Driving forces behind risk management in banking

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Abstract

This paper investigates the factors influencing banks' decision to engage in active risk management, from both a theoretical and an empirical perspective. In recent decades, credit risk management in banks has become highly sophisticated and banks have become more active in the management of credit risks. We identify two driving factors: bank competition and sector concentration in the loan market. We find empirical support for our hypotheses, using a unique data set of 249 German banks, partially raised by hand. Bank competition pushes banks to implement active risk management. Sector concentration in the loan market promotes credit portfolio modeling, but inhibits credit risk transfer.

Key words: risk management, credit risk, credit portfolio modelling, credit risk transfer, credit derivatives

1. Introduction

Credit risk management in banks has become highly sophisticated in recent years. This development was encouraged by regulators even before the financial crisis. However, the recent market turmoil has exposed weaknesses in the analysis of credit risks. A report of

☆We thank the German Savings Banks Association (DSGV) for providing the data used in this study. We are grateful to the participants in the Southern Finance Associaton Conference 2010 in Asheville, the INFINITI Conference on International Finance 2010 in Dublin, the International Risk Management Conference 2010 in Florence, the International Tor Vergata Conference in Banking and Finance 2010 in Rome, and the Conference of the Swiss Society for Financial Market Research 2011 (SGF) in Zürich for their useful comments and feedback. The paper represents the authors' personal opinions and not necessarily those of the German Savings Banks Association. All remaining errors are our own.

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the Senior Supervisors Group (2008), which identifies risk management practices during the recent market turbulence, shows that risk measures did not perform as expected. This has drawn further attention to banks' credit risk management, and shown how crucial the implementation and maintenance of risk management instruments is to the banking industry.

As financial institutions have grown more complex, the demand for risk management has grown rapidly (Bank for International Settlements, 2009). Hence, risk management has become one of banks' main activities (see e. g. Allen and Santomero, 1997; Santomero, 1997) and can be seen as banks' core competence (Hakenes, 2004).

Ambitious risk management tools have been developed over the last two decades for the modern practice of bank management. Altman and Saunders (1998) emphasize the development of credit-scoring systems, the development of models to measure and manage credit concentration in loan portfolios and the expansion of off-balance sheet instruments such as credit risk derivatives. Nevertheless, the financial industry has adopted such instruments only gradually, and their use is still not widespread among banks. Cebenoyan and Strahan (2004) emphasize that the use of risk management affects investment decisions, the value of a firm and its profitability. The cost of financial distress and the existence of capital market imperfections are also given as rationales for active risk management (see e. g. Stultz, 1984; Froot and Stein, 1993). However, because the implementation and upgrade of risk management involves a certain cost, it appears that there must be some trade-off.

However, what determines whether the expected benefits of sophisticated risk management outweigh its costs? We aim to understand what factors influence banks' decisions to engage in active risk management from both a theoretical and an empirical perspective. We first develop a framework to analyze banks' decisions to engage in active risk management. In the model, a bank can implement credit portfolio modeling, engage in credit risk transfer, or be more active in managing credit risk by implementing both. Credit portfolio modeling allows the bank to understands its portfolio structure and, thus, to adjust its risk buffers. With credit risk transfer, the bank diversifies its portfolio by selling part of that portfolio.

We show that bank competition pushes banks to implement credit portfolio modeling and engage in risk transfer markets. If competition is low, profit margins are relatively high and the bank is stable, therefore benefits of buffer adjustments and diversification cannot be high. Sector concentration on the loan market promotes credit portfolio modeling but inhibits credit risk transfer. If sector concentration is low, the bank already knows that its portfolio will be diversified, credit portfolio modeling is, therefore, less beneficial. On the other hand, with low sector concentration, it is easy to diversify even within the region.

To empirically test these theoretical results, we use a probit regression model on cross-sectional data. We conducted a survey in 2009 among 438 savings banks of the German Savings Banks Finance Group. In total, 279 completed questionnaires were returned; the response rate is, thus, higher than 60 percent. We combined this data with a unique data set of detailed balance-sheet and income-statement data and regional economic data. First, we can directly relate the use of different risk management instruments to bank characteristics, and to market and regional conditions. The so-called "regional principle" which limits the business activities of the banks in our sample to a specific geographical area, allows for a bank-level analysis of bank competition and sector concentration in the respective region. Second, we are able to provide unbiased results because the banks in our sample face identical prices to implement credit risk management instruments and can access the same credit management instruments. They operate within the same regulatory environment and have a common business model but they are legally and economically independent in their business decisions. Finally, the German banking system is representative of other European economies such as Spain, France, Italy and Switzerland. Our results can, thus, be generalized to other banking systems with a long history of savings banks.

We find that the determinants for banks' decision to engage in risk management are not only bank characteristics. We provide empirical evidence that sector concentration and competition among banks is positively related to a banks active risk management. We find evidence for the hypothesis that credit portfolio modeling should be prevalent when the sector concentration is relatively high. The depth of implementation and the integration of active credit risk management are primarily driven by competition among banks. The main results prove to be robust regarding different model specifications.

Our findings contribute to the broad body of literature on the impact of competition on banks' risk-taking behavior (see e. g. Keeley, 1990; Jiménez et al., 2010; Bergstresser, 2008) and are consistent with the "charter value" argument. However, we also make a complementary addition to the literature by explicitly incorporating risk management into the model and testing for it empirically. Furthermore, our findings coincide with those of Hakenes and Schnabel (2010) who investigate the role of banking competition for the credit derivative markets. They provide arguments to describe why credit risk transfer markets developed in an environment of increasing competition. We can also empirically confirm the results of Khandwalla (1972, 1973) who investigates conditions under which sophisticated management controls are extensively used. He stresses that firms under competitive pressure use sophisticated controls more extensively and more selectively than firms facing less intense competition.

The empirical literature on active risk management has mainly focused on the investigation of individual risk management instruments. Cebenoyan and Strahan (2004) investi-

gates empirically active risk management, proxied by loan sales and purchases. Numerous studies have examined the factors underlying banks' decisions to use derivatives (see e. g. Sinkey and Carter, 2000; Ashraf et al., 2007; Minton et al., 2009). To our knowledge, there are no papers that investigate the underlying decisions to adopt credit portfolio models. A paper by Acharya et al. (2006) studies the effect of diversification on the risk-return profile of banks. This study evaluates the decision of whether to focus or diversify loan portfolios, but it does not provide the factors for the underlying decision to engage in active portfolio management.

Whereas earlier research focused on individual risk management instruments, our study expands on prior work by modeling and empirically investigating banks' motivation to engage in active risk management through both credit portfolio modeling and participation in the credit risk transfer markets. This more integrated view of active risk management provides a sound understanding of the drivers of risk management in banking.

The remainder of the paper is structured as follows. Section 2 develops the model and derives the predictions, which are tested empirically. Section 3 describes the risk management of the banks and provides background information. Section 4 introduces the sample and variables used for the empirical analyses and presents tables of descriptive statistics. The empirical results are presented and discussed in Section 5. Section 6 concludes the study.

2. A Model of Active Risk Management

2.1. The Model

Competition. We model a bank that holds a portfolio of two assets, each with a volume of 1. The expected return of an asset is $R > 1$, such that R can be interpreted as a measure of competition, which is treated as exogenous in the model. A high R denotes for low competition, and vice versa. Assets are risky. For exposition, assume that the return is normally distributed with standard deviation σ. Going forward, let us call the assets loans, bearing in mind that they could be any type of risky asset.

Banks are financed with deposits d and equity k. The balance sheet equation is thus $d + k = 2$. Depositors demand a return of r_d (equal to 1 plus the rate of return) which is taken as exogenously given. Deposits are covered by deposit insurance, and the deposit rate is normalized to zero, thus $r_d = 1$. To obtain an interior solution for the capital structure and for simplicity, assume that the cost of equity is increasing in volume and the rate is $r_k = 1 + \phi\, k/2$. If banks cannot repay deposits from their loan portfolio, they

default at a cost $c > 0$. Note that k can also be interpreted as a buffer or reserve against potential loan losses.[1]

Sector Concentration. Loans come from different industrial sectors. Assume that there is a discrete sector of mass ρ^2, and a continuum of infinitesimal sectors of aggregate mass $1-\rho^2$. The sector Herfindahl-Hirschman-Index (SHHI) is then ρ^2.[2] Furthermore, assume that loans from the same sector are perfectly correlated, while loans from different sectors are stochastically independent. The correlation of two random loans is then ρ^2.

Risk Management Tools. First, let us assume that banks can implement *credit portfolio modelling* (CPM) to learn the correlation structure of their loan portfolio, at a cost. In the above context, the bank learns whether the loans are in the discrete sector or not. This is a sufficient statistic for the correlation structure. Banks can use CPM to fine-tune their buffers (or capital structure) to their portfolio structure. Without the information from CPM, the correlation of two loans is ρ^2, and with CPM, it is either 1 (if both loans are in the discrete sector) or zero.

Second, banks can engage in *credit risk transfer* (CRT), at a cost. Doing so, they swap half of their loan portfolio for the loan portfolio of another bank. CRT is, of course, used as a way to diversify.

Finally, banks can be more active in their management of credit risk, hencethey can implement both CPM and CRT, at acost. This will be referred to as *active risk management* (ARM). In this way, banks can diversify and fine-tune their buffers. Note that the potential value of CPM depends on whether banks are engaged in credit risk transfer or not. Hence, ARM is more (or less) than the sum of its components, CPM and CRT.

2.2. The Optimal Strategy

We use the following procedure to derive our hypotheses. First, we calculate a bank's expected profits for a benchmark case without any risk management, and we then calculate

[1]Note that there are no capital requirements in our model. However, in an alternative approach with capital requirements, there may also be an additional buffer to ensure that, after potential losses from the loan portfolio, the bank still meets these requirements. There will be a cost of not meeting the requirements. Thus, this approach would be a mere re-normalization of our modeling choice with identical empirical predictions. Note that we implicitly assume that markets are segmented, otherwise, depositors would prefer to earn higher expected returns by investing in bank equity. To this extent, the model is a stylized version of the trade-off theory of optimal capital structure.

