, Acharya et al find that both industrial and sectoral loan diversification reduces banks' returns while endogenously producing riskier loans for high risk banks in their sample, so that a diversification of banks' assets is not guaranteed to result in a superior return performance and/or greater safety on the part of Italian banks.

The question now arises as to whether the Italian results are valid for other European countries, too. Our study attempts to fill this gap by studying the situation of the German banking industry. Based on a unique data set of Deutsche Bundesbank involving data on individual bank loan portfolios disaggregated at a very fine and micro level for the period from 1996 to 2002, we assess the impact of sectoral, industrial and geographical diversification on banks' profitability by looking at three major aspects. Firstly, we are interested in the average effect on banks' returns of banks' portfolio diversification across industries, sectors and regions. Secondly, we try to gain an insight into whether diversification is used as an instrument to induce shifts in banks' risk-return efficiency. Thirdly, we test how monitoring effectiveness on the part of low, medium and high-risk banks impacts on the relationship between banks' portfolio diversification and banks' returns. Here – in contrast to previous studies – we apply a Value at Risk approach to measure banks' risk and derive unexpected losses for each individual bank as, in our opinion, unexpected losses are better suited to capturing banks' riskiness than the more common proxy of expected losses.

Our main findings are as follows. Firstly, we find that portfolio diversification across different sectors, industries and regions tends to have a detrimental effect on banks' profitability rather than to lead to improved returns. The highest benefits are associated with geographical focus, whereas benefits from industrial focus appear to be only moderate. Secondly, there is evidence that, instead of operating at a constant risk-return efficiency level, banks use diversification in order to change their risk-return profile. As banks with highly risky credit portfolios are not systematically more profitable than banks with low risk portfolios, it seems that, overall, banks are not risk-return efficient. Thirdly, the profitability benefits associated with diversification are strongly dependent on the banks' risk level. In addition, the type of focus plays a crucial role. While the effect of sectoral focus on return declines monotonously with increasing risk, there is mixed evidence to suggest either a monotonously decreasing or a U-shaped relationship for regional focus as well as a rather distinct indication of a U-shape with respect to industrial focus. Therefore, our results at least partly confirm Winton's theory that diversification benefits are highest for moderate risk levels. Finally, our data shows that diversification significantly improves banks' profitability only in the case of moderate risk levels and industrial diversification. Hence, from a policy point of view, our findings suggest that bank regulations which may force banks to increase the level of industrial, sectoral or geographical diversification should be evaluated carefully.

The remainder of this paper is structured as follows: in Section 2 we describe our data and in Section 3 we present the empirical results before reaching a conclusion in Section 4.

1 Data

1.1 Data sources

The main data source for our analysis originates in the database of the credit register for loans of 1.5 million euro (formerly 3 million Deutsche Mark) or more at the Deutsche Bundesbank. German banks have to provide quarterly reports on all claims exceeding the threshold of 1.5 million euro. Bank claims are defined fairly broadly, covering details of types of claims [1], types of borrowers by industries and sectors, international claims by individual foreign countries and regions [2]. In addition to balance sheet bank activities, claims also incorporate information on off-balance-sheet activities [3]. This credit register data set on the exposures of individual banks is combined with financial data from the second Bundesbank data source, namely BAKIS (BAKred [4] Information System). BAKIS incorporates information derived from the bank balance sheets and supervisory reports of all German banks. Since the data on bank balance sheets is mostly of annual frequency, we used annual data for the period from 1996 to 2002. Both the credit register and BAKIS represent unique data sources never before exploited to investigate the relationship between the diversification and performance of German banks.

Our data sample not only includes banks but also their subsidiaries and amounts to 3760 individual entities. However, as small banks usually grant only very few large loans, the loans reported to the credit register sometimes cover only a rather small fraction of the total credit volume outstanding according to the banks' balance sheets. This implies that it might be misleading to analyse the diversification structure of these small banks based on the information from the credit register, as the breakdown of the total portfolio could differ significantly from that of one of the large loans. Therefore, our study focuses only on those banks where the ratio of the reported loans to the total amount of loans according to the balance sheet exceeds 50%.[5] We also exclude affiliates of German banks abroad, mortgage banks and special purpose banks from our analysis. This reduces the number of eligible banks to 983.

1.2 Diversification measures

The data from the credit register provides considerable details about the industrial, broader sectoral and geographical breakdown of German bank claims. On an individual bank basis, the following information on the portfolio breakdown is available.

1. The disaggregated industrial sector breakdown includes (1) agricultural, forestry and fishing products, (2) energy products, (3) iron and non–iron material and ore, (4) ores and products based on non-metallic minerals, (5) chemicals, (6) metal products, apart from machinery and means of conveyance, (7) agricultural and industrial machinery, (8) office, EDP machinery and others, (9) electrical material, (10) transport, (11) food products, beverages and tobacco-based products, (12) textiles, leather, shoes and clothing products, (13) paper, publishing and printing products, (14) rubber and plastic products, (15) other industrial products, (16) construction, (17) services trade and similar, (18) hotel and public firms' products, (19) internal transport services, (20) sea and air transport, (21) transport-related services, (22) communication services and (23) other sales-related services. It should be noted that, in aggregate, these exposures (collectively defined in the data as non–financial and household exposures) constitute the dominant part of most banks' portfolios.

2. The broader sectoral breakdown includes (1) financial institutions and banks, (2) non-financial corporations, (3) households, (4) the public sector and (5) other counter-parties.

3. The geographical breakdown includes (1) Germany, six regions according to the IMF classification: (2) industrial countries, (3) Asia, (4) Africa, (5) the Middle East, (6) the Western hemisphere, (7) emerging Europe, and (8) others.[6]

To measure diversification (or respectively focus), we use the Hirschmann-Herfindahl Index. It is calculated as the sum of the squares of exposures as a fraction of total exposure under a given classification and is represented by the following formula

$$H = \sum_{i=1}^{n} \left(\frac{X_i}{X} \right)^2 ,$$

where n is the number of groups and X_i measures exposure to industry, sector or region i. The smallest and largest possible values for the Herfindahl Index are given by 1/n = H = 1. Hence, lending is more concentrated the closer the Herfindahl Index is to one and is perfectly diversified if H equals 1/n.

In our case, we constructed three different kinds of Herfindahl Indices: one industrial (and household) sector Herfindahl Index (HI), one broad asset type (or sectoral) Herfindahl Index (HT) and one regional (or geographical) Herfindahl Index (HR).

1.3 Balance-sheet variables

We employed the following (annual) variables obtained from the balance sheet data for the banks in our sample in the period from 1996 to 2002.

