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What influences banks' choice of credit risk management practices? Theory and evidence☆

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ABSTRACT

Banks use different risk management practices with varying levels of sophistication. This paper examines the factors that determine the choice of risk-management practices. In a theoretical model, we identify two main determinants for the choice of risk management tools: bank competition and sector concentration in the loan market. We empirically test the predictions of our model using hand-collected data on the credit risk management of 249 German savings banks. The results are in line with our theory: Competition pushes banks to implement advanced risk management practices. Sector concentration in the loan market promotes credit portfolio modeling, but it inhibits credit risk transfer.

1. Introduction

Credit risk management has evolved immensely in recent decades. Due to advances in information technology, the monitoring of credit risk has improved. Due to financial innovations, risk sharing has become easier to access. Some basic level of risk management is imposed upon banks by financial regulation. Above this basic level, banks can choose whether to gather additional information on credit risk, and whether to share credit risk. The determinants of these choices are virtually unexplored.

At the heart of our paper is our own survey, collecting data on risk management practices of German savings banks. Banks were asked whether they gather information on credit risk (credit portfolio modeling, CPM), whether they mitigate credit risk by pooling loans or with credit derivatives (credit risk transfer, CRT), or both (advanced risk management, ARM). These practices go beyond the risk management mandated by financial regulation.

In this paper, we examine the factors driving banks decision to implement a specific set of risk management instruments. We aim to understand what explains cross-sectional differences in the depth of implementation of risk management in banks. For this purpose, we first construct a model that captures CPM and CRT, and we show under which conditions banks are more prone to implement CPM or CRT, or both. We then test these hypotheses, using our hand-collected data set.

In the model, a bank has a portfolio of two loans of unknown correlation. Using credit portfolio modeling, it can find out the correlation structure, and use this information to adjust its risk buffer, for example liquidity, equity or reserves. Using credit risk transfer, it can pool loans, that way spreading the same aggregate risk over more banks. Advanced risk management means that the banks

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does both. In the model, the higher the sector concentration in the loan market the more valuable the additional information by CPM becomes. However, in a very concentrated region, the additional information by CPM becomes less valuable, as the bank knows about the extreme correlation. With a higher level of competition between banks, it is more costly to build up a buffer, so fine-tuning becomes more valuable. We prove three general propositions that analyze how the desirability of the three practices depends on competition and sector concentration.

We then bring the implications of our theoretical model to the data. To this end, we need detailed bank-level data, in particular information on the explicit use of credit risk management tools; data that is typically hard to obtain. Therefore, as mentioned above, we conducted a paper questionnaire survey to elicit the necessary information on credit risk management. The survey was distributed among 438 savings banks of the German Savings Banks Finance Group in 2009. In total, 279 completed questionnaires were returned; a response rate of 63.7%. We combined this data with detailed balance-sheet data, which is not publicly available, income-statement data and regional economic data.

Consequently, we can directly relate the use of different risk management instruments to bank characteristics, and to market and regional conditions. Furthermore, our sample allows for a bank-level analysis of bank competition and sector concentration because the business activities of the banks in our sample are limited to a specific geographical area, following the so-called "regional principle". Finally, we are able to provide unbiased results because the banks in our sample face equal access conditions to implement credit risk management instruments and can access the same credit risk management instruments. They operate within the same regulatory environment and have a common business model but are legally and economically independent in their business decisions.

Our results show that differences in the implementation of advanced risk management can be explained by differences in competition and sector concentration: Banks that act in a competitive environment with highly concentrated sectors are more likely to implement sophisticated credit risk instruments and measures. We find evidence that managing risk via credit portfolio models is prevalent when the sector concentration is relatively high. In this case the bank can learn the correlation in its portfolio and adjust (precautionary) capital buffers relative to the risk of the loan portfolio. The depth of implementation and the integration of a credit transfer technology is primarily driven by competition among banks. If interest margins on originated loans are high (which is typically the case in an environment with low competition), then the probability of default is small even if loans are not securitized. The benefit of implementing a credit risk transfer technology is therefore most beneficial when competition is high. Contrariwise, the lower the sector concentration, the larger the benefit of the credit risk transfer technology since the probability of arriving at a balanced portfolio becomes larger.

Our paper is related to two seminal theoretical papers on the impact of competition on banks' risk-taking behavior (Boyd and De Nicolo, 2005; Keeley, 1990) that arrive at different conclusions: Under the competition fragility view banks chose more risky portfolios in an environment with high competition (Keeley, 1990), whereas under the competition stability view incentive mechanisms are disclosed that can explain riskier portfolios in more concentrated markets. These results are supported by empirical papers, for example Jiménez et al. (2013) and Bergstresser (2004) who identify a negative relationship between market power and risk-taking, in line with the franchise value view. Hakenes and Schnabel (2010) show what happens when the quality of loans in credit risk transfer markets is private information: banks issue unprofitable loans that contribute to aggregate risk, a situation that is even exacerbated when competition is high.

Our paper complements this literature by explicitly testing how concentration influences banks' decision to engage in advanced credit risk management. Closely related is the literature that investigates conditions under which sophisticated management controls are extensively used, showing that in particular firms under competitive pressure use sophisticated controls more extensively and more selectively than firms that face less intense competition. Numerous (mainly empirical) studies examine the factors underlying banks' decisions to use derivatives (Sinkey and Carter, 2000; Ashraf et al., 2007). Sinkey and Carter (2000) find that user banks, compared to nonusers, are associated with riskier capital structures, larger maturity mismatches between assets and liabilities. Other relevant studies identify the cost of financial distress and the existence of capital market imperfections as rationales to actively manage risk (Froot and Stein, 1998; Froot et al., 1993; Stulz, 1984). To our knowledge, there are no papers specifically investigating the underlying decisions to adopt credit portfolio models.

Our paper is further related to various papers on risk management, studying both quantitative and qualitative aspects against the background that risk management has become one of banks' main activities (Allen and Santomero, 1997) and essentially one of banks' core competences (Hellwig, 2010; Hakenes, 2004). Papers that study qualitative dimensions of risk management include Ellul and Yerramilli (2013), who link organizational risk controls and risk taking at bank holding level and Fahlenbrach et al. (2012), who show that persistence in (bad) risk culture make banks sensitive to crises. Research on quantitative aspects of risk management (e.g. techniques and instruments) include Cebenoyan and Strahan (2004), who show how differences in the intensity of advanced risk management affect investment decisions, the value of a firm, and its profitability. Minton et al. (2009) analyze whether credit derivatives generally contribute towards sounder banks, a point often made by regulators prior to the crisis.

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 advanced risk management through both credit portfolio models and participation in the credit risk transfer markets. This more integrated view of advanced risk management provides insights of the interplay of risk management practises and its drivers.

The remainder of the paper is structured as follows. Section 2 develops the model and derives the predictions, which are later tested empirically. In Section 3, we take our model to the data. Section 4 concludes the study.

2. A model of bank risk management

In this section, we construct a frugal theoretical model on bank risk management. The main requirement is that the endogenous variables in our data, the choice of risk management tools, are also endogenous in the model. The right hand side variables in the regression, sector concentration and bank competition, are exogenous parameters in the model. That way, the model can be used to generate testable hypotheses.

Theories on risk management. The literature on credit risk transfer is large and growing, especially due to the significance of CRT during the 2007 financial crisis. Most papers, such as the seminal Pennacchi (1988) and Parlour and Plantin (2008), focus on banks' monitoring activities, thus concentrating more on expected returns rather than on risk. One notable exception is the contribution by Feess and Hege (2013), where banks can screen loans and choose how far to participate in systemic risk. Banks then specialize: only some banks implement sophisticated scoring systems.

Some recent papers consider the effect of risk transfer and diversification on financial (in)stability (see (Allen and Carletti, 2006; Wagner, 2010; Purnanandam, 2011; Ibragimov et al., 2011; Stephens and Thompson, 2017; Van Oordt, 2017), just to name a few important contributions). Our paper focuses on the determinants of a single bank's decision, abstracting from any macro effects.

The second type of risk management in our model is CPM. It considers a banks' benefit of simply assessing the risk structure of its portfolio. Of course, there is a wealth of research on the statistical and technical aspects of the quantification of bank risk. In many theoretical models, banks screen their borrowers, hence they collect information on the risk of a single loan. We are not aware, however, of any theoretical model where banks gather information on its portfolio structure. In reality, risk management comprises both, information on single assets and on correlations.