[2]Assume that, in addition to the discrete sector with mass ρ, there are n sectors with mass $(1-\rho)/n$ each. The SHHI is then $\rho \cdot \rho + \sum_{i=1}^{n}(1-\rho)/n^2 = \rho^2 + (1-\rho)/n$. For large n, the limit is SHHI $= \rho^2$.

consecutively expected profits for the different risk management tools. There will always be a critical cost of implementing this tool. However, the larger the difference in the expected profits, the higher this critical cost of implementation will be. We hypothesize that banks are then more likely to implement the tool.

The Benchmark Case. The two loans of the bank are correlated with probability ρ^2, and uncorrelated with probability $1-\rho^2$. The loan portfolio has the mean return $2\,R$. If the loans are both in the discrete sector, they are correlated, and the standard deviation is $2\,\sigma$. Hence the yield Y is normally distributed with mean $2\,R$ and standard deviation $2\,\sigma$. We want to determine the probability that the yield cannot cover deposit repayments, $Y > 2-k$. After a z-transformation, the probability of financial distress is given by

$$\mathrm{PD}_1 = \Pr\{Y < 2-k\} = \Phi\Big(\frac{2-k-2\,R}{2\,\sigma}\Big), \tag{1}$$

where Φ is the standard normal distribution function. If the loans are uncorrelated, the standard deviation is $\sqrt{2}\,\sigma$, and the probability of distress is

$$\mathrm{PD}_0 = \Pr\{Y < 2-k\} = \Phi\Big(\frac{2-k-2\,R}{\sqrt{2}\,\sigma}\Big). \tag{2}$$

The aggregate expected profit of the bank then equals the expected return, the net of refinancing costs and the expected cost of financial distress,

$$\begin{aligned}\Pi &= 2\,R - d\,r_d - k\,(1+\phi\,k/2) - \phi\,k^2/2 - c\,\big(\rho^2\,\mathrm{PD}_1 + (1-\rho^2)\,\mathrm{PD}_0\big)\\ &= 2\,R - 2 - \phi\,k^2/2 - c\,\big(\rho^2\,\mathrm{PD}_1 + (1-\rho^2)\,\mathrm{PD}_0\big).\end{aligned} \tag{3}$$

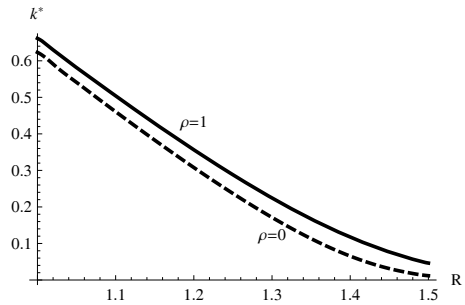
The bank will choose the buffer k to maximize the expected profits,

$$\begin{aligned}\frac{\partial\Pi}{\partial k} &= -\phi\,k^* + \frac{c}{2\sqrt{2\,\pi}\,\sigma}\,\big(\rho^2\,X + \sqrt{2}\,(1-\rho^2)\,X^2\big) = 0, \quad \text{where}\\ X &= \exp\Big(-\frac{(2-k^*-2\,R)^2}{8\,\sigma^2}\Big)\end{aligned} \tag{4}$$

is an auxiliary variable. There is no algebraic solution to this implicit equation. However, the implicit function theorem can be used to compute some comparative statics. Most importantly to this study, $\partial k^*/\partial R < 0$. The more competition between banks, the smaller their interest margins, and the smaller the R, the more buffers banks need to hold against financial distress. Second, $\partial k^*/\partial\rho > 0$. In the absence of credit portfolio management, banks do not know the exact correlation structure of their loan portfolio. However, if the sector concentration is high, the probability of a correlated portfolio is large, hence, the bank will hold higher buffers. The following figure 1 shows the optimal k^* depending on R for the extreme cases of $\rho = 1$ and $\rho = 0$. In the numerical example, $c = 10$, $\phi = 2$,

and $\sigma = 0.2$. This numerical example will be used throughout this modelling section. For different parameter values, the picture still appears qualitatively identical.

Figure 1: Optimal capital buffer k^* depending on competition and correlation



In equilibrium, the bank will adjust its buffers to the optimum k^*. The expected profits will depend positively on R, for two reasons. First, A higher R directly increases bank profits. Second, it allows banks to reduce costly buffers. Furthermore, expected profits depend negatively on the sector concentration ρ. A higher ρ increases the probability of distress and forces banks to hold more buffers.

Credit Portfolio Modelling. By implementing a credit portfolio model (CPM), banks find out the correlation within their loan portfolio. In other words, they determine whether each of the loans is in the discrete sector. We aim to calculate the benefit of this piece of information. With probability ρ^2, the banks will find that both loans are in the discrete sector, hence, they are perfectly correlated. The probability of default is then PD_1, as defined above. The bank will then maximize the expected profit

$$\Pi_1 = 2\,R - 2 - \phi\,k^2/2 - c\,\mathrm{PD}_1, \tag{5}$$

which is maximized for k_1^*, as defined by

$$\frac{\partial \Pi_1}{\partial k} = -\phi\,k_1^* + \frac{c}{2\sqrt{2\,\pi}\,\sigma}\,X = 0, \tag{6}$$

where X is the auxiliary variable defined in (4). If, with probability $1-\rho^2$, the bank finds that the loans are uncorrelated, the probability of default is PD_0, as defined above. The expected profit is $\Pi_0 = 2\,R - 2 - \phi\,k^2/2 - c\,\mathrm{PD}_0$, and the bank can reduce the buffer to k_0^*, according to the first order condition

$$\frac{\partial \Pi_0}{\partial k} = -\phi\,k_0^* + \frac{c}{2\sqrt{2\,\pi}\,\sigma}\,\sqrt{2}\,X^2 = 0. \tag{7}$$

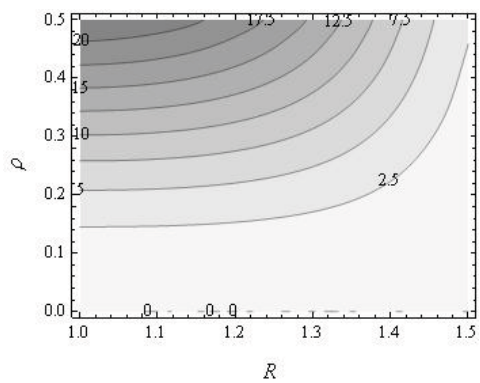
Ex ante, the expected profit is then the average of Π_1 and Π_0,

$$\Pi_{\text{CPM}} = \rho^2 \, \Pi_1 + (1 - \rho^2) \, \Pi_0. \tag{8}$$

Thus, the benefit of credit portfolio modeling equals the difference between the expected profits with and without the information about correlations. Some facts are intuitive. For example, if $\rho = 0$, then all the loans in a loan portfolio must be uncorrelated. Consequently, the correlation structure is already known, and the value added by further information is zero. For $\rho = 1$, all the loans in a portfolio are perfectly correlated, and nothing more can be learned. Again, the value of additional information is zero. Third, the value of the information can never be negative.

Figure 2 demonstrates the difference between the expected profits for different degrees of competition and sector concentration in a contour plot. On each contour, the benefit is constant. The difference in profits is plotted on the contours (multiplied by a factor of 1000 for readability). White shading means that additional profits are small, dark gray implies that the additional profits are large, and the bank will be eager to implement CPM.

Figure 2: Difference in profits, credit portfolio modelling (CPM) vs. benchmark



There are two apparent properties. *First*, CPM is especially valuable if competition is large, hence, R is small. If R is large, the probability of distress is small even in the absence of buffers. Regardless of whether the portfolio is correlated, the bank will hold only small buffers. Therefore, the impact of CPM information on the bank's behavior will be marginal. As a consequence, the information is not valuable. In contrast, if competition is high, the bank will likely suffer financial distress, and it will hold large buffers to insure against distress. By learning that its portfolio is relatively balanced, the bank can save a major fraction of these buffers. Hence, the CPM information is valuable if competition is high.

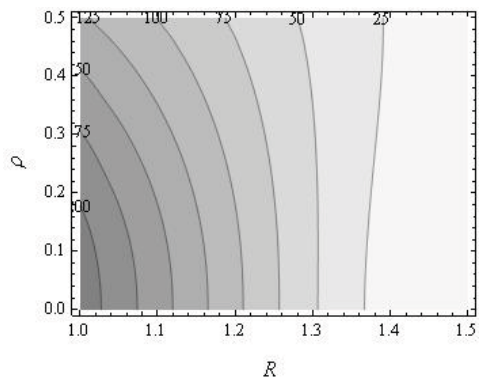
Second, CPM is especially valuable if the sector concentration is large. The reason, as mentioned above, is that for $\rho = 0$, the correlation structure can be guessed even in the absence of CPM. (The same would true for $\rho = 1$, but given that ρ^2 equals the sector Herfindahl-Hirschman index, ρ will realistically be closer to 0 than to 1., Therefore, we have plotted figure 2 only for $0 \leq \rho \leq 1$.) Hence, the larger the sector concentration, the more can be learned about the portfolio structure, and the more valuable CPM becomes. We arrive at the following proposition, delivering two hypotheses that will be tested in the empirical section of the paper. The proof is in C.