Return measures

"Operating Profit / Assets" serves as the principal measure of return. All of the results displayed are based on this measure. However, we also performed robustness checks using other measures, such as "Operating Profit / Equity". We found that, overall, the results are robust with respect to the return measure employed .

Risk measures

The simplest method of measuring risk would be to look at a balance sheet ratio such as "Doubtful and Non-Performing Loans / Total Loans", which could be interpreted as capturing the level of expected losses. However, we consider that risk is more accurately represented by unexpected losses, which is the reason why we focused on a Value at Risk (VaR) measure.

Value at Risk is the most widespread method of determining a bank's loan portfolio risk. The Value at Risk of bank i in period t, VaR_{it}, is the maximum loss over a target horizon such that with a pre-specified probability p the realised loss will be smaller. The unexpected loss can be determined from the distribution of the portfolio losses at the target horizon as the difference between the mean of the portfolio value and the value at the p-percentile. In our calculations, p is 99.9%. This is based on the observation that banks typically work with percentiles higher than 99.5%. Since the following estimations are fixed-effects panel models where the levels of the variables are differenced out, the exact level of p will not affect our results. The values for the VaR have to be taken from the distribution of the portfolio value. We estimated the portfolio's value distribution using a simplified version of CreditMetrics.[7] The basic assumptions of CreditMetrics are that the returns of a creditor's assets are normally distributed and that a default occurs when the returns of a creditor fall below a certain threshold. The default threshold is determined from the probability of default (PD).

As our data set does not comprise rating information for individual loans, we used the average insolvency rate of the industry associated with the loan to proxy the default probability for a loan and to calculate its return threshold. We further assumed that the correlation between the returns of creditors can be approximated by the correlation between the industries' insolvency rates.[8] Using equal probabilities of default for each bank, however, may bias the results since, for example, focused banks may have more effective monitoring systems and therefore grant loans with lower PDs than diversified banks. Therefore, as no information on the risk of loans at an industry and individual bank level is available for German banks, we had to adjust the (observed) industry insolvency ratios by bank-specific factors. To do so, we defined the industry insolvency ratio multiplied by a scale parameter which is related to a bank's loan loss provisions as a bank-specific PD.[9] As a result, banks with high loan loss provisions (divided by the amount of total loans) are assigned higher PDs for loans to a specific industry than banks with lower provisions. It should be noted that bank loans to all industries are adjusted using the same scale factor because, unfortunately, the data does not allow for a more precise adjustment.

The current value of a bank's overall portfolio at the beginning of a period is given by the sum of the bank's individual exposures to each industry, which we took from the credit register as described above. We then simulated returns using a multivariate normal distribution with mean zero and the correlation matrix from the insolvency data.[10] Defaults occur when the simulated returns fall below the threshold given by the critical values derived from the industries' annual insolvency rates. The simulated value of the portfolio at the end of the period is equal to the value at the beginning of the period less 45% of the loans defaulting in the simulations, which means that we assume a loss given default (LGD) of 45% in line with the Basel II proposal (see Basel Committee on Banking Supervision (2004)).[11] We then repeated this exercise 50,000 times in order to obtain the simulated loss distribution of a single bank in a specific period. Using the loss distribution, we calculated the unexpected loss as the difference between the 99.9% quantile and the mean. Finally, the variable $Risk_{it}$ was calculated as

$$Risk_{it} = Unexpected\ Loss_{it} / Assets_{it}$$

In order to obtain a panel of observations for $Risk_{it}$, we repeated the simulations for each bank and each period of our sample.

Control variables

Banks' returns might not only be dependent on the respective banks' diversification and risk but are also likely to differ as a result of other criteria. In the estimation, we controlled for unobservable individual and time effects by using dummy variables. The bank-specific dummies check for all effects which do not change for individual banks over time. These effects include eg characteristics which differ between banking groups, such as regional constraints on the part of German savings or cooperative banks or different ownership structures. In addition to these fixed effects, we also monitored characteristics which may change over time.

$$Personal_{it} = Personal\ Costs_{it} / Assets_{it}$$

$$Size_{it} = Ln(Assets_{it}).$$

In line with Acharya et al (2004) we used the variable $Personal_{it}$ to proxy cost efficiency. The rationale is that banks with different cost efficiency levels may transform the benefits from diversification in a different way. The variable $Size_{it}$ captures the possible effects of scale on return.

The banks' equity ratio is a common control variable in many empirical studies.

$$Equity_{it} = Equity\ Capital_{it} \ / \ Assets_{it}$$

According to the capital buffer theory, equity ratios above the regulatory minimum requirement of 8% serve as a buffer to shield banks from insolvencies due to unexpected losses. The amount of the buffer depends on the banks' risks and risk preferences. Correspondingly, $Equity_{it}$ depends on $Risk_{it}$ and the Herfindahl Indices. We tried to avoid the emergence of bias from this dependency and thus estimated the influence of diversification on returns without controlling for equity. However, in order to compare our results with those from other studies (eg Acharya et al (2004)) we report results which include $Equity_{it}$, too.

1.4 Summary statistics

Table 1 presents univariate descriptive statistics for the variables used in the following estimations. Note that the mean (median) bank's size in the sample is about 4.2 billion (0.9 billion) EUR. The average industrial and sectoral focus measures (HI and HT) are quite low suggesting a significant degree of diversification in these areas. However, the average geographical focus HR is rather high capturing the fact that most German banks primarily do business with domestic counter-parties.

Besides, Table 1 presents the correlation matrix among the explanatory variables of the following estimations. As it illustrates, the three Herfindahl Indices are not highly correlated. This suggests that the effects of industrial, sectoral and regional diversification on the banks' return might be different.

Insert Table 1 here.

2 Empirical framework

Our aim is to assess the impact of diversification on banks' profitability for German banks. We address this question by looking at three aspects. First of all, we are interested in the average effect of diversification on return. Subsequently, we try to answer the question of whether the link between return and diversification is consistent with portfolio theory. Finally, we test how monitoring effectiveness affects the relationship between diversification and return.

2.1 Average impact of diversification

We investigated the average impact of diversification on banks' performance in a panel regression where we regressed return on the Hirschman-Herfindahl Indices. More precisely, we estimated the following equation.

$$Return_{it} = a_0 + a_1 HT_{it} + a_2 HR_{it} + a_3 HI_{it} + \sum_{n=4}^{N} a_n X_{nit} + v_{it}, \qquad (1)$$

where $Return_{it}$, HT_{it}, HR_{it} and HI_{it} are measured as described in the previous section. X_n is the set of control variables described above, which comprises time dummies, individual dummies,[12] $Personal_{it}$, $Size_{it}$ and – for reasons of comparability with other studies – $Equity_{it}$. Owing to the presence of the dummy variables, estimating (1) with OLS is equivalent to adopting the two-way fixed effects estimator. w_{it} is iid with mean zero and a constant variance. The coefficients a_1, a_2 and a_3 capture the average impact of focus on bank performance, which means that they are not conditioned by the banks' risk levels.