2.1. The model

Competition. In a static model, there is 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 low competition, and vice versa. Assets are risky. For exposition, assume that the return is normally distributed with standard deviation σ. Henceforth, let us call the assets loans, bearing in mind that they could be any type of risky asset.

The bank can choose its balance sheet structure, consisting of deposits d and equity k. The balance sheet equation is $d + k = 2$, thus $d = 2 - k$. A capital requirement would stipulate $k \geq \alpha 2$ under the standardized approach, other approaches are discussed below. A leverage ratio would also stipulate $k \geq \tilde{\alpha} \cdot 2$. Depositors demand a constant gross return of r_d (equal to 1 plus the net rate of return). 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 the bank cannot repay deposits from their loan portfolio, it defaults at a cost $c > 0$. Note that k can also be interpreted as a buffer or reserve against potential loan losses. For our results, it is crucial that the bank has a choice variable whose optimal choice depends on credit risk.

Sector concentration. Loans come from different correlation classes, which we call industrial sectors. Sectors have masses μ_1, $\mu_2, \ldots$, such that $\sum_i \mu_i = 1$. The returns of loans from the same sector have a higher correlation than the returns of loans from different sector. For simplicity, set $\rho = \rho_H$ within a sector, and $\rho = \rho_L < \rho_H$ between sectors. To be precise, assume that the risk σ stems from three factors: one common factor with the distribution $N(0, \sigma_0)$, one idiosyncratic factor with the distribution $N(0, \sigma_i)$, and one sector-specific factor with the distribution $N(0, \sigma_S)$. For two loans from the same sector, the sector-specific factor is identical; otherwise this factor is stochastically independent. Then the standard deviation of a loan is

$$\sigma = \sqrt{\sigma_0^2 + \sigma_i^2 + \sigma_S^2},$$

and the correlation between two loans is either

$$\rho_H = \frac{\sigma_0^2 + \sigma_S^2}{\sigma_0^2 + \sigma_i^2 + \sigma_S^2} \quad \text{or} \quad \rho_L = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_i^2 + \sigma_S^2}.$$

Sector concentration can be measured by the Herfindahl–Hirschman index (HHI), $\sum_i \mu_i^2$. It is assumed to be public information, and has a second interpretation. If the bank picked two loans at random out of the pool, then the expected correlation would be

$$E[\rho] = \frac{\sigma_0^2 + (\sum_{i,j} \mu_i\, \mu_j\, \rho_{i,j})\, \sigma_S^2}{\sigma_0^2 + \sigma_i^2 + \sigma_S^2} = \frac{\sigma_0^2 + \mathrm{HHI}\, \sigma_S^2}{\sigma_0^2 + \sigma_i^2 + \sigma_S^2}.$$

The sector concentration HHI is thus simultaneously a measure for the (lack of) diversification within a "natural" loan portfolio. Finally, assume that one of the sectors has discrete mass $\mu > 0$, whereas the others have infinitesimal mass. The HHI then equals μ^2. As we will see, this assumption simplifies the discussion of portfolios with many loans.

Risk management tools. The bank has access to three risk management tools. First of all, some risk management is mandatory. Because we are interested in the banks' choice between risk management tools, we assume that the loans have the characteristics R and σ after the bank has applied these mandatory methods. Next, *credit portfolio modeling* (CPM), is a passive risk management tool. The bank learns the correlation structure of its loan portfolio, at a cost c_{CPM}. Without CPM, the bank has expectations about the likely correlation between its loans. With CPM, it learns whether the correlation is ρ_H or ρ_L. In the above context, the bank learns whether the loans are in the same sector or not. Banks can use the information generated by CPM to fine-tune their capital structure, depending on their portfolio. Without the information from CPM, the expected correlation of two loans is equal to HHI; with CPM, it is either ρ_H (if loans are in the same sector) or ρ_L.

The second tool is called *credit risk transfer* (CRT). It costs c_{CRT} to implement. A bank originally has a balance sheet total of 2, it can grant two loans. With CRT, it can sell a fraction of these loans, and use the receipts to grant new loans. One could think of the securitization of loans, or the use of credit derivatives in order to recycle regulatory capital. Let us assume, however, that this process cannot be driven *ad infinitum*. For concreteness, assume that the bank sells 50% of each loan, and grants two more loans, of which again it sells 50%. The balance sheet total is then again 2. The same allocation would be obtained from initially granting two loans, then securitizing and selling 50% of each, and then using the receipts to buy securitized loans from another bank. CRT is thus a way to diversify.[1]

Finally, the bank can be maximally advanced in its management of credit risk by implementing both CPM and CRT. This is called *advanced risk management* (ARM), it comes at a cost of c_{ARM}. Possibly, $c_{\mathrm{ARM}} \neq c_{\mathrm{CPM}} + c_{\mathrm{CRT}}$ due to (dis)economies of scope. This way, a bank can both diversify *and* fine-tune their buffers. Note that the value of CPM depends on whether the bank also uses CRT or not. Hence, ARM is more (or less) than the sum of its components, CPM and CRT. The relative value of each strategy, CRT, CPM or ARM, will depend on parameters, especially the level of competition and the sector concentration.

As mentioned above, the capital requirement under the standardized approach would be $k \geq \alpha \cdot 2$. Under the foundational IRB approach, it would be also be $k \geq \alpha' \cdot 2$ in our model, possibly with $\alpha' \neq \alpha$. The reason for the similar structure is that R and σ are assumed to be the loan characteristics after mandatory risk management procedures, and the bank knows both R and σ. Under the foundational IRB approach, the banks can only estimate the PD for individual clients, so the information from the voluntary methods is useless. In our model, the advanced IRB would stipulate $k \geq \alpha(m_1, m_2, \ldots)2$, where $m_1, m_2, \ldots$ are the volumes of loans in the different sectors 1, 2, ... Because the sectors are assumed to be symmetri-

[1] In the model there is only one bank, thus financial networks and contagion cannot be modeled. In reality, if banks insure credit risk using credit derivatives, its individual risk may decrease, but financial fragility may increase, see Krause and Giansante (2012) and other contributions on that special issue.

cal, $\alpha(\cdot)$ will typically be invariant with respect to permutations of the vector $(m_1, m_2, \ldots)$. There will also be some monotonicity, such as $\alpha(2, 0, \ldots) > \alpha(1, 1, \ldots)$. In our analysis, we will concentrate on banks that use either the standardized of the foundational IRB approach, and discuss the advanced IRB approach at the end of this section.

2.2. The optimal strategy

The optimal risk management strategy depends on the cost of implementation, and on the value of the according strategy. We start with calculating the expected profit if the benchmark case, where the bank uses neither credit portfolio modeling (CPM) nor credit risk transfer (CRT). We then calculate the bank's expected profit after the implementation of credit portfolio modeling (CPM). If the difference between the two exceeds the cost c_{CPM}, the bank will prefer CPM, and vice versa. We continue with the same calculation for credit risk transfer (CRT). ARM is the sum of CPM and CRT, hence we must compare it to the better of these two. We derive comparative static results for a situation when the bank prefers CPM, CRT or ARM.