Proposition 1 (Credit Portfolio Modeling). *CPM is more desirable when competition is high. For small ρ, CPM is more desirable for larger sector concentrations.*

Credit Risk Transfer. Assume now that banks can implement a credit risk transfer (CRT) technology. By doing so, banks can securitize some part of each loan. Doing so, they can increase the number of loans they can grant. We assume ad hoc that this process cannot be driven *ad infinitum*, otherwise banks would end up with perfectly diversified portfolios. Assume that half of each loan can be securitized, such that the number of loans doubles. By using CRT, the asset side of the balance sheet will consist of four "half" loans. With the correlation structure as before, there are five different possible constellations. All the loans can come from the discrete sector (probability ρ^4), all but one loan can come from the discrete sector (probability $4\,\rho^3\,(1-\rho)$), all but two loans can come from the discrete sector (probability $6\,\rho^2\,(1-\rho)^2$), only one loan can come from the discrete sector (probability $4\,\rho\,(1-\rho)^3$), and all loans can stem from the continuum of sectors (probability $(1-\rho)^4$). In the latter two cases, all the loans are stochastically independent, so with probability $4\,\rho\,(1-\rho)^3 + (1-\rho)^4$, the portfolio has maximal diversification. Depending on the correlation structure, the probability of default will differ. In the absence of credit portfolio modelling (CPM), however, the bank cannot adjust buffers to the different scenarios. In the first scenario (probability ρ^4), the standard deviation of the portfolio is $2\,\sigma$, hence, the probability of default is $\Pr\{Y < 2-k\} = \Phi\big(\frac{2-k-2\,R}{2\,\sigma}\big)$. In the second scenario (probability $4\,\rho^3\,(1-\rho)$), three loans are correlated, the fourth is independent. The standard deviation is $\sqrt{(3\,\sigma/2)^2 + (\sigma/2)^2} = \sqrt{5/2}\,\sigma$, and accordingly, the probability of default is $\Phi\big(\frac{2-k-2\,R}{\sqrt{5/2}\,\sigma}\big)$. In the third scenario (probability $6\,\rho^2\,(1-\rho)^2$), two loans are correlated, and all others are mutually independent. The standard deviation is $\sqrt{(2\,\sigma/2)^2 + (\sigma/2)^2 + (\sigma/2)^2} = \sqrt{3/2}\,\sigma$, and the probability of default is $\Phi\big(\frac{2-k-2\,R}{\sqrt{3/2}\,\sigma}\big)$. Finally, with four independent loans (probability $4\,\rho\,(1-\rho)^3 + (1-\rho)^4$), the standard deviation is $\sqrt{(\sigma/2)^2 + (\sigma/2)^2 + (\sigma/2)^2 + (\sigma/2)^2} = \sigma$, and the probability of default accordingly. Taking these default probabilities into account, the bank will set the optimal buffer k^*. Inserting this into the profit function and comparing it with the expected profits

in the benchmark case, we can plot the following figure 3. Again, dark gray denotes for large benefits of CRT, and white denotes for small benefits. Note that a more diversified portfolio always has a smaller probability of default. Therefore, the bank can economize on buffers. Hence, the profits with CRT always exceed those in the benchmark case.

Figure 3: Difference in profits, credit risk transfer (CRT) vs. benchmark



We observe a number of further regularities. *First*, the higher the competition, the lower R is, the more beneficial credit risk transfer becomes. The intuition is similar to that for CPM. If R is rather large, then the probability of default is small even in the absence of CRT. CRT then lowers the probability of default even further. However, given that the PD is already at a low level, the benefit cannot be large. Hence, if competition is low, there is not much scope for large benefits from CRT. In the figure, the shading is white for large R. For smaller R, the argument goes in the opposite direction, hence, the benefits from CRT can be large, and the shading in the numerical example is darker.

Second, the benefit of CRT is highest if sector concentration is low. To understand why, take the extreme of $\rho = 1$. Then, both loans are perfectly correlated with probability 1. If these loans are securitized, the two new loans will also be perfectly correlated. The correlation structure is unchanged by CRT. Thus for $\rho = 1$, the benefit of CRT is exactly zero. The lower the sector concentration, the larger the benefit of CRT is because the probability of arriving at a balanced portfolio becomes larger. Therefore, we have darker shading especially for low degrees of ρ. Again, we arrive at a proposition containing two hypotheses, which will be tested in the empirical section of the paper.

Proposition 2 (Credit Risk Transfer). *CRT is more desirable when competition is high. For small ρ, CRT is more desirable for a smaller sector concentration.*

Active Risk Management. We have considered the benefits to banks of gathering information about their portfolio structure (CPM), and diversifying to reduce the granularity of their loan portfolio (CRT). Now let us define active risk management (ARM) as the choice to implement both. In our model, this is the most sophisticated level of risk management: risk is measured and diversified, and the buffers are adjusted. Using ARM, a bank can learn exactly how its portfolio is structured within its portfolio, ending up in four cases, as discussed above. All four loans can be correlated, all but one can be correlated, all but two can be correlated, or all may be uncorrelated. The bank will then adjust the buffer accordingly. In the first case, the buffer will be relatively high, and in the last case, it will be relatively low. Calculating the profits in all four scenarios, weighting them with the according probabilities, and calculating the aggregate expected profits, we can calculate the benefits of ARM in comparison to the second-best alternative. Because CRT and CPM always dominate the benchmark case, only CRT or CPM can be the best alternative. The numerical simulation results in the following figure 4.

Figure 4: Difference in profits, active risk management (ARM) vs. best alternative

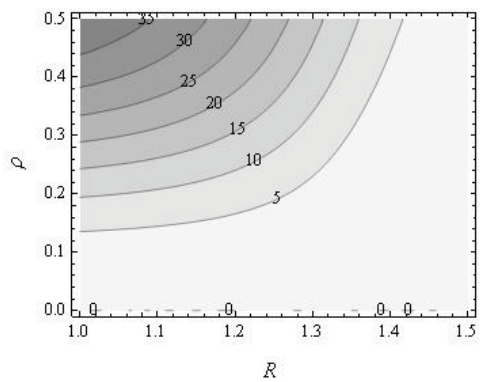


Figure 4 demonstrates a couple of regularities. First, and under the same reasoning used previously, a higher level of competition (low R) implies larger benefits of active risk management (ARM). If R is large, the probability of distress is small in the first place, so risk management cannot have large benefits. Second, the value added of ARM is larger for larger sector concentration. If the sector concentration is low, then the correlation structure is obvious to the banker, and all the loans must be uncorrelated. Consequently, ARM must be equally as beneficial as CRT. The same argument applies for $\rho = 1$, but because ρ^2 gives the sector Herfindahl-Hirschmann index, $\rho = 1$ would be unrealistically high. We arrive at two hypotheses, to be tested in the empirical section of the paper.

Proposition 3 (Active Risk Management). *ARM is more desirable when competition is high. For small ρ, ARM is more desirable for a larger sector concentration.*

3. Institutional Background

This section provides background information on the credit risk management of the banks in our sample. The banks in the sample are public banks belonging to the German Savings Banks Finance Group – the *Sparkassen-Finanzgruppe*. This banking group constitutes one pillar of the German "three-pillar" banking system. The other two pillars are private banks and cooperative banks. The public banks are legally and economically independent institutions. In their municipalities they provide financial services to retail customers and small and medium-sized enterprises, which is referred to as the "regional principle". This principle implies that individual banks are expected to conduct business only within the defined region in which they operate and are not allowed to expand their business to other regions.

The German Savings Banks Association (DSGV) is the umbrella organization of the German Savings Banks Finance Group and represents the interests of the group. It is responsible for realizing economies of scale in the infrastructure, developing standardized financial products and providing business services to all banks within the group.[3] The DSGV developed a standardized approach to determining credit risk by creating a joint internal rating system and introduced it in 2002. All the banks in our sample have implemented the same approved internal rating system. Therefore, all the banks follow similar processes to generate the rating classes. The rating classes are assigned to individual borrowers to indicate their degrees of creditworthiness. There are 18 rating classes, which can be translated to Moody's and Standard & Poor's rating classes. The ratings are used for internal risk management and regulatory capital calculations. The available ratings allow banks to calculate the credit risk on the individual and portfolio levels. In our sample almost all the banks calculate their credit risk using the Standardized Approach.[4]

In principle, the banks may use any credit portfolio model for assessing and managing their risk exposure at the portfolio level. Crouhy et al. (2000) compares various credit portfolio models, such as CreditMetrics, KMV, CreditRisk+ and CreditPortfolioView and concludes that any of these can be considered reasonable internal models. Therefore, credit portfolio models represent a way to actively manage risk at the portfolio level.

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[3]For detailed descriptions and analyses of the German banking sector, see Krahnen and Schmidt (2004). A detailed discussion of the German Savings Banks Finance Group is provided by Schmidt (2009). Further information can be obtained from the German Savings Banks Association (DSGV, 2011).

[4]Only one bank uses the IRB (Internal Ratings Based) Approach. With the Standardized Approach, risk weights are assigned to corporate loans depending on the ratings. The risk weight ranges from 20 to 150 percent.

The majority of the banks in our sample use CreditPorfolioView (McKinsey), which was adapted to the specific needs of the banks in the German Savings Banks Finance Group. This project was conducted by the umbrella organization of the banking group. Moody's (2010) confirms that back-office credit activities benefit from a standardized approach supported by uniform instruments and are available to all banks. Therefore, basically all the banks have the same access to the same product with comparable costs. The cost structure of the use of the portfolio model is twofold. The banks are required to pay a one-time fee when obtaining the model and, in addition, a monthly fee on a regular basis. While the one-time fee is negligibly low, the monthly fee takes the size of the bank into account. Thus, smaller banks are required to pay less than larger banks. Therefore, the adoption of credit portfolio models is also affordable for smaller banks.

CreditPortfolioView considers changes in market values and credit ratings and the model correlates default probabilities with macroeconomic factors (i. e., default frequencies increase during a recession). The model links default statistics with factor models to industry- and country-specific variables. The model is used for the determination of key risk figures. One commonly used risk measure to determine a bank's loan portfolio risk is Value-at-Risk (VaR). With the credit portfolio model, the bank can assess the impact of new loans in existing or new sectors on its overall portfolio risk. On the portfolio level, the default correlation within a credit risk model framework is taken into account. The bank can analyze the impact of rating changes and macro or micro changes. The bank can undertake stress testing on a daily basis or up to once a month, depending on the type of credit exposures in its portfolio, ranging from simple unsecured exposure to more complex products such as structured exposures or securitization to derive appropriate strategies.

Furthermore, banks become involved in active credit risk management by participating in credit risk transfer markets. The banks in our sample either participate in internal risk transfer markets through credit pooling (*Kreditpooling*) or make use of market-based solutions, such as Credit Default Swaps (CDSs) or Collateralized Debt Obligations (CDOs). The banks can participate in the external risk transfer market and in the internal loan pool, both as issuers of risk (protection buyer) and as buyers of risk (protection seller). The inter-regional credit pooling transactions are effected via Credit Linked Notes (CLNs). Since 2002, one credit basket has been issued within the banking group approximately every year. According to Gintschel and Hackethal (2004) banks participating in credit pooling transactions can significantly reduce the risk of loans by diversifying their loan portfolio. The underlying credit risk of the loan remains in the bank's portfolio, hence, the relationships with the participating banks and their customers remain unaffected. From the annual statements of the banks in our sample, it is apparent that credit derivatives are used for both purposes.