We estimate (1) with several restrictions. The results are reported in Table 2. In all specifications, the coefficients for the Herfindahl Indices are positive; in most cases they are also highly significant. The results are remarkably stable for the estimations (1a) – (1d); however, they change when $Equity_{it}$ is added to the equation, see specification (1e). In specification (1e), the coefficients for the Herfindahl Indices are considerably lower in terms of both absolute magnitude and significance level; at the same time, $Equity_{it}$ is highly significant. Hence, the inclusion of $Equity_{it}$ reduces the impact of the Herfindahl Index on $Return_{it}$. This is consistent with our assumption that $Equity_{it}$ is determined by banks' risk preferences and that the coefficients a_1, a_2 and a_3 in (1e) thus no longer reflect the average impact of focus on $Return_{it}$. Aside from this assumption, the results of all specifications confirm a positive impact of geographical focus at a 1% confidence level and a positive impact of sectoral focus at a level of at least 10%. Furthermore, concerning the magnitude of the coefficients, all estimations reveal the same order with HR_{it} having the highest and HI_{it} having the lowest coefficient.

Insert Table 2 here.

The positive coefficients of the Herfindahl Indices can be interpreted as a confirmation that (at least on average) the mean profits arising from focusing loan portfolios exceed the mean profits achievable through diversification. The highest benefits seem to be attainable through geographical focus, whereas the benefits from industrial focus appear to be only moderate.

In the following subsections, we will analyse whether the results are in line with portfolio theory and/or how the quality of monitoring influences the link between diversification and returns.

2.2 Consistency with portfolio theory

Portfolio theory describes the relationship between diversification, expected returns and risk in a liquid portfolio. For our purpose, the most important implication is that diversification is an instrument to increase expected returns for a given risk value and may therefore be used to induce shifts in banks' risk-return efficiency. Alternatively, banks may use diversification to change their risk-return profile at the same efficiency level. In order to test which policy is prevalent, we added the variable $Risk_{it}$ (measured as described above) to Equation (1).

$$Return_{it} = b_0 + b_1 HT_{it} + b_2 HR_{it} + b_3 HI_{it} + b_4\, Risk_{it} + \sum_{n=5}^{N} b_n X_{nit} ? e_{it}. \qquad (2)$$

Here, the coefficients b_1, b_2, and b_3 capture the impact of a variation in focus on return conditioned by the banks' risk level. If banks have operated at the same efficiency level, the conditional coefficients take the value zero and b_4 is positive. Deviations from zero in b_1, b_2, and b_3 and/or non-negative values for b_4 indicate that banks have used diversification to change their risk-return efficiency. It should be noted that $Risk_{it}$ is endogenous in HT_{it}, HR_{it} and HI_{it}. Therefore, (1) can be interpreted as the reduced form of (2).

Table 3 shows the estimated coefficients. Interestingly, conditioning by risk does not change the results from (1) since the conditional coefficients b_1, b_2, and b_3 are almost equal to the average coefficients a_1, a_2 and a_3 in Table 2. At the same time, $Risk_{it}$ is significantly negative in specifications (2a), (2c) and (2d). In the other specifications, the coefficient for $Risk_{it}$ is insignificant. It should be noted that the outcome does not seem to result from a potential multicollinearity between $Risk_{it}$ and the Herfindahl Indices as b_4 remains stable when the Herfindahl Indices are excluded from Equation (2), see specification (2e). When $Equity_{it}$ is added to the equation (see specification (2f)), the coefficients of both $Risk_{it}$ and the Herfindahl Indices become insignificant. Again, we believe that this finding is induced by the fact that $Equity_{it}$ depends on the banks' risk preferences.

Insert Table 3 here.

Since there is no evidence of a positive relationship between risk and return, it appears that banks have not used diversification to operate at a constant risk-return efficiency level. Banks with highly risky credit portfolios were not systematically more profitable than banks with low risk portfolios. One conclusion derived from this finding is that, overall, banks were not risk-return efficient. This is confirmed by the non-zero coefficients of the Herfindahl Indices.

To sum up, the positive Herfindahl Indices in Table 3 indicate that banks with a higher level of focus tend to be more profitable than diversified banks and, at the same time, banks with a higher risk level seem to be less profitable. Accordingly, instead of operating at a constant risk-return efficiency level, banks appear to have used diversification as an instrument to change their risk-return profiles.

2.3 Diversification, monitoring effectiveness and returns

Finally, we analysed how monitoring effectiveness affects the link between diversification and banks' returns. In Winton's (1999) model, effective loan monitoring is the force that prevents banks from failure by catching problem loans before the situation deteriorates too far. Therefore, the monitoring of loans allows banks to improve their loan returns and reduce their default probability. When deciding whether to diversify or not, banks take into account the impact of diversification on their incentives to monitor their loans and their probability of failure. Specialised banks which are exposed to sectors with low downside risk will derive only moderate benefits from diversification as they have a low default probability anyway. Alternatively, in the case of diversified banks with loans of sufficiently high downside risk, bank owners (equity holders or managers) have only few incentives to monitor as, on an expected basis, most of the benefits from monitoring will accrue only to the bank's creditors (uninsured depositors and providers of borrowed funds) and diversification could actually increase the banks' default probability. Accordingly, the benefits from diversification are greatest if banks' loans have moderate levels of downside risk and if banks' monitoring incentives need to be strengthened.

In terms of empirically testable hypotheses, Winton's theory implies that the relationship between return and focus (or respectively diversification) should be expected to be non-linear and U-shaped in risk. To try to capture this, we first of all reproduced the tests proposed by Acharya et al. (2004). They expanded Equation (2) by non-linear terms.

$$
\begin{aligned}
Return_{it} = {} & b_0 + b_1 HT_{it} + b_2 HR_{it} + b_3 HI_{it} + b_4\, Risk_{it} + \sum_{n=5}^{N} b_n X_{nit} \\
& + a_{11} HT_{it} * RISK_{it} + a_{12} HT_{it} * RISK^2_{it} \\
& + a_{21} HR_{it} * RISK_{it} + a_{22} HR_{it} * RISK^2_{it} \\
& + a_{31} HI_{it} * RISK_{it} + a_{32} HI_{it} * RISK^2_{it} + \vartheta_{it}\,. \qquad (3)
\end{aligned}
$$

By calculating the first derivative of return on focus, it is easy to see that a U-shape in risk is given if

$$a_{11} < 0,\ a_{12} > 0,\ a_{21} < 0,\ a_{22} > 0,\ a_{31} < 0 \text{ and } a_{32} > 0,$$

see Acharya et al. (2004).