The benchmark case. In the benchmark case, the bank uses none of the above risk management instruments. In reality, of course, banks are required by law to have some basic risk management. We are interested in the endogenous method choice of banks, hence these basic instruments are outside the focus of our model. The bank has a balance sheet total of 2, hence it grants two loans with the mean return of $2R$. These loans have high correlation ρ_H with probability $\text{HHI} = \mu^2$, they have low correlation ρ_L with probability $1-\mu^2$. If *both* loans are in the discrete sector, the standard deviation of the aggregate portfolio is

$$\sigma_H^2 = \sigma^2 + \sigma^2 + 2\,\rho_H\,\sigma^2 = 2\left(1 + \frac{\sigma_0^2 + \sigma_S^2}{\sigma_0^2 + \sigma_i^2 + \sigma_S^2}\right)$$
$$(\sigma_0^2 + \sigma_i^2 + \sigma_S^2) = 4\,\sigma_0^2 + 2\,\sigma_i^2 + 4\,\sigma_S^2.$$

Hence the aggregate return Y is normally distributed with mean $2R$ and standard deviation σ_H^2, thus $Y \sim \mathcal{N}(2R, \sigma_H^2)$. The bank has debt (deposits) of $d = 2 - k$. We want to determine the probability that the yield cannot cover deposit repayments, $Y < 2 - k$. The probability of such financial distress is given by the probability that the

$$\text{PD}_1 = Pr\{Y < 2 - k\} = \Phi\left(\frac{2 - k - 2R}{\sigma_H^2}\right), \tag{1}$$

where $\Phi(\cdot)$ is the standard normal distribution function. With probability $2\,\mu\,(1-\mu)$, one of the loans is in the discrete sector, the other is in one of the infinitesimal sectors. With probability $(1-\mu)^2$, both loans are in one of the infinitesimal sectors. In both cases (aggregate probability $1-\mu^2$), the standard deviation is then

$$\sigma_L^2 = \sigma^2 + \sigma^2 + 2\,\rho_L\,\sigma^2 = 2\left(1 + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_i^2 + \sigma_S^2}\right)$$
$$(\sigma_0^2 + \sigma_i^2 + \sigma_S^2) = 4\,\sigma_0^2 + 2\,\sigma_i^2 + 2\,\sigma_S^2,$$

thus $Y \sim \mathcal{N}(2R, \sigma_L)$, and the probability of distress is

$$\text{PD}_0 = Pr\{Y < 2 - k\} = \Phi\left(\frac{2 - k - 2R}{\sigma_L}\right). \tag{2}$$

From now on, set $\sigma_0 = \sigma_i = 0$ without loss of generality, to concentrate on the effect of the larger or smaller correlation between sectors. The aggregate expected profit of the bank equals the expected return, net of refinancing costs and the expected cost of financial distress,

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

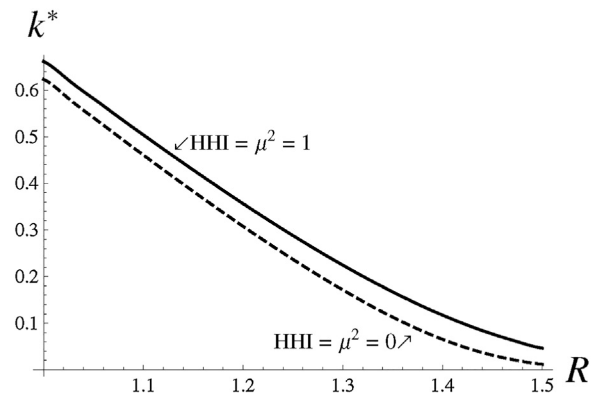

Fig. 1. Optimal capital buffer k^* depending on competition (low R) and sector concentration. This figure shows the optimal k^* depending on R for the extreme cases of $\text{HHI} = \mu^2 = 1$ and $\text{HHI} = \mu^2 = 0$. In the numerical example, $c = 10$, $\phi = 2$, and $\sigma = 0.2$. This numerical example is used throughout the modeling section. For different parameter values, the picture is qualitatively identical. Two things can be seen from this figure. First, the bank will hold higher equity buffers for high competition (low R). For high competition, the bank's profits are small, so the bank prefers to insure itself against distress with a higher capital buffer k^*. Second, for a high sector concentration HHI, the bank prefers higher buffers k^*. The reason is that the bank does not know the precise correlation structure between loans, but it has expectations for a given sector concentration. The higher the concentration, the more likely are the loans to be correlated. More buffers are then needed. Both comparative statics are unsurprising. The more important question is, how can buffers be saved by the use of CPM, and under what conditions (competition, sector concentration).

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

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

is an auxiliary variable. There is no algebraic solution to this implicit definition of k^*. However, the implicit function theorem can be used to compute some comparative statics. Most importantly for this paper, $\partial k^*/\partial R < 0$. 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, $\partial k^*/\partial \mu > 0$. 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 (Fig. 1).

Credit portfolio modeling (CPM). By implementing a credit portfolio model (CPM), the bank finds out the correlation within their loan portfolio. In other words, it determines whether each of the loans is in the discrete sector. Using this information, it can fine-tune the buffer. If it finds the correlation in its portfolio to be high, the aggregate standard deviation is high, and it needs larger buffers.

We now calculate the benefit of this piece of information. With probability μ^2, the bank finds that both loans are in the discrete sector, hence, they are perfectly correlated. The probability of default is then PD_1, as defined above in (1). The bank will then maximize

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

This expected profit 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 $1-\mu^2$, the bank finds that the loans are uncorrelated, the probability of default is PD_0, as defined in (2). The expected profit is

$\Pi_0 = 2R - 2 - \phi k^2/2 - c\,\mathrm{PD}_0$, 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,

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

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 $\mu = 0$, 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 $\mu = 1$, 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. We arrive at the following proposition, delivering two hypotheses that will be tested in the empirical section of the paper.

Proposition 1 (Credit portfolio modeling). *For higher competition (lower R), CPM becomes (weakly) more desirable. For larger sector concentration (higher μ, up to a certain level), CPM becomes (weakly) more desirable.*

The proof is in Appendix A. As a direct consequence, *ceteris paribus*, a bank in a region with high sector concentration will tend to implement CPM. A bank under tense competition will also tend to implement CPM (Fig. 2). Let us now discuss the implications for the second risk management tool, credit risk transfer (CRT).

Credit risk transfer (CRT). Assume now that the bank can implement a credit risk transfer (CRT) technology. By doing so, it can securitize some part of each loan, thus increasing the number of loans it can grant. As argued above, we assume that this process cannot be driven *ad infinitum* (otherwise banks would end up with perfectly diversified portfolios). Only 50% of each loan can be securitized, the bank keeps the other 50% in its books. This implies that, with a balance sheet total of 2, the bank can grant 4 half loans. With the correlation structure as before, there are five different possible constellations: (i) all the loans can come from the discrete sector (probability μ^4); (ii) all but one loan can come from the discrete sector (probability $4\mu^3(1-\mu)$); (iii) all but two loans can come from the discrete sector (probability $6\mu^2(1-\mu)^2$); (iv) only one loan can come from the discrete sector (probability $4\mu(1-\mu)^3$); and (v) all loans can stem from the infinitesimal sectors (probability $(1-\mu)^4$). Depending on the correlation structure, the probability of default will differ. However, the benefit of CRT consists only in the increased diversification within the portfolio. In the absence of further information (that could stem from CPM), the bank cannot adjust buffers to the different constellations.

In the first scenario (case (i), probability μ^4), the standard deviation of the portfolio is 2σ, hence, the probability of default is $Pr\{Y < 2-k\} = \Phi(\frac{2-k-2R}{2\sigma})$. In the second scenario (case (ii), probability $4\mu^3(1-\mu)$), 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 $\Phi(\frac{2-k-2R}{\sqrt{5/2}\,\sigma})$. In the third scenario (case (iii), probability $6\mu^2(1-\mu)^2$), 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 $\Phi(\frac{2-k-2R}{\sqrt{3/2}\,\sigma})$. Finally, in the latter two cases (iv) and (v), all the loans are stochastically independent, so with probability $4\mu(1-\mu)^3 + (1-\mu)^4$, the portfolio has maximal diversification. The standard deviation is $\sqrt{(\sigma/2)^2 + (\sigma/2)^2 + (\sigma/2)^2 + (\sigma/2)^2} = \sigma$, and the according probability of default is $\Phi(\frac{2-k-2R}{\sigma})$. Taking these default probabilities into account, the bank will set the optimal buffer k^*. Again, we arrive at a proposition containing two hypotheses, which will be tested in the empirical section of the paper.