Given the theoretical advantages of active risk management through credit portfolio models and credit risk transfer instruments, banks should be inclined to operate these instruments. However, from our sample, we observe that only a limited number of banks adopt these advanced risk management tools. This phenomenon is not unique to our sample. For example, in the U. S. market although the volumes in the derivatives markets are high, only a limited number of banks participate in risk transfer markets. According to the Office of the Comptroller of the Currency (2009), five large commercial banks represent 97 percent of the total U. S. banking industry notional amounts. Moreover, the Joint Forum (2008) of the Bank for International Settlements prepared a report based on a 2008 survey to explore the progress that financial conglomerates have made in identifying, measuring, and managing risk concentration. It is reported that most of the surveyed firms stated that they manage credit risk concentration through traditional methods, such as the use of internal risk limits on exposures to particular obligor names, industry sectors, geographic regions, and product types. In this sense, banks have always been engaged in loan portfolio management. However, traditional methods do not explicitly incorporate the correlation of loan positions as is the case with the advanced technique of credit portfolio modeling. The interdependency of credit risk is measured by correlation. Credit portfolio modeling accounts for that, otherwise the risk of the portfolio could be underestimated. Similarly, Düllmann and Masschelein (2007) find that, for a concentrated portfolio, the required economic capital increases.

4. Empirical Strategy and Descriptive Statistics

This section describes the data and variables we use to test the hypotheses described in the preceding sections. We provide descriptive statistics for the variables used in the empirical analyses.

4.1. Data

For our analyses, we merged three data sets: Banks' balance-sheet and income-statement data, regional economic data and survey data.

We examine a data sample of regional banks operating in a single market area in Germany. In 2008, a total of 438 regional banks existed in Germany, operating in rural and metropolitan areas. We have access to a unique panel data set provided by the German Savings Banks Association (DSGV). Our data includes balance-sheet and income-statement data observed annually and covers the period from 2002 to 2006.

For our analyses, we also used regional economic data provided by the Statistical State Offices available for the 439 administrative districts in Germany.[5]

Additionally, we have conducted a paper questionnaire survey to elicit the necessary information on credit risk management. The survey was conducted in April 2009 and was answered primarily by the top management level. Of 438 questionnaires sent to all savings banks from the German Savings Banks Finance Group, a total of 279 completed questionnaires were returned. This equals a response rate of more than 60 percent. For our analyses we used 249 responses because some banks returned the questionnaire without the front page containing the name of the bank. Banks that had been involved in a merger since 2006 are not included in the sample because no historical data for the new entities are available. Comprising 57 percent of the banks participating in the survey, our sample is highly representative of all regions and asset classes. Because the survey was sent to the entire population of savings banks of the German Savings Banks Group, the analyses are robust in terms of response bias, with a response rate of 57% (63%).

The respondents were asked to provide information on the instruments used in their daily corporate businesses to manage credit risk. The banks were asked to qualify the intensity of their use of different risk management tools as frequent, occasional or no use. A detailed description of the questionnaire can be found in the appendix A.

For our analyses we use data from 2002-2006 for the following reason: In 2002, the banks in our sample adopted a group-wide strategy including large reorganizational activities and introducing standardized approaches to risk management and other business areas. Therefore, we conduct our analyses beginning in 2002, thereby accounting for the structural changes.[6] To avoid measuring any effect caused specifically by the financial crisis, we do not incorporate the years 2007 through 2009. Furthermore, risk management instruments such as CreditPortfolioView or Credit Pooling and the Rating System were first introduced in 2002, partly as a consequence of a group-wide strategy. Successfully acquiring knowledge about operating risk management instruments is a long-term endeavor. Therefore, the choice of risk management tools is likely to be constant over the years for those banks indicating the use of these instruments in the survey.

[5]These administrative districts are classified as level 3, according to the *Nomenclature of Territorial Units for Statistics* (NUTS). This definition allows us to investigate region-specific variables such as the regional GDP, number of inhabitants, and sector concentration.

[6]The savings banks have traditionally benefited from State guarantees, but according t a letter dated April11, 2002, the German government accepted the amendment of the European Commission's proposal for appropriate measures regarding the system of State guarantees to German public banks (see Moser and Soukup, 2002). The discussion of the removal of the State guarantees began much earlier, but with the abolishment of the State guarantees, the restructuring of the public banks was inevitable to guarantee competitiveness.

4.2. Variables

Based on the survey data, we constructed three dependent variables: ARM, CRT and CPM. The dependent variables are a binary variable taking the value 0 for non-use and 1 for the use of advanced credit risk management instruments.

These variables are constructed from the following survey items:

- CRT: Which of the following instruments are used to manage credit risk in daily corporate business?
  – Credit risk transfer (credit pooling)
  – Credit risk transfer (credit derivatives)
- CPM: How intensively does your bank use the results from quantitative credit portfolio analyses (CPV, other) for active management of the credit portfolio?

The intensity of the use of risk management instruments is classifed as no use, occasional use or frequent use.

Risk Management. To construct the dependent variable "Active Risk Management" (ARM) we explore the use of credit portfolio models (CPM) and credit risk transfer (CRT). The dependent variable ARM is said to be one when credit risk transfer (CRT) and credit portfolio models (CPM) are used simultaneously.

The variable credit risk transfer (CRT) is one when either internal markets for credit derivatives (credit pooling) or the market-based solution for credit derivatives is used frequently or occasionally, and it s zero otherwise. Therefore, the credit risk transfer is considered to be one, whether the instrument is used frequently or occasionally. Intuitively, this makes sense, as the frequency of participation in the credit risk transfer market is dependent on the specific business of the bank. Therefore participating in either of these credit risk transfer markets by itself is recognized.

Credit portfolio model (CPM) is said to be one when the quantitative credit portfolio analysis for measuring and managing credit risk is frequently used, and it is zero otherwise. This variable indicates whether the bank employs active portfolio management to derive strategies for its lending business.

To investigate the motivation for active risk management through the use of advanced risk management instruments, we define the following explanatory variables – obtained from banks' balance sheets, banks' income statement data and regional economic data – that appear in the empirical model.

Risk-Return Profile. We proxy the risk-return profile of the bank by measuring the net-interest income to total income (see e. g. Ashraf et al., 2007) and by measuring the ratio of loan loss provisions to total assets (see e. g. Minton et al., 2009). We consider net-interest income because the income is directly related to the bank's lending business. Banks‘ motivation to participate in risk transfer markets is due either to hedging to reduce risk exposure or the goal of generating fee income by selling risk management services. Banks concerned with profits may have an incentive to use credit derivatives toward profit creation rather than pure risk hedging. Furthermore, banks can manage the risk-return profiles of their portfolios through active portfolio management. Banks may engage in active risk management to generate additional profits and/or reduce risk exposure. Therefore, we expect banks with less interest income and higher loan loss provisions to be more likely to involve themselves in active credit risk management.

Capital adequacy. We include the equity to total asset ratio (see e. g. Minton et al., 2009). Becaue banks face regulations such as capital requirements, which are dependent on the risk of assets, the use of advanced instruments that allow banks to measure and manage risk become important. Banks must maintain adequate capital to have a sufficient buffer for unexpected losses. However, it is not a bank's interest to hold capital in excess of the regulatory requirements because capital is costly and could otherwise be used to expand the lending business. Therefore, it is important to the banks and the regulatory authorities that the optimal level of capital is estimated precisely. The adoption of credit portfolio models can enhance the quality of risk management. Credit risk transfer facilitates the cost-effective use of capital. By fine-tuning the compositions of their loan portfolios through participating in credit risk transfer markets and credit portfolio modeling banks can influence their amounts of capital. The motivation to engage in active risk management should be influenced by the level of equity available to each bank.

Portfolio concentration. The Herfindahl-Hirschman-Index is used to estimate the sector concentration in region i for banks i and is calculated as

$$\mathrm{SHHI(x)}_i = \sum_{n=j}^{N} \mathrm{x}_j^2 \tag{9}$$

where x_j is the share of the number of firms conducting business by the sectors j over all the firms in the region i as of 2005.[7]

[7] According to the Statistical Classification of Economic Activities in the European Community twelve sectors are specified: (i) Mining and Quarrying, (ii) Manufacturing, (iii) Electricity, Gas, Steam and Air

Given that the banks in our sample conduct business in a defined regional area, the sector concentration in the respective region proxies the lending portfolio of each bank.

A bank with a concentrated loan portfolio will typically be more risky. Credit risk concentration has played a critical role in past bank failures in mature economies. The Basel Committee on Banking Supervision (2004) studied the patterns of bank failures in highly developed economies with long-functioning banking systems that were exposed to significant bank failures or banking crises during the past 30 years. They found that credit concentration risk was cited in nine of 13 bank failures. Involvement in active risk management (ARM) may prevent risk concentration in the loan business.[8] Düllmann and Masschelein (2007) claim that it is necessary to take inter-sector dependency into account in the measurement of credit risk. Credit portfolio models account for this. According to Batten and Hogan (2002) credit derivatives have a much more flexible approach to managing the risks associated with concentration. Both advanced instruments can be used to manage credit risk in the way that a lending portfolio is diversified by reducing its credit risk concentration. We expect banks with credit risk concentration proxied by sector concentration to be more likely to be involved in active risk management.

Competition. A broad range of literature exists on the relationship between competition and the risk-taking behavior of banks. One body of literature argues that higher competition can lead to higher risk-taking in a bank (see e. g. Keeley, 1990; Hellmann et al., 2000; Jiménez et al., 2010; Bergstresser, 2008). According to recent studies, higher competition can also lead to less risk-taking by a bank (see e. g. Boyd and De Nicolo, 2005; Boyd and Jalal, 2006). Because risk-taking behavior and the use of risk management instruments should be related, we expect competition to have a significant effect on banks' decisions to be involved in active risk management. Given the relationship between competition and the risk-taking behavior of banks, we expect banks exposed to higher competition to be more likely to be involved in active credit risk management through the use of credit portfolio models and by participating in credit risk transfer markets. We use the Lerner index as a proxy for market power. We construct the Lerner index following Berger et al. (2009). The Lerner index (LERNER) measures how far banks can set prices above their

Conditioning Supply, (iv) Construction, (v) Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles Transportation and Storage, (vi) Accommodation and Food Service Activities, (vii) Transportation and Storage, (viii) Financial and Insurance Activities, (ix) Real Estate Activities, (x) Education, (xi) Human Health and Social Work Activities and (xii) Other Service Activities.