The estimated coefficients (see Table 4) are in line with the patterns associated with a U-shaped form, the only exception being the specification which contains $Equity_{it}$. In all other equations, the coefficients of the Herfindahl Indices interactant with $RISK_{it}$ are negative, whereas they are positive when interactant with $RISK^2_{it}$. Most of the coefficients are significant at a 5% or even at a 1% confidence level. Thus, the results could be interpreted as strong evidence of a U-shaped relationship between focus and return depending on the level of risk.

Insert Table 4 here.

However, to better understand the economic significance of this potential U–shaped relationship, Figure 1 plots the marginal effect d(return)/d(focus) for different values of risk for all three types of diversification based on the estimated coefficients from (3b), (3c) and (3d). The range of risk is taken to be between 0% and 50%, which represents the minimum and the maximum value over our entire sample period. It should be noted that the mean (median) risk is about 3.4% (2.6%), while the 90th percentile is about 9%.

As can be seen in Figure 1, in our sample a small increase in industrial focus (HI_{it}) has a rather minor and positive effect on return in the case of the mean (median) bank. For risk levels above 10%, the effect becomes slightly negative, but returns to a positive and sharply rising curve at a risk level of about 22% (corresponding to the 99th percentile of risk). Hence, we conclude that, within the range of risk levels observed in our sample, the marginal effect of industrial focus on return might indeed be U-shaped.

However, the result of the graphical analysis is different for sectoral and geographical focus (HT_{it} and HR_{it}). Here, an increase in focus also leads to rising returns for banks with risk levels below 12% and 27% respectively, but then the effect of focus stays negative and decreases for all of the risk levels observed. In fact, the effect becomes positive again only at hypothetical risk levels as high as 110% and 160%. Therefore, we suspect that the true impact of sectoral and geographical focus on return might be a linear or at least monotonous decrease with risk rather than a U-shaped relationship.

Insert Figure 1 here.

To further explore this issue, we have to overcome the drawback of the above test, ie the restrictions imposed by the parameterisation of the non-linearities between diversification, risk and return in (3).

Richer patterns of non-linearity can be detected with non-parametric methods. To this end, we follow the example of Acharya et al. (2004) and define a set of dummy variables which measure different risk levels. The dummy variables are as follows:

$D_1 = 1$ if $Risk^{[10]} < Risk_{it} \leq Risk^{[25]}$ and zero otherwise,

$D_2 = 1$ if $Risk^{[25]} < Risk_{it} \leq Risk^{[50]}$ and zero otherwise,

$D_3 = 1$ if $Risk^{[50]} < Risk_{it} \leq Risk^{[75]}$ and zero otherwise,

$D_4 = 1$ if $Risk^{[75]} < Risk_{it} \leq Risk^{[90]}$ and zero otherwise,

$D_5 = 1$ if $Risk_{it} \geq Risk^{[90]}$ and zero otherwise,

where $Risk^{[p]}$ is the p^{th} percentile of $Risk_{it}$. We then interacted the dummies with the Herfindahl Indices and regressed the resulting variables on risk. The estimation results are shown in Table 5.

It should be noted that the coefficients of the Herfindahl Indices which are not interactant with the dummy variables capture the impact of focus on return when risk is low. These coefficients of the Herfindahl Indices which are not interactant are generally positive (again the only exception being the equation which includes equity) and highly significant. In the specifications where the Herfindahl Indices are analysed separately, the coefficients of sectoral and geographical focus are significantly negative when interactant with the dummies. At the same time, they exhibit a slight decrease in magnitude with rising risk (see (4b) and (4c)). This pattern confirms the hypothesis that the benefits from focus are greater for low-risk banks than for banks with higher levels of risk.

Insert Table 5 here.

Furthermore, similar to the parametric analysis above, the overall influence of sectoral and geographical focus on return stays positive for all levels of risk as the absolute magnitude of the (negative) coefficients of the terms interactant with the risk dummies is lower than the (positive) baseline coefficient of the respective Herfindahl Index without interaction. However, in the case of industrial focus, the overall impact on return is negative for moderate levels of risk (compare the coefficients for HI_{it} and D_1*HI_{it} in (4d)) and a U-shaped relationship with return can be detected as the overall impact of industrial focus increases to slightly positive (though insignificant) levels for the banks with the greatest risk.

Although these patterns are less pronounced for the estimations (4a) and (4d), in all cases the coefficients reveal evidence of a nonlinear relationship between diversification and risk, with a strong positive impact of Herfindahl Indices in the case of low-risk banks and a moderate or insignificant impact for higher-risk banks. The more sluggish results for sectoral and geographical diversification in specification (4a) as compared with (4b) and (4c) may be attributed to the lower degree of freedom in the estimation.

To sum up, the dummy variable approach provides strong evidence that the impact of a bank's portfolio diversification on its return depends strongly on the bank's risk level. Industrial, sectoral and geographical focus yield the highest benefits when risk is low. The benefits from focus decrease and, hence, the benefits from diversification increase with rising risk levels. For industrial focus, the impact becomes insignificant for high risk levels. The findings in Tables 2 and 3, namely that on average industrial focus has a lesser impact on returns than sectoral and geographical focus, can be attributed mostly to banks with moderate risk.

However, it is still difficult to test the hypothesis of a U-shaped form, since the classes which define the dummy variables are fixed heuristically and may be too rough to detect the underlying structure of the relationship between diversification, risk and return. In order to gain a more precise picture of the shape of the non-linearities, we performed a second non-parametric procedure. We classified the data set according to risk level. We then estimated (1) with a window of 1,000 observations shifting from the lowest risk level to the highest risk level. More precisely, we first of all used a sub-sample of 1,000 observations with the lowest risk level to estimate (1), then shifted the sample by one observation and repeated the estimation. The result is a series of roughly 2,500 estimations for a_1, a_2 and a_3 of Equation (1), which are classified according to the risk level. Plotting the series provides information about the impact of risk on the relationship between focus and return. Figures 2, 3 and 4 represent estimations for the specifications (1b), (1c) and (1d).

Insert Figures 2 to 4 here.