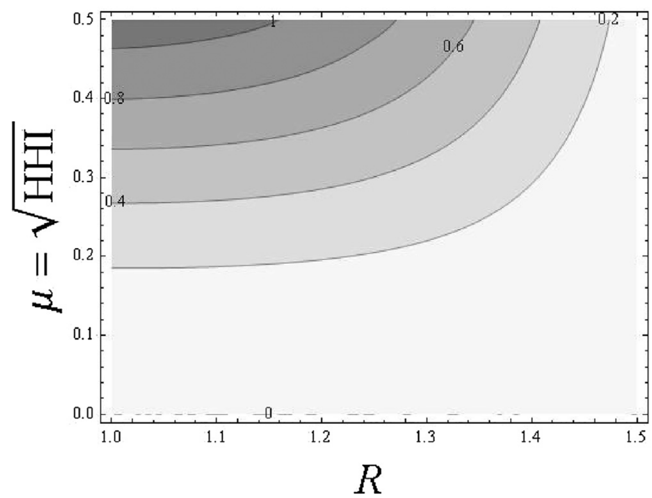

Fig. 2. Difference in profits, credit portfolio modeling (CPM) vs. benchmark. Parameters in this figure are the same as in Fig. 1. It shows the *difference* between the expected profits with and without CPM, for different degrees of competition and sector concentration. On each curve, the benefit of implementing CPM is constant. The difference in profits is plotted on the contours (in percentage points of the balance sheet total). Light shading means that the benefit of CPM is small, dark gray implies that the benefit is large. For example, take $R = 1.0$ and $\mu = 0.4$. The corresponding point in the figure is exactly on the 0.8-curve. This implies that the benefit of having CPM implemented is 0.8% of the balance sheet total. If the cost of CPM were $c_{\mathrm{CPM}} = 0.8$, the bank would be indifferent with respect to its implementation. For $c_{\mathrm{CPM}} < 0.8\%\cdot 2 = 0.016$, it would go ahead and implement CPM. One can thus read the figure as follows. For a given c_{CPM}, find the according curve. The bank will implement CPM for all parameter constellations northeast of this curve. 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 $\mu = 0$, the correlation structure can be guessed even in the absence of CPM. (The same would true for $\mu = 1$, but given that μ^2 equals the sector Herfindahl–Hirschman index, μ will realistically be closer to 0 than to 1. Therefore, we have plotted this figure only for $0 \le \mu \le 1$.) Hence, the larger the sector concentration, the more can be learned about the portfolio structure, and the more valuable CPM becomes.

Proposition 2 (Credit risk transfer). *For higher competition (lower R), CRT becomes (weakly) more desirable. For larger sector concentration (higher μ), CRT becomes (weakly) less desirable (Fig. 3).*

Advanced risk management (ARM). 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 advanced 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 five cases, as discussed above: (i) all four loans can be correlated; (ii) all but one can be correlated; (iii) all but two can be correlated; or (iv and v) all may be uncorrelated. In each case, the bank will then set a different buffer. 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

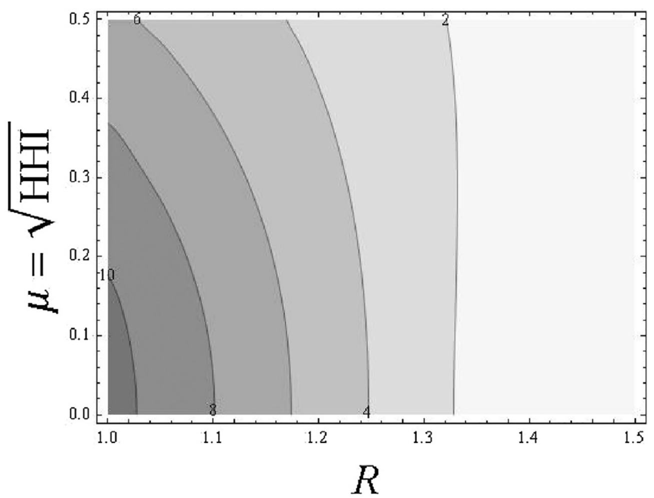

Fig. 3. Difference in profits, credit risk transfer (CRT) vs. benchmark. This plot shows the difference of the profits with CRT and the benchmark case. Again, dark gray denotes for large benefits of CRT, and white denotes for small benefits. Note that a more diversified portfolio always has a smaller probability of default. Therefore, the bank can economize on buffers. Hence, the profits with CRT always exceed those in the benchmark case. We observe a number of further properties. *First*, the higher the competition (lower *R*), 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 $\mu = 1$. 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 $\mu = 1$, 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 μ.

the benchmark case, only CRT or CPM can be the best alternative. Fig. 4 shows a numerical simulation.

Proposition 3 (Advanced risk management). *For higher competition (lower R), ARM becomes (weakly) more desirable. For larger sector concentration (higher μ), ARM becomes (weakly) less desirable.*

3. Empirical evidence

We bring the implications of our theoretical model to the data and provide empirical evidence on the validity of our assumptions. To test our theoretical model the banks in our sample belonging to the German Savings Banks Finance Group (*Sparkassen-Finanzgruppe*) provide an ideal set up.

The German Savings Banks Finance Group. The savings banks are not only ideally suited because of their specific features and organizational structure but also for the fact that we deal here on the one hand with legally and economically independent banks with rather homogeneous business models but more importantly on the other hand with banks taking independent business decisions. This is of relevance as banks independently take the decision for use or non-use of particular risk management instruments.

Moreover, we are able to assess the competitive environment and to determine the sector concentration which reflects the portfolio concentration of each bank in our sample as their business activities are limited to certain defined regions. In fact, due to their "regional principle" the German savings banks are not allowed to expand their business to other regions. This specific feature among others allows us to investigate empirically the main influencing factors identified by our model. For a comprehensive list of banking groups' special features see Bülbül et al. (2014).

The organizational structure of the banking network is very crucial for the unrestricted access of each bank to risk management instruments. The savings banks and other financial institutions in the group are organized and connected by a multi-level network. In addition, there also exists a parallel structure of associations. This structure consists of 11 regional associations and comprise all independent savings banks in their respective regions as their members. The German Savings Banks Association (DSGV) is the umbrella organization of the German Savings Banks Group. This association takes over central tasks. In our specific case, the DSGV has adapted the credit portfolio model called CreditPortfolioView to the specific needs of the saving banks and provide access to all banks in the group. The credit portfolio model is affordable also for smaller banks because the monthly fee is proportional to bank size. So the banks in our sample face equal access conditions.

Furthermore, the banks in our sample participate in internal risk transfer markets through credit pooling (*Kreditpooling*) organized internally within the banking network or credit risk transfer through international capital markets. The banks can participate in the internal loan pool and external risk transfer market, both as issuers of risk (protection buyer) and as buyers of risk (protection seller).

Our survey. Apparently the information of the usage of risk management instruments of each bank is not publicly available. The particular information on the explicit use of credit risk management tools is typically hard to obtain. Therefore, we used a paper questionnaire survey to elicit the necessary information on credit risk management.

In order to find out the information of usage of credit portfolio models and risk transfer we conducted a survey in 2009 among the German savings banks. Of 438 questionnaires sent to all savings banks from the German Savings Banks Finance Group, a total of 279 completed questionnaires were returned. For our analyses we used 249 responses (57%) because some banks returned the questionnaire without the front page containing the name of the bank or were involved in a recent merger. Thus, comprising 57% of the banks participating in the survey, our sample is highly representative of all regions and asset classes. For more descriptive information, see Bülbül (2013).

3.1. Risk management strategies of banks

In the following we explain how risk management strategies of banks can be derived from the survey. In the questionnaire the banks were asked to provide information on their risk management strategies in their daily corporate business to manage credit risk, from applying of traditional methods such as limiting their exposure to regions, sectors etc. up to the use of sophisticated risk management tools. The banks were able to classify the intensity of the use of risk management instruments as no use, occasional use, or frequent use.[2] Concentrating on the more sophisticated risk management strategies we construct three dependent variables from the survey data: CRT, CPM and ARM following our model. The variables are constructed from the following survey questions, ARM being a combination of CRT and CPM[3]:

[2] In the survey we did not require the participants to quantify their intensity of use by the number of applications per month. As the quantity is very much dependent on the specific business of the bank, we believe that banks' qualitative judgement (own judgement) on this issue is more appropriate to use. For a detailed description of the questionnaire see Appendix B.

[3] We construct this variable from questions 12-10, 12-11, 13-3 of the survey in Appendix B.

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

Credit risk transfer (CRT). We define the binary variable CRT to be one when either internal markets for credit derivatives (credit pooling) or the market-based solution for credit derivatives is used frequently or occasionally, and zero otherwise. As such, we impose that either frequent or occasional use of these instruments is sufficient for a bank to be classified as being active in credit risk transfer markets. Intuitively, this makes sense, as the frequency of participation in the credit risk transfer market depends on the specific business of the bank. Consequently, either form of participation is recognized.