[8]The Deutsche Bundesbank (2006) defines credit risk concentration as "concentration of loans to individual borrowers [...] and an uneven distribution across sectors of industry or geographical regions (sectoral concentration). A further risk category consists of risks arising from a concentration of exposures to enterprises connected with one another through bilateral business relations."

marginal costs and is calculated as

$$\text{LERNER}_{it} = \frac{(P_{it} - \text{MC}_{it})}{P_{it}}. \tag{10}$$

where P_{it} is the price proxied by the ratio of total revenues (interest and non-interest income) to total assets and MC_{it} is the marginal cost, which is derived from the following translog cost function

$$\begin{aligned}\ln \text{Cost}_{it} = \beta_0 + \beta_1 \ln \text{TA}_{it} + \frac{\beta_2}{2} \ln \text{TA}_{it}{}^2 + \sum_{k=1}^{3} \gamma_{kt} \ln W_{k,it} + \sum_{k=1}^{3} \phi_k \ln \text{TA}_{it} \ln W_{k,it} \\ + \sum_{k=1}^{3} \sum_{j=1}^{3} \ln W_{k,it} \ln W_{j,it} + \epsilon_{it}\end{aligned} \tag{11}$$

where banking output is proxied by the total assets TA_{it} (see e. g. Carbo et al., 2009), and three input prices $W_{k,it}$ are defined as the ratio of personnel expenses to total assets (price of labor), the ratio of interest expenses to total deposits (price of funding) and the ratio of operating and administrative expenses to total assets (price of capital). We estimate the equation by introducing year-fixed and bank-specific effects with robust standard errors using panel data covering all the banks from 1996 to 2006. We average the Lerner index for the observation period because we are interested in the competitive stance of the bank.

Size. We proxy bank size by total assets. Because the adoption of advanced credit risk management tools is associated with the size of the bank, larger banks are more likely to have the required resources to be involved in active risk management (see e. g. Booth et al., 1984; Kim and Koppenhaver, 1993). Moreover, Memmel et al. (2007) provide empirical evidence assessing the determinants of relationship banking in Germany. They find that the number of relationships within a bank declines with size. Therefore, increasing the opaqueness of their clients may induce banks to use advanced credit risk instruments. Accordingly, we expect the size of the bank to have a significant effect on banks' decisions to engage in active risk management. To allow for nonlinearities between size and the use of risk management instruments we define four asset classes following Cebenoyan and Strahan (2004) and Demsetz (2000). The smallest quartile acts as the omitted category.

Lending structure. The lending structure is proxied by the ratio of corporate loans over total non-bank loans. A bank's decision to engage in active risk management might be related to its loan exposure.

Funding structure. The funding structure is measured by the total deposits over the total non-bank loans.

Earnings in the region. We account for regional characteristics on the bank level and include regional indicators in our model, such as regional earnings calculated by GDP per capita. An East dummy indicates whether the bank is located in East-Germany.

In view of the above arguments we conclude that the risk-return structure of a bank, regional and market conditions and banks' ability to operate their businesses may lead banks to become involved in active risk management.

4.3. Descriptive Statistics

This section provides descriptive statistics on the banks in our sample. Summary statistics and correlation analysis are presented.

We present the mean values of the variables we use throughout our analyses in Table 1. We have observations for 249 banks on hand. We calculate the mean values of the variables for the period between 2002 and 2006. We report descriptive statistics for the banks' net interest incomes and loan loss provisions. We present other bank-specific variables, such as banks' total assets, banks' equity to assets ratio, the ratio of corporate loans to total non-bank loans and the ratio of total deposits to total non-bank loans. We further report descriptive statistics for regional economic indicators, i. e., GDP per capita for each region and the Herfindahl-Hirschman Index for sector concentration per region. We derive the Lerner index to capture the competitive stance of each bank in the region. We conduct our analyses using these variables on the right-hand side of our empirical model.

The descriptive statistics in Table 1 show that differences exist across the banks in our sample, despite the fact that we investigate homogeneous banks relative to their business model.

The German banking sector is highly competitive. Carbo et al. (2009) estimates the average Lerner index for Germany for the period 1995 through 2001 to be 14%, while Fernandez de Guevara et al. (2007) estimates a Lerner index between 10.63% and 13.65% for the period 1993 through2000. Koetter and Wedow (2010) estimates a Lerner index of 23 percent for the period 1995 through 2005, while Carbo Valverde and Rodriguez Fernandez (2007) provides a Lerner index of 35% for the period 1994 through 2001 for the German banking sector. Fernandez de Guevara et al. (2007) show that inequalities in the levels of competition exist among the banking groups in Europe and that banks with greater traditional deposits and loan activities enjoy higher and increasing margins. Following that line of argument, it is not surprising that the estimated Lerner index for the average bank in our sample is higher than the average Lerner index of the entire German banking sector, which includes all banking groups, such as investment banks and specialized

Table 1: Summary Statistics

Table 1 presents the values of banks' characteristics, performance measures and regional characteristics for the five years between 2002 and 2006. The sample comprises a total of 249 banks. Total assets (TA) are in millions of EUR. Equity is the banks equity to asset ratio. NIM measures the banks' net interest income over their total income. Loan Loss Provisions is the ratio of loan loss provisions over total assets. Corporate Loans is the ratio of total corporate loans to total non-bank loans. Deposits is measured by the total deposits over total non-bank loans. GDP is the GDP per capita for each region. SHHI is the Herfindahl-Hirschman Index for the sector concentration in each region. LERNER indices measure how far banks can set prices above their marginal costs.

	mean	**sd**	**min**	**max**
LERNER	0.2861	0.0710	0.0887	0.4517
SHHI	0.1583	0.0133	0.1312	0.2155
NIM	0.4264	0.0426	0.2920	0.5821
Loan Loss Provisions	0.0206	0.0103	0.0006	0.0750
Total Assets	2447.5	3170.9	161.7	29344.9
Corporate Loans	0.3126	0.0684	0.1067	0.6062
Equity	0.0469	0.0095	0.0231	0.0907
Deposits	0.5581	0.2348	0.1487	1.6966
GDP	24.2540	7.8501	12.6179	77.0719
Observations	249			

banks. The banks in our sample are active in the traditional deposit and loan business and enjoy higher market power.

Table 2 shows that a correlation exists among the uses of the different credit risk management instruments. We compare credit risk transfer instruments (CRT) and the credit portfolio model (CPM). The use of credit risk transfer instruments is significantly and positively correlated with the use of credit portfolio models. Table 8 in B reports correlation coefficients for the explanatory variables used in the regressions.

Table 2: Pearson correlations of dependent variables

Table 2 shows the correlation matrix of advanced credit risk management instruments. *, **, and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

	CRT	CPM
CRT	1	
CPM	0.0795**	1

Table 3 depicts the distribution of the instruments. In our sample, 41 banks employ active portfolio management in the sense of actually deriving strategies for their lending businesses. Table 3 shows that the intensive use of advanced risk management instruments is not widespread among banks. There are fewer users than non-users of these instruments. Credit risk transfer instruments (CRT) and credit portfolio models (CPM) are seldom used simultaneously.

Table 3: Number of Banks

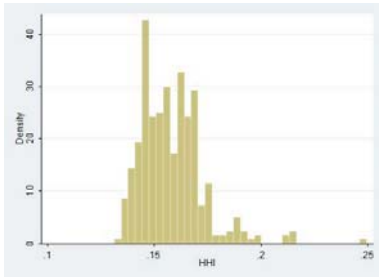
Table 3 presents the number of banks using advanced credit risk management instruments.

Instruments	**Usage**	**Non-Usage**
Credit Portfolio Models (CPM)	41	208
Credit Risk Transfer (CRT)	88	161
CRT and CPM (ARM)	18	231

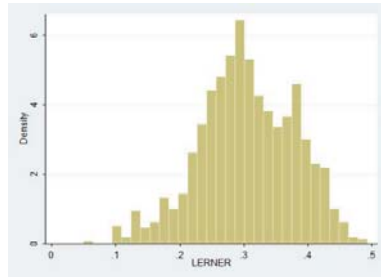
The graphs depic the distribution of the Herfindahl-Hirschman-index for sector concentration (SHHI) and the LERNER index for bank competition.

5. Empirical Analyses

In this section we introduce the empirical model. We estimate a probit model for the period 2002 through 2006 and account for robust standard errors. The results for active risk management are provided, and further results and sensitivity analyses are presented.



(a) Sector concentration



(b) Lerner

5.1. Empirical Model

This subsection presents the empirical results. Our theoretical model predicts that active risk management is profitable, especially if competition is high and R is low. Additionally, active risk management is profitable, especially if the sectors are concentrated.

We define a dummy variable as the dependent variable. The dependent variable is coded "1" for banks engaging in active credit risk management and "0" otherwise. The results tables report the marginal effect, and the coefficient represents the change in the probability associated with moving the dependent variable from 0 to 1.

We estimate the following empirical model.

$$\begin{aligned}\mathrm{ARM}_i = \beta_0 + \beta_1\,\mathrm{NIM}_i + \beta_2\,\mathrm{LLP}_i + \beta_3\,\mathrm{EA}_i + \beta_4\,\mathrm{CORP}_i + \beta_5\,\mathrm{TA}_i + \beta_6\,\mathrm{DL}_i \\ + \beta_7\,\mathrm{EAST}_i + \beta_8\,\mathrm{GDP}_i + \beta_9\,\mathrm{SHHI}_i + \beta_{10}\,\mathrm{LERNER}_i + \epsilon_i \end{aligned} \tag{12}$$

where ARMi is the binary dependent variable, NIM_i is the net interest income ratio, LLP_i is the loan loss provisions ratio, EA_i represents for the equity ratio, CORP_i is the total corporate loans over nonbank loans, TA_i represents the four asset classes, DL_i is the deposits over the total nonbank loans, GDP_i is the GDP per capita, SHHI_i is the sector concentration in the region and LERNER_i measures the market power. EAST is a dummy for East-Germany.