As expected, all of the charts reveal that the coefficients for the Herfindahl Indices (a_i) vary according to the risk level. Although some of the coefficients of the Herfindahl Indices fluctuate considerably, there is some evidence to suggest that the relationships are either U-shaped or monotonously decreasing. In addition, taken all together, the influences depicted are comparable to those derived using the parametric and dummy variables approaches. Sectoral focus (HT_{it}), for example, has a positive coefficient for a low risk level. However, in the case of increasing risk values, a_1 decreases and becomes slightly (and insignificantly) negative. Therefore, as with the former approaches, the effect of sectoral focus on return seems to monotonously decrease with risk. On the other hand, the coefficient of regional focus (HR_{it}) now shows – in contrast to former results – a U-shaped form. It is highly positive for low risk levels, decreases for moderate risk levels (although it remains positive) and then rises again for high-risk banks. Finally, industrial focus (HI_{it}) has a positive coefficient only at low risk levels. For moderate risk levels, it is slightly but significantly negative, while the coefficient becomes insignificantly negative for the highest risk. As such, the rolling window approach provides less distinct evidence of a U-shaped relationship between industrial focus and banks' returns than the above results.

To sum up, in order to assess the impact of banks' portfolio diversification or focus on their returns at different risk levels, we applied and compared three different approaches. We first of all introduced non-linear terms in the base specification and then applied two non-parametric tests by interacting the Herfindahl Indices with dummies for different risk levels and using a rolling window approach for each type of diversification. Table 6 goes some way towards summarising the different results.

Insert Table 6 here.

Table 6 clearly demonstrates that the benefits from industrial, sectoral and geographical diversification systematically and noticeably vary according to banks' risk levels. Therefore, banks' decisions on whether or not to diversify their loan portfolio should be closely linked to their current risk level. Moreover, the type of focus plays a crucial role. According to all three approaches, sectoral focus, for example, is moderately beneficial for low-risk banks, while its influence on return decreases monotonously for higher risk levels. This effect either stays positive for all banks or becomes only (insignificantly) negative for rather high risk levels. In the case of geographical focus, however, all of the results indicate a positive effect on return for all risk profiles. However, while the parametric and dummy variables approaches reveal a monotonous decline in this positive relationship for higher-risk banks, the rolling window approach clearly depicts a U-shaped form. Furthermore, for industrial focus, we found evidence of a U-shaped link to return, as the results show a positive influence for low risk, a significantly negative impact for moderate risk and almost no effect for very high-risk banks. Hence, our analyses at least partly confirm Winton's theory that the diversification benefits are highest at moderate risk levels.

3 Conclusions

Should banks diversify across different geographical regions and industrial sectors, or should they specialise in a few related fields? In this paper, we tried to shed some light on this question by empirically investigating the situation of German banks. By exploiting a unique data set of individual bank loan portfolios for the period from 1996 to 2002, we analysed the link between banks' profitability and their portfolio diversification across different industries, broader economic sectors and geographical regions. To the best of the authors' knowledge, this is the first paper studying the effect of all three types of diversification jointly based on micro-level data on German banks.

The relevant academic literature puts forward two conflicting theories concerning the optimum degree of diversification. While traditional banking theory based on a delegated monitoring argument (see, for example, Diamond (1984) and Boyd and Prescott (1986)) recommends that the optimum organisation of a bank is one where it is as diversified as possible, corporate finance theory suggests that a firm should focus so as to obtain the greatest possible benefit from management's expertise and to reduce agency problems (see Jensen (1986), Denis et al. (1997) and Rajan et al. (2000)). Our results clearly support the latter theory, as the evidence we present indicates that each kind of diversification tends to lower German banks' returns, ie focusing generally leads to greater profitability benefits.

However, the impact of all types of diversification on banks' returns changes according to the risk level. While the effect of sectoral focus on return declines monotonously with increasing risk, there is mixed evidence to suggest either a monotonously decreasing or a U-shaped relationship for regional focus as well as a rather distinct indication of a U-shape with respect to industrial focus. Therefore, our results at least partly confirm Winton's theory regarding poor monitoring incentives for high-risk banks, which – in terms of empirically testable hypotheses – implies that the relationship between return and focus should be non-linear and U-shaped in risk.

Furthermore, in the case of our data, diversification improves banks' profitability only in the case of moderate risk levels and industrial diversification. Hence, from a policy point of view, our results suggest that bank regulations which may increase the level of industrial, sectoral or geographical diversification should be carefully evaluated

[1] For example, lease receivables, mortgage loans, publicly guaranteed loans, interbank loans (with a residual maturity of up to one year) are listed separately under on balance sheet activities.

[2] The following items are deemed not to be credit exposures: shares in other enterprises irrespective of how they are shown in the balance sheet and securities in the trading portfolio (Deutsche Bundesbank, 1998).

[3] Off balance sheet items include derivatives (other than written option positions), guarantees assumed in respect of these and other off balance sheet transactions (Deutsche Bundesbank, 1998).

[4]The former Federal Banking Supervisory Authority, now BaFin (*Bundesanstalt für Finanzdienst-leistungsaufsicht*), i.e. the Federal Financial Supervisory Authority.

[5] For these banks, the average coverage rate is about 70%.

[6] For further details, see Nestmann *et al*. (2003).

[7] J.P. Morgan (1997)

[8] The insolvency data used were that of the Federal Statistical Office (*Statistisches Bundesamt)*. The industry codes of the insolvency data correspond to the industry codes of the credit register. The insolvency rate of a specific industry is calculated as the number of insolvencies divided by the total number of companies in the industry. The probability of default of a specific industry is then calculated as the average of the annual data from 1994 to 2002. The correlation between insolvencies of the industries is calculated using monthly data for the same period.

[9] More precisely, the scale parameter for bank i is defined as

$$Scale_{it} = \frac{LoanLoss\ Provisions_{it}}{TotalLoans_{it}} \Bigg/ \frac{\sum_j InsolvencyRate_{jt} Exposure_{jit}}{\sum_j Exposure_{jit}}$$

where i, t and j index the bank, the period and the industry. *Loan Loss Provisions* and *Total Loans* are taken from the balance sheet data and *Exposure* is derived from the credit register. In line with Moody's KMV Credit Monitor, we introduce a cap of 20% for the resulting PD; see Bohn et al (2005).

[10] Insolvency data are used as a proxy for asset correlations since the latter are not observable. As a result VaR_{it} might be negatively biased as asset correlations usually are higher than insolvency correlations. However, with the assumption that the difference between the correlations of assets and insolvency are constant over time, the bias will difference out in the fixed-effects estimation.

[11] As mentioned above, the VaR level differences out in the fixed effects estimations, which means that the value of the LGD will not affect our results.

[12] To facilitate disposition, the coefficients of the dummies will not be reported here.

References

Acharya, V., I. Hasan and A. Saunders (forthcoming), Should Banks be Diversified? Evidence from Individual Bank Loan Portfolios, Journal of Business.

Basel Committee on Banking Supervision (2004), International Convergence of Capital Measurement and Capital Standards: A Revised Framework, June.