Credit portfolio modeling (CRM). The binary variable CPM is one when the credit portfolio model is employed frequently to measure and manage credit risk, and zero otherwise. Employing a credit portfolio model for monitoring and actively managing the portfolio occasionally means using the instrument at most once a month, whereas frequent use implies using the instrument much more often. Given that frequent use allows the bank to actively monitor and manage their credit portfolio, we therefore, only include these banks. Reasonable lending strategies of banks can be derived if banks actively monitor their portfolio and also use the results for their business decisions.

Advanced risk management (ARM). Finally, ARM is a binary variable equal to one if CRT and CPM are used simultaneously, and zero otherwise. Here, the bank engages in the highest level of advanced risk management as defined in our theoretical model.

3.2. Potential determinants of risk management strategies

In this section we provide an overview of potential determinants influencing banks' decision to implement advanced risk management tools. We would like to develop first the main variables identified by our model, namely competition and portfolio concentration and, second further variables to control for (control variables).

Competition. We use the Lerner index as a proxy for market power. It measures how far banks can set prices above marginal costs and is calculated as $\text{LERNER}_{it} = (P_{it} - \text{MC}_{it})/P_{it}$ 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 (Berger et al., 2009; Bülbül, 2013). Marginal cost is derived from a translog cost function[4] where banking output is proxied by the total assets TA_{it} (Carbó 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 average the Lerner index for the observation period because we are interested in the competitive stance of the bank.

Portfolio concentration. Given that the banks in our sample conduct business in a defined regional area according to the "regional principle", the sector concentration in the respective region proxies the lending portfolio of each bank. The Herfindahl–Hirschman index is used to estimate the sector concentration in region i (for bank i) and is calculated as $\text{HHI}(x)_i = \sum_{n=j}^{N} x_j^2$ 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.[5]

A bank with a concentrated loan portfoore risky. Thus, it is not surprising that credit risk concentration has played a critical role in past bank failulio will typically be mres in mature economies (Basel Committee on Banking Supervision, 2004). Both advanced instruments can be used to manage credit risk such that a lending portfolio is diversified by reducing its credit risk concentration.[6] Düllmann and Masschelein (2007) show that it is necessary to take inter-sector dependency into account when measuring credit risk, for which credit portfolio models are a typical instrument. According to Batten and Hogan (2002) credit derivatives have a much more flexible approach to managing the risks associated with concentration. We expect banks with credit risk concentration proxied by sector concentration to be more likely to involve in advanced risk management.

Control variables. There may be other determinants influencing banks' decision for risk management besides the main determinants postulated by our model. We use the following control variables. We measure the risk-return profile of a bank using three separate variables: net-interest income to total income (Ashraf et al., 2007), net-commission income (non-interest) to total income (Beltratti and Stulz, 2012) and the ratio of loan loss provisions to total assets (Minton et al., 2009). We expect banks with less interest income and higher loan loss provisions to be more likely to use advanced credit risk management. We include the equity to total asset ratio (Minton et al., 2009) because banks' have to fulfill minimum capital requirements in accordance with the risk they carry. As a consequence this may influence a bank's decision to implement advanced risk management tools. We proxy bank size by total assets. To allow for nonlinearities between size and the use of risk management instruments we define four asset classes following Cebenoyan and Strahan (2004). The smallest quartile acts as the omitted category. We expect the size of the bank to have a significant effect on banks' decisions to engage in advanced risk management due to their potentially more opaque lending business and typically access to larger resources to run adequately risk management tools. We also account for the lending structure and funding structure of the bank. We proxy the lending structure as the ratio of corporate loans over total non-bank loans. The funding structure is represented by total deposits over total non-bank loans. A bank's decision to engage in advanced risk management is potentially related to the composition of the loan portfolio and the bank's refinancing situation. To account for regional disparities on the bank level, we include regional earnings calculated by GDP per capita in our model. Furthermore, to capture effects which may be driven by disparities in economic development after the German reunification, we control for the regional area by including a binary variable east being one when the bank is in former East Germany.

[4] We estimate the equation $\ln \text{Cost}_{it} = \beta_0 + \beta_1 \ln \text{TA}_{it} + \frac{\beta_2}{2} \ln {\text{TA}_{it}}^2 + \sum_{k=1}^{3} \gamma_{kt} \ln W_{k,it} + \sum_{k=1}^{3} \phi_k \ln \text{TA}_{it} \ln W_{k,it} + \sum_{k=1}^{3} \sum_{j=1}^{3} \ln W_{k,it} \ln W_{j,it} + \epsilon_{it}$ by including yearly time-fixed and bank-fixed effects with robust standard errors using panel data covering the period from 1996 to 2006.

[5] 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 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.

[6] 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."

Table 1
Summary statistics and differences in means.

	(1) All banks		(2) ARM users		(3) ARM non-users		Difference	*p*-Values
	Mean	sd	Mean	sd	Mean	sd		
HHI	0.1583	0.0133	0.1692	0.0146	0.1574	0.0128	−0.0118***	(−3.73)
Lerner	0.2861	0.0711	0.2189	0.0622	0.2913	0.0692	0.0724***	(4.31)
Interest Income	0.4263	0.0352	0.4092	0.0334	0.4276	0.0351	0.0184*	(2.15)
Commission	0.0997	0.0162	0.1032	0.0097	0.0994	0.0166	−0.00383	(−0.97)
LLP	0.0206	0.0095	0.0225	0.0083	0.0204	0.0096	−0.00204	(−0.87)
Corporate Loans	0.3127	0.0652	0.3162	0.0684	0.3124	0.0651	−0.00382	(−0.24)
Equity	0.0469	0.0088	0.0441	0.0054	0.0472	0.0090	0.00309	(1.43)
Deposits	0.5583	0.2320	0.5527	0.2945	0.5588	0.2272	0.00611	(0.11)
East	0.1165	0.3214	0.1111	0.3234	0.1169	0.3220	0.00577	(0.07)
GDP	24.2590	7.7944	30.6938	16.8464	23.7576	6.4060	−6.936***	(−3.73)
Total Assets	14.2482	0.9369	15.0644	0.9066	14.1846	0.9108	−0.880***	(−3.95)
No. Employees	459.8781	474.4064	861.0739	525.1171	428.6161	456.8537	−432.5***	(−3.83)
Observations	249		18		231			
	(1) All banks		(2) CPM users		(3) CPM non-users		Difference	*p*-Values
	Mean	sd	Mean	sd	Mean	sd		
HHI	0.1583	0.0133	0.1657	0.0162	0.1568	0.0122	−0.00889***	(−4.03)
Lerner	0.2861	0.0711	0.2469	0.0739	0.2938	0.0681	0.0469***	(3.98)
Interest Income	0.4263	0.0352	0.4167	0.0305	0.4281	0.0359	0.0114	(1.91)
Commission	0.0997	0.0162	0.1038	0.0124	0.0988	0.0167	−0.00501	(−1.82)
LLP	0.0206	0.0095	0.0221	0.0083	0.0203	0.0097	−0.00183	(−1.13)
Corporate Loans	0.3127	0.0652	0.3168	0.0593	0.3118	0.0664	−0.00497	(−0.45)
Equity	0.0469	0.0088	0.0460	0.0083	0.0471	0.0089	0.00118	(0.78)
Deposits	0.5583	0.2320	0.5458	0.3023	0.5608	0.2163	0.0150	(0.38)
East	0.1165	0.3214	0.1220	0.3313	0.1154	0.3203	−0.00657	(−0.12)
GDP	24.2590	7.7944	27.1312	12.1808	23.6929	6.4929	−3.438**	(−2.61)
Total Assets	14.2482	0.9369	14.7221	1.0246	14.1548	0.8920	−0.567***	(−3.63)
No. Employees	459.8781	474.4064	687.0227	493.8885	415.1045	458.5518	−271.9***	(−3.43)
Observations	249		41		208			
	(1) All banks		(2) CRT users		(3) CRT non-users		Difference	*p*-Values
	Mean	sd	Mean	sd	Mean	sd		
HHI	0.1583	0.0133	0.1597	0.0152	0.1575	0.0121	−0.00225	(−1.28)
Lerner	0.2861	0.0711	0.2541	0.0727	0.3035	0.0640	0.0494***	(5.55)
Interest Income	0.4263	0.0352	0.4166	0.0305	0.4315	0.0366	0.0150**	(3.26)
Commission	0.0997	0.0162	0.1002	0.0150	0.0994	0.0168	−0.000777	(−0.36)
LLP	0.0206	0.0095	0.0224	0.0087	0.0195	0.0098	−0.00288*	(−2.30)
Corporate Loans	0.3127	0.0652	0.3332	0.0678	0.3015	0.0610	−0.0317***	(−3.77)
Equity	0.0469	0.0088	0.0458	0.0079	0.0476	0.0093	0.00180	(1.54)
Deposits	0.5583	0.2320	0.5326	0.2031	0.5724	0.2459	0.0398	(1.30)
East	0.1165	0.3214	0.1136	0.3192	0.1180	0.3236	0.00438	(0.10)
GDP	24.2590	7.7944	26.4233	10.8798	23.0760	5.0811	−3.347**	(−3.30)
Total Assets	14.2482	0.9369	14.6905	0.9116	14.0065	0.8616	−0.684***	(−5.87)
No. Employees	459.8781	474.4064	662.4841	630.5190	349.1370	312.6625	−313.3***	(−5.24)
Observations	249		88		161			