In conducting the analyses, we do not explicitly address endogeneity issues with our model. The presence of endogenous explanatory variables on the right-hand side would bias the results.[9] Nevertheless, we are convinced that the endogeneity problems are not

[9]Commonly, endogeneity issues are addressed by applying instrumental variables (IVs) with a two-step estimator for continuous regressors and binary dependent variables (Newey, 1987). However, this approach is not applicable to our analyses. If we suspect endogeneity in the model, then we must expect all the right -hand regressors to be potentially endogenous. Finding valid instrumental variables is a challenge, and to obtain good IVs for more than one endogenous regressor in the model appears nearly impossible. The System GMM method would address the problem of all the right-hand variables to be

severe in our model. First, the empirical model is based on a theoretical model with clear causality. It is more convincing to view competition as the determinant for the use of risk management instruments than the other way around. An individual banks' decision to use a particular risk management instrument should not have the power to affect bank competition in a region to any considerable and measurable extent. Second, the dependent variable was observed in 2009 wheras the right-hand variables are observations made during the time period 2002-2006. The distance in time also prohibits severe endogeneity issues: the right- and left-hand side variables are observed at different points in time. Therefore, the estimators provide consistent results. This implies that competition and sector concentration causally influence the use of risk management instruments.

5.2. Empirical Results – Active Risk Management (ARM)

Considering banks that engage in active risk management – meaning the simultaneous use of credit risk transfer and credit portfolio models to manage credit risk – we observe that only a small number of banks employ these instruments: only 18 banks in our sample of 249 use both instruments intensively. What is special about these banks? To answer this question, we first provide descriptive statistics of these 18 banks in Table 4.

From Table 4, we can see that in particular larger banks engage in active risk management. Concerning total assets, these banks are on average twice as large as the mean bank in our sample. It is also apparent that banks engaging in active risk management have considerably less market power and higher sector concentration. Banks net interest income and GDP per capita also differ significantly.

To draw conclusions from the structure of these banks for the determinants of engaging in active risk management we test the relationship among bank characteristics and market and regional aspects and the use of advanced instruments for active risk management.

We investigate the relationship of active risk management with respect to the banks' characteristics and regional and market conditions. We apply a standard probit regression model to cross-sectional data and account for robust standard errors.

In Table 5, we present the results of the probit regressions investigating banks' motivation to engage in active risk management. In the first column of Table 5, we relate active risk management to bank characteristic variables and GDP per capita, controlling for East-Germany on the right-hand side. We find that the probit estimations show significant

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potentially endogenous in using IVs from the information set of the model. However, this method would not be applicable to our analyses, becuse the dependent variable is not a continuous variable and does not change over time.

Table 4: t-Statistics for selected banks

Table 4 depicts the difference between the mean values of the selected banks' characteristics and the market and regional characteristics calculated for the five years from 2002 to 2006. The sample comprises a total of 18 banks that engage in active risk management (ARM) and 231 banks that do not engage in active risk management, but in traditional risk management (RM). Total assets (TA) are in billions of EUR. NIM measures the banks' net interest income over total income. Corporate Loans is the ratio of total corporate loans to total non-bank loans. Deposits are measured by total deposits over total non-bank loans. SHHI is the Herfindahl-Hirschman Index for sector concentration in each region. LERNER indices measure how far banks can set prices above their marginal costs.

	RM	ARM	Diff	p-Value
LERNER	0.29	0.22	0.07	0.00
SHHI	0.16	0.17	-0.01	0.00
NIM	0.43	0.41	0.02	0.00
Loan Loss Provisions	0.02	0.02	-0.00	0.08
Total Assets	2.25	4.96	-2.71	0.00
Corporate Loans	0.31	0.32	-0.00	0.57
Equity	0.05	0.04	0.00	0.00
Deposits	0.56	0.55	0.01	0.82
GDP	23.75	30.69	-6.93	0.00

results for the GDP, suggesting that banks operating in regions with higher economic power are more likely to adopt advanced instruments for active risk management.

By adding regional and market characteristics to the equation we find competition in column 2 and sector concentration in column 3 to have a crucial effect on banks' decisions to engage in active risk management. The results suggest that a marginal increase in sector concentration, as measured by the Herfindahl-Hirschman index from an average of 0.16, results in a 273 percent increase in the likelihood of participating in the use of advanced instruments for active risk management.

A marginal increase in market power as measured by the Lerner index from the average of 0.28 results in an 81 percent decrease in the likelihood of participating in the use of sophisticated credit risk instruments. An increase in the Lerner index, which is equivalent to a diminishing level of competition, is associated with a decrease in the likelihood of involvement in active risk management (column 2). Differently expressed, higher competition leads banks to engage in active risk management.

Adding both sector concentration and competition to the equation proves to have a significant effect on the full model in the last column. The Lerner index enters at the 1% significance level while the sector concentration enters at the 10% significance level. This result is quite revealing, and our findings are well in line with the studies by Khand-

Table 5: Active Risk Management

Table 5 presents the result of the probit regression investigating banks' motivation to engage in active credit risk management. The dependent variable is a binary variable, taking the values 0 for non-usage and 1 for usage. Assets below EUR 847 million is the omitted category for the size indicator variables. We report the marginal effects. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Variable	**(1) ARM**	**(2) ARM**	**(3) ARM**	**(4) ARM**
NIM	-0.5035	-0.1743	-0.6407	-0.2837
	(0.5449)	(0.4771)	(0.5000)	(0.4519)
Loan Loss Provisions	1.0958	0.2075	0.8967	0.0628
	(1.7527)	(1.6220)	(1.5595)	(1.4555)
EUR 0.847 bil < Assets < EUR 1.482 bil	-0.0203	-0.0205	-0.0114	-0.0118
	(0.0354)	(0.0304)	(0.0330)	(0.0281)
EUR 1.482 bil < Assets < EUR 2.906 bil	0.0089	-0.0088	0.0141	-0.0031
	(0.0173)	(0.0147)	(0.0160)	(0.0139)
Assets > EUR 2.906 bil	0.0051	-0.0047	0.0018	-0.0065
	(0.0038)	(0.0040)	(0.0036)	(0.0042)
Corporate Loans	-0.0719	-0.1314	0.0702	-0.0054
	(0.2176)	(0.2038)	(0.2032)	(0.1836)
Equity	-1.0228	-0.4047	-0.3822	0.0748
	(2.0531)	(1.8897)	(1.8689)	(1.7198)
Deposits	0.0755	0.0246	0.1004	0.0546
	(0.0926)	(0.0828)	(0.0879)	(0.0792)
EAST	-0.0204	0.0444	-0.0053	0.0543
	(0.0617)	(0.1117)	(0.0731)	(0.1220)
GDP	0.0025*	0.0020	0.0007	0.0006
	(0.0015)	(0.0012)	(0.0015)	(0.0012)
SHHI			2.7354**	2.1487*
			(1.1893)	(1.1050)
LERNER		-0.8107***		-0.7299***
		(0.2773)		(0.2629)
pseudo R2	0.1135	0.1746	0.1464	0.2031
log pseudolikelihood	-57.2843	-53.3372	-55.1575	-51.4976
Wald	28.4022	38.2909	29.3690	34.8127
N	249	249	249	249

walla (1972) and Khandwalla (1973), confirming that firms under competitive pressure use controls more extensively and more selectively.

The interaction between competition and sector concentration appears to have relevance. Cetorelli and Strahan (2006) points to a potential trade-off between banking competition in the market and industry concentration. They suggest that banks are likely to restrict the market with respect to new entrants. Given increased competition through new entries, the market participants' profitability may be endangered. Thus, it is not surprising that banks influence the sector structure in the region.

Interestingly, bank variables do not enter significantly into our regression. In some respects, this is not surprising because the univariate analysis in Table 4 has already shown that the bank variables differ only slightly between the two groups. However, regional and market indicators differ more. The multivariate analyses in Table 5 are in line with the first results. Thus, our results demonstrate that regional and market indicators seem to be of crucial importance regarding banks' decisions to engage in active risk management.

In line with proposition 3, we find strong empirical evidence that both competition and sector concentration are positively related to active risk management. It appears that the depth of implementation and the integration of active risk management instruments are primarily influenced by competition. When we examine the separate effects of each risk management instrument, our results confirm that competition is the dominant driver for the decision to engage in active risk management instruments which will be presented in the next section.

5.3. Further Results

Credit Portfolio Management (CPM). Up to this point, we have investigated banks‘ motivation to engage in active risk management through the use of advanced risk management instruments. To acquire a better understanding of the separate effects of each risk management instrument, we investigate the use of credit portfolio models and the use of credit risk transfer instruments separately.

In Table 6, we present the results of the probit regressions investigating the determinants of the use of credit portfolio models. In the first column of Table 6, we relate credit portfolio management to bank characteristic variables and GDP per capita, controlling for East-Germany on the right-hand side. We find that in terms of their total assets, smaller banks are less likely to engage in active credit portfolio management through the intensive use of credit portfolio models. This holds true for the first two model specifications and for the full model.

Adding the Lerner index to the equation in the second model specification, we observe a significant relationship between our dependent variable and the Lerner index. Banks with less market power (higher competition) are more likely to engage in credit portfolio modeling.

As reported in the model specification of column 3 in Table 6, we detect a significant relationship between our dependent variable and sector concentration. Our estimation on the Herfindahl index suggests that an increase in industry sector concentration significantly increases the likelihood of using credit portfolio models. With a higher sector concentration, the bank is more likely to employ credit portfolio models to manage concentration risk. We also find a negative relationship between the net interest income of the bank and our dependent variable. The results on the Lerner index, sector concentration and size remain robust when controlling for all variables in the full model, supporting the hypotheses of proposition 1. In the full model, the size of the bank also has a positive impact on banks' decisions to engage in credit portfolio management.