Berger, P. and E. Ofek (1996), Bustup Takeovers of Value-Destroying Diversified Firms, Journal of Finance 51, 1175-1200.

Berger, A. and R. DeYoung (2001), The Effects of Geographic Expansion on Bank Efficiency, Journal of Financial Services Research, 19, No 2/3, 163-185.

Bohn, J., N. Arora, and I. Korablev (2005), Power and Level Validation of the EDF™ Credit Measure in the U.S. Market, White Paper, Moody's KMV Company, March.

Boyd, J., and E. Prescott (1986), Financial Intermediary Coalitions, Journal of Economic Theory, 38, 211-232.

Buch, C.M., J.C. Driscoll and C. Ostergaard (2004), Cross-Border Diversification in Bank Asset Portfolios, Working Paper No. 04-26, Federal Reserve Board of Washington.

Caprio, G. and B. Wilson (1997), On Not Putting All the Eggs in One Basket: the Role of Diversification in Banking, Working Paper, World Bank.

Dahl, D. and A. Logan (2003), Granularity and International Diversification: An Empirical Analysis of Overdue Claims at Banks, mimeo, Bank of England.

DeLong, G. (2001), Stockholder Gains from Focusing Versus Diversifying Bank Mergers, Journal of Financial Economics, 59(2), 221-252.

Denis, D., D. Denis, and A. Sarin (1997), Agency Problems, Equity Ownership, and Corporate Diversification, Journal of Finance, 52, 135-160.

Deutsche Bundesbank (1998), Monthly Report, August 1998.

Diamond, D. (1984), Financial Intermediation and Delegated Monitoring, Review of Economic Studies, 59; 393-414.

Gehrig, T. (1998), Screening, Cross-Border Banking, and the Allocation of Credit, Review in

Economics, 52, 387-407.

Hughes, J., W. Lang, L. Mester and C. Moon (1996), Safety in Numbers? Geographic Diversification and Bank Insolvency Risk, Working Paper No. 96-14, Federal Reserve Bank of Philadelphia.

J. P. Morgan (1997), “CreditMetrics-Technical Document”, New York, April.

Jensen, M.C. (1986), Agency Costs of Fee Cash Flow, Corporate Finance, and Takeovers, American Economic Review, 76, 323-329.

Klein and Saidenberg (1998), Diversification, Organization, and Efficiency: Evidence from Bank Holding Companies, Center for Financial Institutions Working Papers 97-27, Wharton School Center for Financial Institutions, University of Pennsylvania.

Morgan, D.P. and K. Samolyk (2003), Geographic Diversification in Banking and Its Implications for Bank Portfolio Choice and Performance, the paper was presented at the BIS Workshop “Banking and Financial Stability”, 20-21 March 2003

Nestmann, T., M. Wedow and N. v. Westernhagen (2003), A Micro Data-Set on Foreign Claims of German Banks, Deutsche Bundesbank, mimeo.

Rajan, R., H. Servaes and L. Zingales (2000), The Cost of Diversity: The Diversification Discount and Inefficient Investment, Journal of Finance, 55(1), 35-80.

Shaffer, S. (1998), The Winner’s Curse in Banking, Journal of Financial Intermediation, 4, 158-187.

Stiroh, K. (2004), Diversification in Banking: Is Noninterest Income the Answer?, Journal of Money, Credit and Banking, 36(5), 853-882.

Stiroh, K. and A. Rumble (2003), The Dark Side of Diversification for U.S. Bank Holding Companies, unpublished paper, Federal Reserve Bank of New York.

Winton, A. (1999), Don’t Put All Your Eggs in One Basket? Diversification and Specialization in Lending, Working Paper No. 00-16, University of Minnesota.

Table 1 Summary Statistics (3,529 observations)

	HT_{it}	HR_{it}	HI_{it}	$Return_{it}$	$Risk_{it}$	$Personal_{it}$	$Size_{it}$	$Equity_{it}$
Mean	0.569	0.929	0.291	0.004	0.034	0.013	20.623	0.052
Median	0.514	0.972	0.204	0.004	0.026	0.013	20.623	0.044
Standard Deviation	0.156	0.076	0.241	0.028	0.041	0.015	1.366	0.054
Minimum	0.299	0.284	0.066	-0.018	0.000	0.001	15.626	0.001
Maximum	1.000	1.000	1.000	0.054	0.493	0.073	26.472	0.305
Correlation								
HT_{it}	1.000							
HR_{it}	0.034	1.000						
HI_{it}	-0.250	-0.243	1.000					
$Return_{it}$	0.030	0.006	0.026	1.000				
$Risk_{it}$	-0.227	-0.085	-0.160	-0.025	1.000			
$Personal_{it}$	0.085	0.048	0.044	-0.164	-0.082	1.000		
$Size_{it}$	-0.438	0.013	0.152	0.016	0.151	-0.283	1.000	
$Equity_{it}$	0.130	-0.200	0.200	0.085	-0.104	0.484	-0.302	1.000

Table 2 Two-way fixed effects estimation of Equation (1) with alternative restrictions
Dependent variable: $Return_{it}$,

	(1a)	(1b)	(1c)	(1d)	(1e)
HT_{it}	0.018***	0.020***			0.005*
	(4.87)	(5.74)			(1.65)
HR_{i1}	0.030***		0.039***		0.017***
	(4.38)		(5.83)		(2.81)
HI_{it}	0.006**			0.005**	0.001
	(2.50)			(2.00)	(0.47)
$Equity_{it}$					0.185***
					(24.66)
$Size_{it}$	-0.022***	-0.023***	-0.023***	-0.022***	-0.006***
	(14.75)	(-15.69)	(-15.13)	(-14.92)	(-4.27)
$Personal_{it}$	-1.439***	-1.433***	-1.434***	-1.408***	-1.780***
	(-15.02)	(-14.89)	(-14.91)	(-14.54)	(-20.55)
Constant	0.429***	0.480***	0.438***	0.476***	0.124***
	(13.39)	(15.66)	(13.77)	(15.22)	(3.99)
No. of obs.	3,529	3,529	3,529	3,529	3,529

T-values in brackets, *, **, *** denotes significance at 10%, 5% and 1%.

Blanks indicate that the coefficient of the variable is restricted to zero.