This table shows the mean values for banks' characteristics, market measures and regional characteristics, averaged for the 2002 to 2006 period for ARM users, CPM users and CRT users, and non-users, including comparison of means between of the group of users and non-users. *HHI* is the Herfindahl index for sector concentration and *Lerner* measures in how far banks can set prices over marginal costs. *Interest Income* is net interest income standardized over total income. *Commission* is net commission income over total income. *LLP* is loan loss provisions standardized over total assets. *Corporate loans* are standardized over non-bank loans. *Equity* is banks' common equity standardized over total assets. *Deposits* are standardized over non-bank loans. *East* is a binary variable, amounting to 1 if the bank is located in the former East Germany, and zero otherwise. *GDP* is measured as GDP over capita. Size is measured as *No. Employees*, the number of employees and *Total assets*, which is the log of banks' total assets.

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

3.3. *Empirical evidence*

This section provides background information on the data used, descriptive statistics pertaining to the banks in our sample, and the empirical model in which we test the implications of our theoretical model and results.

Data. We merge balance-sheet and income-statement data for each individual bank with banks' survey responses plus regional economic data, to create a comprehensive overview of each individual bank and its business region. Balance-sheet and income-statement data is provided by the German Savings Banks Association (DSGV), the regional economic data by the Statistical State Offices (*Statistisches Bundesamt*) for each of the 439 administrative districts.[7] The resulting data covers the period 2002–2006.[8]

[7] 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.

[8] For our analyses we also use balance sheet and income statement data for the 2002 to 2006 period for three reasons. First, we are restricted to data before 2006, simply because we use unique, and as such, very detailed balance sheet data, which

Table 2
Pearson correlations of dependent variables.

	CRT	CPM	ARM
CRT	1		
CPM	0.0795	1	
ARM	0.378***	0.629***	1

The correlation matrix of the different risk management instruments the banks employ. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Summary statistics. In Table 1, we present the mean values of variables averaged over the period 2002 to 2006. We provide descriptive statistics for the full sample and different subsamples. Table 1 summarizes the results for the full sample of 249 bank observations covering 2002 to 2006 period. We report the bank-, regional- and market- characteristics of all of the banks in our sample in Column (1). In Column (2) of Table 1, we provide the means of the relevant variables for the banks that engage in advanced risk management, credit risk transfer and credit portfolio modelling. Similarly, Column (3) of Table 1 presents the characteristics of the banks that do not use advanced risk management.

A general observation is that differences exist across the banks that engage in advanced risk management, credit risk transfer and credit portfolio modelling and those that engage in more traditional risk management, despite the fact that we investigate homogeneous banks relative to their business model. From the univariate inspection, we observe that in particular larger banks engage in advanced risk management, including the individual use of CPM and CRT. It is also apparent that these banks have considerably higher sector concentration and less market power.[9] We observe that only 18 banks engage in advanced risk management, hence only a limited number of banks simultaneously employ CPM and CRT, while a larger number of banks individually monitor through CPM and transfer risk through CRT.

This relationship is supported when looking at the correlation of banks risk management strategies in Table 2. In Table 2 we observe that ARM is correlated with both CRT and CPM. Employing a credit portfolio model, however, is not necessarily correlated with the decision to engage in risk transfer markets.

So while most of the banks in our sample engage in traditional risk management (e.g. limit systems), there is some apparent heterogeneity across banks as regards their organisational and strategic decision to implement these advanced risk management strategies. In the next chapter we more closely assess underlying fundamentals of this discrepancy.

Empirical model. The theoretical model in Section 2 predicts that advanced risk management is profitable, especially if competition is high and if the sectors are concentrated. To test the implications of our theoretical model, we estimate the model

$$\begin{aligned} \mathrm{ARM}_i = {} & \beta_0 + \beta_1\,\mathrm{HHI_g} + \beta_2\,\mathrm{Lerner}_i + \beta_3\,\mathrm{NetInterestIncome}_i \\ & + \beta_4\,\mathrm{NetCommissionIncome}_i + \beta_5\,\mathrm{LoanLossProvision}_i \\ & + \beta_6\,\mathrm{TotalAsset}_i + \beta_7\,\mathrm{CorporateLoan}_i + \beta_8\,\mathrm{Equity}_i \\ & + \beta_9\,\mathrm{Deposit}_i + \beta_{10}\,\mathrm{East}_i + \beta_{11}\,\mathrm{GDP}_i + \epsilon_i \end{aligned} \tag{9}$$

ARM_i is the binary dependent variable indicating whether bank i engages in advanced risk management employing both credit portfolio models (to monitor) and credit risk transfer (to diversify). ARM_i is one if the bank simultaneously uses both tools, and zero otherwise. HHI_g represents the portfolio concentration of the respective bank, measured by the Herfindahl–Hirschman index for sector concentration, where the calculation is based on the number of firms conducting business by sectors in each region.[10] $Lerner_i$ is the Lerner index, a measure for market power of the respective bank and calculated in how far banks can set prices above marginal cost. $Net\ InterestIncome_i$ is measured as net interest income over total income and $Net\ CommissionIncome_i$ is calculated as net non-interest income over total income. $Loan\ lossprovision_i$ is the ratio of loan loss provisions over total assets. $TotalAsset_i$ represents the four asset classes, which we define as: (i) EUR 0.847 bil < Assets < EUR 1.482 bil; (ii) EUR 1.482 bil < Assets < EUR 2.906 bil; and (iii) Assets > EUR 2.906 bil. The fourth class, assets below EUR 847 million, is the omitted category for the size indicator variables. $CorporateLoan_i$ is total corporate loans over nonbank loans. $Equity_i$ is measured as total equity over assets. $Deposit_i$ is measured as deposits over the total nonbank loans. East is a binary variable being one if the bank is in former East Germany, and zero otherwise. GDP_i is measured as GDP per capita on regional level; ϵ_i is the idiosyncratic error term.

We reduce the panel structure of our data to a cross sectional structure since our endogenous variable for the different risk strategies does not vary over time. Thereby, we average the years 2002 to 2006. We employ a probit regression framework to estimate the model.

Results. Following the theoretical model we investigate empirically whether competition and sector concentration influence a bank's decision to implement advanced risk management techniques relative to traditional risk management instruments. For 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 3, we present the results of the probit regressions investigating banks' motivation to engage in ARM, CRT and CPM. In Column (1) to (3) of Table 3, we first present in how far competition and sector concentration influence the organisational decision of the bank to implement these specific instruments. Doing so, we control for bank characteristics, GDP and the location of the bank (East). In Columns (4) to (6) we present the same set of results, however, replace leverage with regulatory capital in order to control for the level of regulatory capital of the bank.

was provided to us from the DSGV only for the period before 2006, also used in other studies, including Puri et al. (2011) and Bülbül (2013). Second, we constrain our sample to the period following 2002 because the banks in our sample adopted a group-wide strategy including large reorganizational activities. These structural changes included the introduction of standardized approaches to risk management and other business areas. Third, since we combine balance sheet data with information on the use of risk management instruments from the survey from 2009, we have to make sure that responses given in the questionnaire apply also to the years before. In general, the implementation and operation of risk management instruments is a long-term endeavor. Risk management instruments such as CreditPortfolioView, credit pooling and the internal rating system were first introduced in 2002, partly as a consequence of the structural changes triggering a new group wide strategy. We spoke to the banks that participated in the survey and learned that the decision to use these risk management tools is likely to be constant over the years after the 2002 implementation. This allows us to merge the survey responses directly with balance sheet data.