Credit Risk Transfer (CRT). In Table 7, we present the results of the probit regressions, investigating the determinants of the use of credit risk transfer instruments. In the first column of Table 7 we relate the credit risk transfer to the bank characteristic variables and GDP per capita, controlling for East-Germany on the right-hand side. We find that in terms of their total assets, the largest banks are more likely to be involved in credit risk transfer markets. This holds true for the first and third model specifications.

We find a robust relationship between the lending structure of the bank and the use of credit risk transfer instruments. Banks with higher corporate loans are more likely to participate in credit risk transfer markets.

In line with proposition 2, we find that banks in a more competitive environment are more likely to involve themselves in credit risk transfer. Interestingly, we find no significant relationship between our dependent variable and the sector concentration. However, the sign of the coefficients is negative, as predicted by proposition 2.

Our results provide strong empirical evidence that competition is positively related to the use of credit risk transfer instruments. It appears that a bank's decision to participate in credit risk transfer markets is mainly influenced by competition. The effect of competition appears strongest when we investigate for the participation in credit risk transfer markets. Thus, these results empirically confirm recent research on the competition and credit transfer markets. According to Hakenes and Schnabel (2010), bank competition plays an important role in the development of credit transfer markets.

Table 6: Credit Portfolio Management

Table 6 presents the result of the probit regression investigating the determinants of banks' decisions to engage in credit portfolio modeling. The dependent variable is a binary variable, taking the values 0 for non-usage and 1 for the use of credit portfolio models. Assets below EUR 847 million is the omitted category for the size indicator variables. We report marginal effects. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Variable	**(1) CPM**	**(2) CPM**	**(3) CPM**	**(4) CPM**
NIM	-1.1143	-0.8366	-1.4118*	-1.1195
	(0.8225)	(0.8348)	(0.8244)	(0.8471)
Loan Loss Provisions	2.0255	0.8581	1.6015	0.5065
	(2.6417)	(2.7126)	(2.4860)	(2.6141)
EUR 0.847 bil < Assets < EUR 1.482 bil	-0.1054*	-0.1272**	-0.0909	-0.1121*
	(0.0588)	(0.0583)	(0.0586)	(0.0582)
EUR 1.482 bil < Assets < EUR 2.906 bil	0.0285	-0.0104	0.0369	-0.0000
	(0.0284)	(0.0298)	(0.0280)	(0.0286)
Assets > EUR 2.906 bil	0.0085	-0.0084	0.0007	-0.0150*
	(0.0073)	(0.0085)	(0.0069)	(0.0090)
Corporate Loans	-0.1269	-0.1681	0.2425	0.1975
	(0.3542)	(0.3630)	(0.3340)	(0.3385)
Equity	2.1398	3.2487	3.2661	4.2243
	(3.3397)	(3.3735)	(3.2697)	(3.3064)
Deposits	0.0267	-0.0360	0.0876	0.0302
	(0.1506)	(0.1510)	(0.1459)	(0.1458)
EAST	0.0928	0.2271	0.1480	0.2793
	(0.1467)	(0.1844)	(0.1647)	(0.1954)
GDP	0.0033	0.0031	-0.0008	-0.0005
	(0.0028)	(0.0027)	(0.0029)	(0.0028)
SHHI			6.5451***	6.2717***
			(2.1282)	(2.1026)
LERNER		-1.2357**		-1.1326**
		(0.5097)		(0.5022)
pseudo R2	0.0788	0.1060	0.1186	0.1423
log pseudolikelihood	-102.6049	-99.5763	-98.1746	-95.5370
Wald	19.6665	23.0056	23.3684	24.0065
N	249	249	249	249

Table 7: Credit Risk Transfer

Table 7 presents the result of the probit regression investigating the determinants of the usage of credit risk transfer instruments. The dependent variable is a binary variable, taking the values 0 for non-usage and 1 for the use of the credit derivatives. Assets below EUR 847 million is the omitted category for the size indicator variables. We report the marginal effects. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Variable	**(1) CRT**	**(2) CRT**	**(3) CRT**	**(4) CRT**
NIM	-1.4082	-1.1223	-1.3067	-1.0393
	(1.2350)	(1.2571)	(1.2479)	(1.2648)
Loan Loss Provisions	2.5005	1.1889	2.6225	1.3399
	(3.7720)	(3.8169)	(3.7835)	(3.8261)
EUR 0.847 bil < Assets < EUR 1.482 bil	0.0171	-0.0480	0.0131	-0.0526
	(0.0734)	(0.0750)	(0.0743)	(0.0762)
EUR 1.482 bil < Assets < EUR 2.906 bil	0.0560	-0.0148	0.0534	-0.0170
	(0.0414)	(0.0474)	(0.0415)	(0.0481)
Assets > EUR 2.906 bil	0.0473***	0.0105	0.0526***	0.0149
	(0.0165)	(0.0167)	(0.0177)	(0.0184)
Corporate Loans	1.2946**	1.3082**	1.1281**	1.1632**
	(0.5343)	(0.5267)	(0.5434)	(0.5374)
Equity	-0.9696	0.3254	-1.2688	0.0331
	(4.5278)	(4.5720)	(4.5754)	(4.6209)
Deposits	-0.1334	-0.1990	-0.1650	-0.2258
	(0.2028)	(0.2066)	(0.2064)	(0.2075)
EAST	0.1338	0.2751	0.1187	0.2601
	(0.1755)	(0.1816)	(0.1745)	(0.1826)
GDP	0.0050	0.0059	0.0070	0.0076
	(0.0053)	(0.0048)	(0.0057)	(0.0051)
SHHI			-3.2055	-2.7961
			(3.1387)	(3.1628)
LERNER		-1.7319**		-1.7130**
		(0.7239)		(0.7323)
pseudo R2	0.1323	0.1453	0.1352	0.1476
log pseudolikelihood	-140.3413	-138.2284	-139.8612	-137.8611
Wald	29.8567	41.8145	29.5536	42.5454
N	249	249	249	249

5.4. Sensitivity Analyses

To control for the sensitivity of the main results of active risk management additional analyses were conducted. First, we estimate the empirical model for each year separately for the observation period 2002-2006. The main results remain robust.

Furthermore, we apply different proxies for bank size. In particular, the number of employees and the logarithm of total assets were employed. The size of the bank enters significantly and positively in the model. If we consider the full model, the main results remain robust for the investigation of active risk management.

Moreover, the bank mergers might have an impact on a bank's credit risk management. To control for that issue, we include a dummy variable for a merger in our model. Repeating the analyses, we find consistent results for active risk management.

6. Conclusion

In this paper, we have identified two major forces in the sophistication of credit risk management, from both a theoretical and an empirical perspective: bank competition and sector concentration.

We have modeled a bank that holds a portfolio of two risky assets, each with a volume of 1. We assumed that loans can come from different industrial sectors, and if they are from the same sector, then they are perfectly correlated. By implementing a credit portfolio model, banks discover the correlation within their loan portfolios and can fine-tune their buffers or capital structures to their portfolio structures. Furthermore, banks can engage in credit risk transfer by swapping half of their loan portfolio for the loan portfolio of another bank. With risk transfer, banks can diversify their portfolios. By implementing both risk management instruments (active risk management), banks can diversify and fine-tune their portfolios.

We find that credit portfolio modeling is more desirable when competition is high; it is also more desirable for higher sector concentration. Credit risk transfer is more desirable when competition is high and more desirable for a lower sector concentration. Implementing both risk management instruments, active risk management is desirable when competition is high and it is also desirable for a higher sector concentration.

After deriving these results theoretically, we tested our predictions empirically on a sample of 249 banks of the German Savings Banks Finance Group. We find that bank competition pushes banks to implement credit portfolio modeling and engage in risk transfer markets. Sector concentration on the loan market promotes credit portfolio modeling but inhibits

credit risk transfer. We confirmed the theoretical results empirically. Whereas earlier work has not taken the incorporated view of active risk management into account, instead concentrating on the analysis of separate risk management instruments, our research has applied a more comprehensive approach to active risk management both theoretically and empirically.

Following the argument of our paper, banks' risk management is likely to become even more sophisticated as bank competition continues to increase. Therefore, more attention must be paid to the appropriate development of sophisticated risk management instruments. Both risk managers and bank regulators must evaluate such instruments with caution.

A. Survey structure

The survey was conducted in 2009. The full questionnaire was 10 pages long (including cover). The questionnaire was accompanied by explanatory cover letters from the CEO of the German Savings Banks Association and the academic project team, which assured the confidentiality of the responses. Each questionnaire was printed with the name and address of the bank to allow the responding banks' characteristics to be identified and match with other data sources. The front page included general instructions for completion and the definitions of the terms used in the questionnaire.

The respondents were asked to provide information about the instruments used in their daily corporate business to manage credit risk. We differentiate between the credit risk instruments used to measure credit risk and those used to actively manage credit risk.

The dependent variables are constructed from Question 12 and Question 13 of the questionnaire. The participants indicate the usage intensity of the instruments as frequently, occasionally or no use.

Question 12: Which of the following instruments are used to manage credit risk in daily corporate business?
1– Internal risk limits on exposure to particular obligor names
2– Internal risk limits on exposure to industry sectors
3– Internal risk limits on exposure to asset classes
4– Syndicated loans with Landesbank
5– Syndicated loans with the neighbor savings bank
6– Guaranteed loans by Landesbank
7– Guaranteed loans by other Institutions
8– Loan sales
9– Bonded loans with Landesbank
10– Credit risk transfer (credit pooling)
11– Credit risk transfer (credit derivatives)
12– Other (please list other used instruments if applicable)

Question 13: Credit portfolio modeling.
1– How intensively does your bank use the credit portfolio model "CreditPortfolioView (CPV)" to analyse credit portfolio risk?
2– How intensively does your bank use other credit portfolio models to analyse credit portfolio risk?
3– How intensively does your bank use the results from quantitative credit portfolio analyses (CPV, other) for active management of the credit portfolio?