Table 3 Two-way fixed effects estimation of Equation (2) with alternative restrictions
Dependent variable: $Return_{it}$,

	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)
HT_{it}	0.017***	0.020***				0.005
	(4.77)	(5.63)				(1.621)
HR_{it}	0.030***		0.039***			0.017***
	(4.38)		(5.82)			(2.81)
HI_{it}	0.007***			0.006**		0.001
	(2.71)			(2.28)		(0.55)
$Risk_{it}$	-0.018*	-0.014	-0.018*	-0.022**	-0.019*	-0.006
	(-1.67)	(-1.27)	(-1.67)	(-2.02)	(-1.71)	(-0.56)
$Equity_{it}$						0.109***
						(24.60)
$Size_{it}$	-0.021***	-0.022***	-0.022***	-0.022***	-0.022***	-0.006***
	(-14.29)	(-15.35)	(-14.76)	(-14.40)	(-15.09)	(-4.17)
$Personal_{it}$	-1.431***	-1.429***	-1.427***	-1.398***	-1.406***	-1.777***
	(-14.92)	(-14.81)	(-14.83)	(-14.43)	(-14.52)	(-20.48)
Constant	0.421**	0.475***	0.431***	0.466***	0.480***	0.122***
	(13.00)	(15.36)	(13.45)	(14.72)	(15.45)	(3.89)
No. of obs.	3,529	3,529	3,529	3,529	3,529	3,529

T-values in brackets, *, **, *** denotes significance at 10%, 5% and 1%.
Blanks indicate that the coefficient of the variable is restricted to zero.

Table 4: Two-way fixed effects estimation of Equation (3) with alternative restrictions
Dependent variable: $Return_{it}$

	(3a)	(3b)	(3c)	(3d)	(3e)
HT_{it}	0.023***	0.022***			0.008**
	(5.64)	(6.02)			(2.12)
$HT_{it}*RISK_{it}$	-0.324***	-0.254***			-0.255
	(-3.25)	(-3.22)			(0.25)
$HT_{it}*RISK^2_{it}$	0.293**	0.215**			0.430
	(1.96)	(2.15)			(0.74)
HR_{it}	0.029***		0.046***		0.022***
	(3.89)		(6.32)		(3.19)
$HR_{it}*RISK_{it}$	-0.123		-0.217***		-0.076
	(-1.16)		(-2.77)		(-0.79)
$HR_{it}*RISK^2_{it}$	0.140**		0.113**		-0.197
	(2.11)		(2.02)		(-0.63)
HI_{it}	0.011***			0.010***	0.001
	(3.58)			(3.40)	(0.48)
$HI_{it}*RISK_{it}$	-0.197*			-0.220***	0.025
	(-1.78)			(-2.89)	(0.25)
$HI_{it}*RISK^2_{it}$	0.603*			0.702***	-0.057
	(1.79)			(3.86)	(-0.19)
$Risk_{it}$	0.166**	0.066*	0.129*	-0.053***	0.173**
	(2.05)	(1.74)	(1.84)	(-2.68)	(2.38)
$Equity_{it}$					0.184***
					(24.06)
$Size_{it}$	-0.021***	-0.022***	-0.022***	-0.022***	-0.006***
	(-14.12)	(-15.26)	(-14.84)	(-14.41)	(-4.14)
$Personal_{it}$	-1.458***	-1.435***	-1.437***	-1.424***	-1.778***
	(-15.23)	(-14.92)	(-14.94)	(-14.71)	(-20.48)
Constant	0.415***	0.471***	0.428***	0.469***	0.117***
	(12.72)	(15.23)	(13.32)	(14.75)	(3.67)

No. of obs.	3,529	3,529	3,529	3,529	3,529

T-values in brackets, *, **, *** denotes significance at 10%, 5% and 1%.
Blanks indicate that the coefficient of the variable is restricted to zero.

Table 5 Two-way fixed effects estimation of Equation (1) with interaction terms for different risk levels, alternative restrictions, dependent variable: $Return_{it}$,

	(4a)	(4b)	(4c)	(4d)	(4e)
HT_{it}	0.026***	0.025***			-0.001
	(2.89)	7.08			(-0.10)
D_1*HT_{it}	-0.003	-0.011***			0.015*
	(-0.40)	(-6.56)			(1.93)
D_2*HT_{it}	-0.017*	-0.012***			0.002
	(-1.86)	(-6.15)			(0.02)
D_3*HT_{it}	-0.018*	-0.013***			0.006
	(-1.86)	(-5.68)			(0.73)
D_4*HT_{it}	-0.013**	-0.014***			0.004
	(-2.53)	(-5.43)			(0.44)
D_5*HT_{it}	-0.014	-0.014***			0.012
	(-1.28)	(-4.38)			(0.20)
HR_{it}	0.038***		0.046***		0.046***
	(3.73)		(6.85)		(5.00)
D_1*HR_{it}	-0.004		-0.010***		-0.016**
	(-0.61)		(-7.08)		(-2.47)
D_2*HR_{it}	0.005		-0.010***		-0.006
	(0.67)		(-6.60)		(-0.82)
D_3*HR_{it}	0.006		-0.011***		-0.007
	(0.81)		(-6.19)		(0.33)
D_4*HR_{it}	0.011		-0.012***		-0.005
	(1.30)		(-5.92)		(0.52)
D_5*HR_{it}	0.004		-0.012***		-0.009
	(0.51)		(-5.23)		(-1.13)
HI_{it}	0.016***			0.023***	-0.025***
	(3.00)			(4.23)	(-4.97)
D_1*HI_{it}	-0.076***			-0.081***	-0.055***
	(-7.22)			(-8.15)	(-5.80)
D_2*HI_{it}	-0.033***			-0.038***	-0.073***
	(-4.30)			(-4.41)	(-10.35)
D_3*HI_{it}	-0.015**			-0.024***	0.029***
	(-2.22)			(-3.59)	(4.62)
D_4*HI_{it}	-0.017***			-0.025	0.023***
	(-2.60)			(-4.00)	(3.86)
D_5*HI_{it}	-0.011			-0.019	0.031***
	(-1.56)			(-2.84)	(4.77)
$Equity_{it}$					0.185***
					(24.22)
$Size_{it}$	-0.019***	-0.022***	-0.021***	-0.020***	-0.009***
	(-13.77)	(-14.90)	(-14.47)	(-12.94)	(-6.36)
$Personal_{it}$	-1.382***	-1.500***	-1.505***	-1.288***	-1.670***
	(-14.65)	(-15.63)	(-15.71)	(-13.20)	(-19.58)
Constant	0.373***	0.463***	0.422***	0.424***	0.151***
	(12.19)	(15.07)	(13.31)	(13.27)	(5.22)
No. of obs.	3,529	3,529	3,529	3,529	3,529

T-values in brackets, *, **, *** denotes significance at 10%, 5% and 1%.

Blanks indicate that the coefficient of the variable is restricted to zero.