[9] Koetter and Wedow (2010) estimates a Lerner index of 23% for 1995 through 2005, while Carbo Valverde and Rodriguez Fernandez (2007) provide a Lerner index of 35% for 1994 through 2001 in the German banking sector. De Guevara and Pérez (2007) estimates a Lerner index between 10.63% and 13.65% for 1993 through 2000. De Guevara and Pérez (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 for the entire German banking sector. The banks in our sample are active in the traditional deposit and loan business and enjoy greater market power.

[10] To note that the subscript g reflects that the sector concentration for each bank is calculated at regional level using the Statistical Classification of Economic Activities in the European Community. The sector concentration in the respective region proxies the lending portfolio of each bank as the banks in our sample conduct business in a defined regional area according to the "regional principle".

Table 3
Results for ARM, CPM and CRT.

Variable	(1) ARM	(2) CPM	(3) CRT	(4) ARM	(5) CPM	(6) CRT
HHI	1.9286*	6.6468***	−2.5886	2.0424**	6.8011***	−1.8649
	(1.0101)	(2.0396)	(3.1910)	(1.0009)	(2.0364)	(3.2467)
LERNER	−0.6390***	−0.9500*	−1.6112**	−0.6412***	−0.9354*	−1.8062**
	(0.2451)	(0.4955)	(0.7605)	(0.2426)	(0.5108)	(0.7353)
Net Interest income	−0.3154	−1.2248	−1.1392	−0.4992	−1.2447	−2.2589*
	(0.4103)	(0.8323)	(1.2760)	(0.3690)	(0.8096)	(1.2349)
Net Commission Income	1.6958**	5.3918***	2.2770	1.7768**	5.9567***	3.0795
	(0.7278)	(1.5177)	(2.5510)	(0.7312)	(1.5670)	(2.6221)
Loan Loss Provision	−0.1898	0.0750	1.2228	0.1036	0.5578	3.2920
	(1.3638)	(2.5773)	(3.8376)	(1.2909)	(2.5864)	(3.9463)
EUR 0.847 bil < Assets < EUR 1.482 bil	−0.0135	−0.1027*	−0.0473	−0.0092	−0.0935*	−0.0460
	(0.0255)	(0.0546)	(0.0762)	(0.0243)	(0.0550)	(0.0755)
EUR 1.482 bil < Assets < EUR 2.906 bil	−0.0021	0.0092	−0.0106	−0.0012	0.0118	−0.0124
	(0.0127)	(0.0276)	(0.0487)	(0.0123)	(0.0275)	(0.0471)
Assets > EUR 2.906 bil	−0.0048	−0.0104	0.0182	−0.0052	−0.0102	0.0125
	(0.0037)	(0.0085)	(0.0197)	(0.0036)	(0.0084)	(0.0175)
Corporate Loans	−0.0082	0.2092	1.1692**	0.0041	0.2626	1.2057**
	(0.1711)	(0.3218)	(0.5385)	(0.1635)	(0.3210)	(0.5471)
Equity	−0.2122	3.1947	−0.3573			
	(1.5875)	(3.0277)	(4.6702)			
Regulatory capital				0.7049	1.7402	3.9426**
				(0.5273)	(1.0954)	(1.7020)
Deposits	0.0475	0.0353	−0.2269	0.0277	−0.0240	−0.3189
	(0.0721)	(0.1422)	(0.2082)	(0.0654)	(0.1391)	(0.2146)
EAST (*d*)	−0.0128	0.0305	0.1839	−0.0133	−0.0304	0.1522
	(0.0552)	(0.1477)	(0.2100)	(0.0442)	(0.1033)	(0.1863)
GDP	0.0003	−0.0016	0.0072	0.0001	−0.0019	0.0066
	(0.0011)	(0.0027)	(0.0052)	(0.0010)	(0.0027)	(0.0052)
ps. R-squared	0.2260	0.1804	0.1499	0.2380	0.1861	0.1658
Log pseudolikelihood	−50.0195	−91.2876	−137.4870	−49.2437	−90.6582	−134.9197
Wald	37.4364	33.6017	44.9236	39.9531	32.5281	52.4916
N	249	249	249	249	249	249

This table shows results for regressions of Eq. (9) with ARM as the dependent variable. The dependent variable is a binary variable, taking the value of one if the bank implements ARM, and zero otherwise. *HHI* is the Herfindahl index for sector concentration and *Lerner* measures in how far banks can set prices over marginal costs.*Net Interest Income* is standardized over total income. *Net Commission Income* is net commission income over total income. *Loan Loss Provisions* are standardized over total assets. Assets below EUR 847 million is the omitted category for the size indicator variables. *Corporate Loans* are standardized over non-bank loans. *Equity* is banks' common equity standardized over total assets. *Regulatory capital* is the sum of banks' Tier1 and Tier2 capital standardised over risk-weighted assets. *Deposits* represents the funding side of banks' balance sheet and is standardized over non-bank loans. *East* is a binary variable, amounting to one if the bank is located in the former East Germany and zero otherwise. *GDP* is measured as GDP over capita. We report the marginal effects.

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

With regard to our main variables of interest competition and sector concentration, we find both are relevant for banks' decisions to engage in advance risk management. The results in Column (1) of Table 3 suggest that a marginal increase in sector concentration (measured by the Herfindahl–Hirschman index), increases the likelihood of implementing advanced instruments in banks. A marginal increase in market power equivalent to a diminishing level of competition (measured by the Lerner index), results in a decrease in the likelihood of participating in the use of advanced risk management instruments. Or put differently, higher competition leads

Table 4
Sensitivity analyses – size.

Variable	ARM		CPM		CRT	
HHI	1.7122*	2.0040**	6.4872***	7.0350***	−2.3040	−1.8913
	(1.0089)	(1.0115)	(2.0137)	(2.0776)	(3.1092)	(3.1955)
Lerner	−0.4895	−0.7174***	−1.1459	−1.2641**	−0.1022	−1.4115*
	(0.4006)	(0.2568)	(0.7338)	(0.6143)	(1.1069)	(0.8127)
Net Interest income	−0.2504	−0.2673	−0.9479	−1.0677	−1.5411	−1.2314
	(0.4432)	(0.4188)	(0.8984)	(0.8917)	(1.2741)	(1.2729)
Net Commission Income	1.9302**	1.7374**	5.4491***	5.5796***	3.4598	2.0733
	(0.7940)	(0.7542)	(1.5819)	(1.5804)	(2.6219)	(2.5730)
Loan Loss Provision	0.0977	−0.2372	0.1884	−0.2761	0.4574	0.6980
	(1.4680)	(1.3843)	(2.6112)	(2.6525)	(3.7592)	(3.8417)
Total Assets	0.0021		−0.0269		0.1692**	
	(0.0299)		(0.0553)		(0.0856)	
No. Employees		−0.0000		−0.0001		0.0001
		(0.0000)		(0.0001)		(0.0001)
Corporate Loans	−0.0226	0.0124	0.2558	0.3107	1.1321**	1.1775**
	(0.1836)	(0.1725)	(0.3427)	(0.3379)	(0.5391)	(0.5389)
Equity	−0.5788	−0.1540	2.6471	2.9375	−2.0287	−0.9291
	(1.5844)	(1.5933)	(3.1872)	(3.1642)	(4.6229)	(4.6590)

Table 4 (*Continued*)

Variable	ARM		CPM		CRT	
Deposits	0.0498	0.0476	0.0153	0.0178	−0.2093	−0.2364
	(0.0759)	(0.0707)	(0.1474)	(0.1447)	(0.2036)	(0.2067)
East	−0.0316	−0.0090	0.0068	0.0373	0.0795	0.1813
	(0.0363)	(0.0613)	(0.1396)	(0.1506)	(0.2064)	(0.2134)
GDP	−0.0000	0.0001	−0.0025	−0.0022	0.0079	0.0077
	(0.0012)	(0.0011)	(0.0029)	(0.0028)	(0.0050)	(0.0050)
	(0.4006)	(0.2568)	(0.7338)	(0.6143)	(1.1069)	(0.8127)
ps. *R*-squared	0.2139	0.2238	0.1528	0.1580	0.1547	0.1458
Log pseudolikelihood	−50.7965	−50.1609	−94.3652	−93.7848	−136.7098	−138.1581
Wald	39.6613	37.6558	31.0849	29.4177	45.1358	43.8838
N	249	249	249	249	249	249

This table shows results for regressions of Eq. (9) with ARM, CPM and CRT as the dependent variable. The dependent variable is a binary variable, taking the value of one if the bank implements the respective risk management strategy, and zero otherwise. *HHI* is the Herfindahl index for sector concentration and *Lerner* measures in how far banks can set prices over marginal costs. *Net Interest Income* is standardized over total income. *Net Commission Income* is net commission income over total income. *Loan Loss Provisions* are standardized over total assets. Size is measured as *No. Employees*, the number of employees and *Total assets*, which is the log of banks' total assets. *Corporate Loans* are standardized over non-bank loans. *Equity* is banks' common equity standardized over total assets. *Deposits* represents the funding side of banks' balance sheet and is standardized over non-bank loans. *East* is a binary variable, amounting to one if the bank is located in the former East Germany and zero otherwise. *GDP* is measured as GDP over capita. We report the marginal effects.