Original German Questions. **Frage 12: Welche der folgenden Instrumente zur Steuerung von Kreditrisiken werden in Ihrer Sparkasse eingesetzt?**
1– Einhaltung von vorgegebenen Kreditrisikolimits im Hinblick auf eine Kreditvolumenbegrenzung
2– Einhaltung von vorgegebenen Kreditrisikolimits im Hinblick auf Branchenlimits
3– Einhaltung von vorgegebenen Kreditrisikolimits im Hinblick auf eine Größenklassenstruktur
4– Konsortialkreditgeschäfte mit Landesbanken (Barbeteiligung)
5– Konsortialkreditgeschäfte mit Nachbarsparkassen

6– Avalierung durch Landesbanken (Ausfallbürgschaften, Haftungsbeteiligung)
7– Avalierung durch Drittinstitute wie z.B. Bürgschaftsbanken (Ausfallbürgschaft)
8– Verkauf von Kreditforderungen
9– Vermittlung von Firmenkrediten an Landesbanken (Schuldscheindarlehen)
10– Kreditpooling (Basket-Transaktionen)
11– Kreditderivate (Einzelkreditabsicherung z.B. über Credit Default Swaps, S-Port)
12– Andere (bitte angeben welche)

Frage 13: Kreditportfoliomodell.
1– Wie intensiv nutzt Ihre Sparkasse das Kreditportfoliomodell "Credit Portfolio View" (CPV) zur Analyse der Risiken im Kreditportfolio?
2– Wie intensiv nutzt Ihre Sparkasse andere Kreditportfoliomodelle zur Analyse der Risiken im Kreditportfolio?
3– Mit welcher Intensität verwendet Ihre Sparkasse die Ergebnisse aus der quantitativen Kreditportfolioanalyse (CPV, andere) zur aktiven Steuerung des Kreditportfolios?

B. Additional Tables

Table 8: Pearson correlations of explanatory variables

Table 8 shows the correlation coefficients for explanatory variables used in the probit regressions. *, **, and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

	NII	LLP	EA	CORP	TA	DL	CI	GDP	SHHI	LERNER
NII	1									
LLP	0.0366	1								
EA	0.239***	-0.255***	1							
CORP	-0.173***	0.219***	-0.00949	1						
TA	-0.224***	0.0672*	-0.0982***	0.129***	1					
DL	0.437***	0.0523	-0.186***	-0.113***	-0.0625*	1				
CI	-0.262***	0.0930**	-0.119***	0.0202	-0.0548	-0.0121	1			
GDP	-0.248***	0.0167	0.0256	0.0624*	0.431***	-0.212***	0.0262	1		
SHHI	-0.200***	-0.0551	-0.00945	-0.161***	0.429***	-0.226***	-0.133***	0.510***	1	
LERNER	0.251***	0.0703*	0.111***	-0.0521	0.343***	0.281***	-0.637***	0.00745	0.177***	1

C. Proofs

Proof of Proposition 1 (CPM). In the benchmark case without CPM and, therefore, without further information on the correlation structure, the optimal buffer k^* is given by the first order condition (4), thus

$$\frac{c}{2\sqrt{2\pi}\,\sigma}\left(\rho^2\, e^{-\frac{(2-k^*-2\,R)^2}{8\,\sigma^2}} + \sqrt{2}\,(1-\rho^2)\, e^{-\frac{(2-k^*-2\,R)^2}{4\,\sigma^2}}\right) = \phi\, k^*. \tag{13}$$

The r. h. s. is positive but decreasing in k^*, the l. h. s. is increasing and starts in the origin, hence the solution to (13) is unique and strictly positive. With CPM, the bank knows whether it is in the correlated situation (probability ρ^2), in which case the buffer k_1^* is defined by (6), thus

$$\frac{c}{2\sqrt{2\pi}\,\sigma}\, e^{-\frac{(2-k^*-2\,R)^2}{8\,\sigma^2}} = \phi\, k_1^*. \tag{14}$$

For the reason stated above, the solution for k_1^* is unique and strictly positive. If the bank is in the uncorrelated situation (probability $1-\rho^2$) the buffer k_0^* is defined by (7),

$$\frac{c}{2\sqrt{2\pi}\,\sigma}\,\sqrt{2}\, e^{-\frac{(2-k^*-2\,R)^2}{4\,\sigma^2}} = \phi\, k_0^*, \tag{15}$$

again with unique and strictly positive solution for k_0^*. Because (13) is a convex combination of (14) and (15), the solution must then be between, $k_0^* < k^* < k_1^*$. By implementing CPM, if the bank obtains a negative information (probability ρ^2), it increases its buffer from $k^* to k_1^*$, otherwise, it reduces the buffer to k_0^*.

Let us now discuss some comparative statics. The r. h. s. of all three of the above equations defines bell-shaped curves with the modal point at $k = 2-2\,R$, which is negative because the $R > 1$. As R increases, the bell moves right, so the intersection k^* (or k_1^* or k_2^*) decreases. In the limit $R \to \infty$, the buffer drops to $k^* \to 0$ (and $k_1^* \to 0$ and $k_2^* \to 0$). Consequently, the larger R, the smaller the difference between the buffer levels $k_1^* - k^*$ and $k^* - k_0^*$. Due to the convex (quadratic) shape of $c(k) = \phi\, k^2/2$, the saving of costs depends on the difference between optimal buffer levels. Thus, as R increases, the benefit of CPM is reduced. In the limit of $R \to \infty$, the benefit of CPM converges to zero. This is visible in Figure 2.

Next consider a change in ρ. The values of k_0^* and k_1^* do not depend on ρ, but k^* increases in ρ, with $k^*|_{\rho=0} = k_0^*$ and $k^*|_{\rho=1} = k_1^*$. As a direct consequence, CPM bears zero benefit in the extreme cases $\rho = 0$ and $\rho = 1$, and the benefit is strictly positive in between. Because the benefit is smooth in ρ, it must increase in ρ for small ρ. This is also visible in figure 2. □

Proof of Proposition 2 (CRT). As argued in the main text, if the bank makes use of credit risk transfer, there are four possible constellations for the correlation structure. Aggregate expected profits are

$$\Pi_{\text{CRT}} = 2\,R - 2 - \phi\,k^2/2 - c\,\Big[\rho^4\,\Phi\Big(\frac{2-k-2\,R}{2\,\sigma}\Big) + 4\,\rho^3\,(1-\rho)\,\Phi\Big(\frac{2-k-2\,R}{\sqrt{5/2}\,\sigma}\Big) + 6\,\rho^2\,(1-\rho)^2\,\Phi\Big(\frac{2-k-2\,R}{\sqrt{3/2}\,\sigma}\Big) + (3\,\rho+1)\,(1-\rho^3)\,\Phi\Big(\frac{2-k-2\,R}{\sigma}\Big)\Big] \tag{16}$$

The first order condition is

$$\frac{c}{\sigma\sqrt{\pi}}\Big[\rho^4\frac{X^{8/8}}{\sqrt{8}}+\rho^3(1-\rho)\frac{X^{8/5}}{\sqrt{5}}+6\rho^2(1-\rho)^2\frac{X^{8/3}}{\sqrt{3}} + (3\,\rho+1)(1-\rho^3)\frac{X^{8/2}}{\sqrt{2}}\Big]=\phi k^*, \tag{17}$$

with X defined by (4). Again, the r. h. s. defines a bell-shaped curve with modal point at $k = 2-2\,R < 0$, and the l. h. s. is an increasing straight line through the origin, hence the intersection point k^* is unique and strictly positive. Next, addressing the comparative statics, with the same argument as in proposition 1, $\partial k^*/\partial R < 0$ with in the extreme $k^* \to 0$ for $R \to \infty$. In addition, the PDs in the four constellations converges to zero. The benefit of diversification (CRT) decreases in R, and converges to zero in the limit. This is visible in figure 3.

The argument for an increase in ρ proceeds differently. For a small ρ, only the fourth constellation applies, thus,

$$\Pi_{\text{CRT}} \approx 2\,R - 2 - \phi\,k^2/2 - c\,\Phi\Big(\frac{2-k-2\,R}{\sigma}\Big) \quad \text{and}$$
$$\phi\,k^* \approx \frac{c}{\sigma\,\sqrt{\pi}}\,\frac{X^{8/2}}{\sqrt{2}}. \tag{18}$$

With $\rho \approx 0$, the diversification through CRT is maximal with probability 1. Hence, the reduction in the bank's PD is maximal, in addition, the bank will reduce the buffer k more than with any other ρ. Consequently, the benefit is maximal for $\rho = 0$. Because the benefit is smooth in ρ, it must *de*crease in ρ for a small ρ. Both properties are visible in figure 3. □

Proof of Proposition 3 (ARM). Under ARM, the bank transfers credit risk and diversifies (CRT), in addition, it gathers information on correlations (CPM). There are four constellations. Let us index them as 4, 3, 2 and 1, according to the maximal number of correlated loans in the portfolio. Constellation 4 occurs with ex ante probability ρ^4. Profit function and first order condition are

$$\Pi_{\text{ARM}} = 2\,R - 2 - \phi\,k_4^2/2 - c\,\Phi\Big(\frac{2-k_4-2\,R}{2\,\sigma}\Big) \quad \text{and}$$

$$\phi\, k_4^* = \frac{c}{\sigma\sqrt{\pi}}\, \frac{e^{-\frac{(2-k_4^*-2\,R)^2}{8\,\sigma^2}}}{\sqrt{8}}. \tag{19}$$

The implicit functions defining the optimal buffer levels in the other three scenarios have similar structures, we omit them here to avoid clutter. In equilibrium, $k_4^* > k_3^* > k_2^* > k_1^*$, and the buffer level of a bank using only CRT is between the extremes, $k_4^* > k^* > k_1^*$. Here, the argument that an increase in R renders ARM less beneficial is the same as in the two proofs above. Therefore, let us turn to a change in ρ. Note that to implement ARM, it must be more beneficial than the best alternative, CPM or CRT. Then for a small ρ, we know that CPM is not much better than the benchmark case, whereas the benefits of CRT in comparison with the benchmark are maximized. Therefore, to complete the proof, we need to consider the value added by ARM when compared with CRT. For $\rho \approx 0$, the additional benefit then vanishes. With probability 1, all four loans are mutually independent. Therefore, because the benefit is smooth in ρ, it must increase in ρ for a small ρ. This is also visible in figure 4. □

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