Table 6 Comparison of the results of the impact of focus on return for different risk levels

Risk percentile	0-1th perc.	-10th perc.	-25th perc.	-50th perc.	-75th perc.	-90th perc.	-99th perc.	-100th perc.
Sectoral focus *(HT_{it})*								
Parametric approach (see Table 4, 4b)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(+/-)** (d)	(-)** (d)
Dummy var. approach (see Table 5, 5b)		(+)***	(+)*** (d)	(+)*** (d)	(+)*** (d)	(+)*** (d)	(+)*** (c)	
Rolling window approach (see Figure 2)			(+)$^{\#}$ (d)	(+)$^{\#}$ (d)	(-) (d)	(-) (i)		
Geographical focus *(HR_{it})*								
Parametric approach (see Table 4, 4c)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(+)** (d)	(-)** (d)
Dummy var. approach (see Table 5, 5c)		(+)***	(+)*** (d)	(+)*** (c)	(+)*** (d)	(+)*** (d)	(+)*** (c)	
Rolling window approach (see Figure 3)			(+)$^{\#}$ (d)	(+) (d)	(+) (i)	(+)$^{\#}$ (i)		
Industrial focus *(HI_{it})*								
Parametric approach (see Table 4, 4d)	(+)*** (d)	(+)*** (d)	(+)*** (d)	(+)*** (d)	(+)*** (d)	(+)*** (d)	(-)*** (d/i)	(+)*** (i)
Dummy var. approach (see Table 5, 5d)		(+)***	(-)*** (d)	(-)*** (i)	(-)*** (i)	(-) (d)	(+) (i)	
Rolling window approach (see Figure 4)			(+) (d)	(-) (d)	(-)$^{\#}$ (d)	(-) (i)		

d / i / c indicate a decreasing / increasing / constant level for the respective risk interval.
*, **, *** denote significance at 10%, 5% and 1%.
highlights that the interval α +/- 2σ does not intersect the x-axis.

Figure 1 The marginal effect of focus on return for different risk values for HT, HR and HI based on the estimated coefficients from (3b), (3c) and (3d)

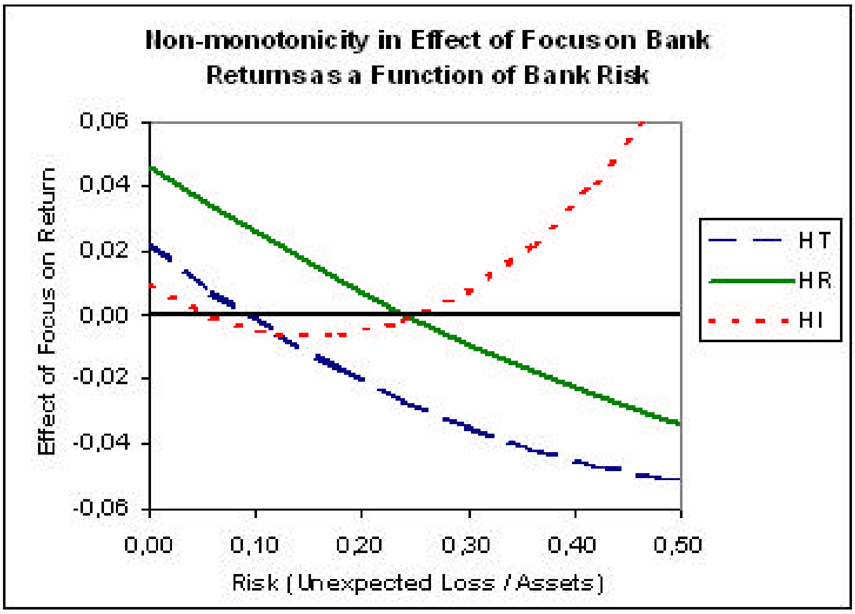

Figure 2: Coefficient of HT_{it} for different risk levels (α_1 in equation (1), specification (1b))

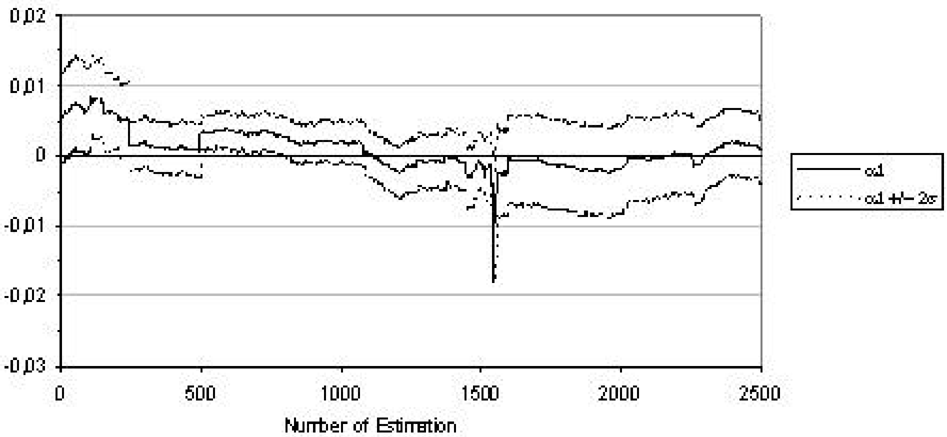

Figure 3: Coefficient of HR_{it} for different risk levels (α_2 in Equation (1), specification (1c))

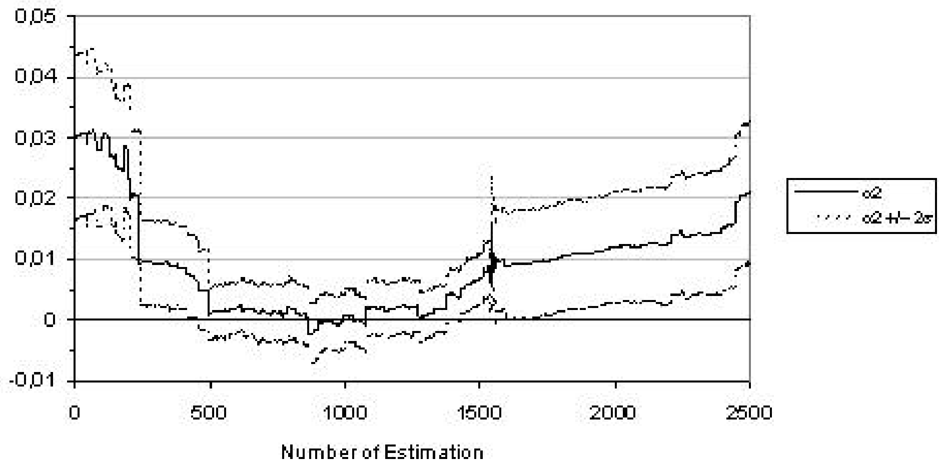

Figure 4: Coefficient of HI_{it} for different risk levels (α_3 in Equation (1), specification (1d))