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

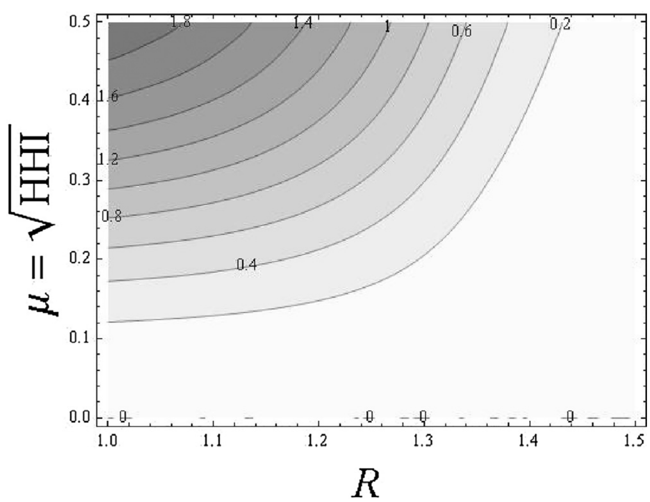

Fig. 4. Difference in profits, advanced risk management (ARM) vs. best alternative. This figure demonstrates a couple of regularities. First, and under the same reasoning used previously, a higher level of competition (low R) implies larger benefits of advanced risk management (ARM). If R is large, the 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 $\mu = 1$, but because μ^2 gives the sector Herfindahl–Hirschman index, $\mu = 1$ would imply that there is only one sector in the region, which is unrealistic. This is the reason why we concentrate on smaller values for μ. We arrive at two hypotheses, to be tested in the empirical section of the paper, and proven in the appendix. Whether the bank implements ARM depends on the cost c_{ARM}.

banks to engage in advanced risk management. Therefore, in line with Proposition 3 of our theoretical model, we find strong empirical evidence that both competition and sector concentration are positively related to advanced risk management. It appears that the depth of implementation and the integration of advanced 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 an important driver for the decision to engage in advanced risk management instruments, which is presented below.

Turning to assessing impact on CPM in Column (2), we observe that both higher competition and higher sector concentration significantly increases the probability for banks to employ CPM, offering support for Proposition 1 of our theoretical model. In line with Proposition 2, we find that banks in a more competitive environment are more likely to involve in credit risk transfer shown in Column (3) of Table 3. In contrast, sector concentration is not driving the participation decision, the sign of the coefficient, however, is negative, as also suggested by Proposition 2. Results remain qualitatively the same when we control for regulatory capital instead of leverage in Columns (4) to (6) of Table 3.[11]

Finally, we conduct a set of robustness checks including tests to assess robustness of our model to the construction of the endogenous variable, different proxies for bank size as well as relevance of mergers during the observation period. Additionally, we also estimate the model for each year separately for the observation period 2002-2006. Results remain qualitatively the same imposing these modifications (Tables 4 and 5).

4. Conclusion

In this paper, we have identified two major forces driving the sophistication of credit risk management and second confirmed our theoretical predictions empirically.

We have modeled a bank that holds a portfolio of two risky assets, assuming 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. Through risk transfer banks can diversify their portfolios. Typically, by implementing both risk management instruments (advanced 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 lower sector concentration.

[11] Interestingly, we find that banks with higher capital requirements are more likely to employ CRT, a result which also points to the theoretical conclusions: If a bank has higher requirements, the potential benefits from good risk management are higher.

Table 5
Sensitivity analyses – bank merger.

	ARM	CPM	CRT
HHI	1.9705*	6.6468***	−2.7162
	(1.0062)	(2.0396)	(3.2166)
Lerner	−0.6174**	−0.9500*	−1.7049**
	(0.2543)	(0.4955)	(0.8035)
Net Interest income	−0.3238	−1.2248	−1.1062
	(0.4160)	(0.8323)	(1.2828)
Net Commission Income	1.6959**	5.3918***	2.2689
	(0.7303)	(1.5177)	(2.5480)
Loan Loss Provision	−0.2536	0.0750	1.3631
	(1.4064)	(2.5773)	(3.8587)
EUR 0.847 bil < Assets < EUR 1.482 bil	−0.0123	−0.1027*	−0.0501
	(0.0250)	(0.0546)	(0.0758)
EUR 1.482 bil < Assets < EUR 2.906 bil	−0.0017	0.0092	−0.0108
	(0.0123)	(0.0276)	(0.0486)
Assets > EUR 2.906 bil	−0.0048	−0.0104	0.0180
	(0.0037)	(0.0085)	(0.0195)
Corporate Loans	−0.0097	0.2092	1.1749**
	(0.1708)	(0.3218)	(0.5386)
Equity	−0.2752	3.1947	−0.1614
	(1.6290)	(3.0277)	(4.7016)
Deposits	0.0473	0.0353	−0.2265
	(0.0718)	(0.1422)	(0.2083)
East	−0.0148	0.0305	0.1961
	(0.0524)	(0.1477)	(0.2121)
GDP	0.0004	−0.0016	0.0071
	(0.0011)	(0.0027)	(0.0052)
Merger	0.0061		−0.0257
	(0.0255)		(0.0759)
ps. *R*-squared	0.2263	0.1804	0.1502
Log pseudolikelihood	−49.9958	−91.2876	−137.4366
Wald	37.4339	33.6017	45.2642
N	249	249	249

This table shows results for regressions of Eq. (9) with ARM, CPM and CRT as the dependent variable. The dependent variable is a binary variable, taking the value of one if the bank implements the respective risk management strategy, and zero otherwise. *HHI* is the Herfindahl index for sector concentration and *Lerner* measures in how far banks can set prices over marginal costs. *Net Interest Income* is standardized over total income. *Net Commission Income* is net commission income over total income. *Loan Loss Provisions* are standardized over total assets. Assets below EUR 847 million is the omitted category for the size indicator variables. *Corporate Loans* are standardized over non-bank loans. *Equity* is banks' common equity standardized over total assets. *Deposits* represents the funding side of banks' balance sheet and is standardized over non-bank loans. *East* is a binary variable, amounting to one if the bank is located in the former East Germany and zero otherwise. *GDP* is measured as GDP over capita. *Merger* is a binary variable, amounting to 1 of the bank was involved in a merger, and zero otherwise. We report the marginal effects.

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Implementing both risk management instruments, advanced risk management, is desirable when competition is high and it is also desirable for a higher sector concentration.

We have tested our predictions empirically on a sample of 249 banks of the German Savings Banks Finance Group, empirically confirming our theoretical results. We find that bank competition pushes banks to implement credit portfolio models and engage in risk transfer markets. Sector concentration in the loan market promotes the decision to monitor through credit portfolio models but inhibits credit risk transfer. In addition, we take the more integrated view in analyzing advanced risk management, being a combination of monitoring and diversifying efforts of the bank. As such, in this study we apply a more comprehensive approach to advanced risk management both theoretically and empirically.

We show that the use of advanced or sophisticated risk management instruments is related to bank competition. Moreover, we shed light on the determinants driving the global risk management strategy of a bank and thereby on the organisational structure of risk management instruments and practices in place. We are not aware of any other study that analyzes how banks organize their credit risk management. Given that credit risk is at the heart of financial stability, our insights may be helpful for financial regulators and supervisors.

Appendix A. Proofs

Proof of Proposition 1 *(CPM).* There are two scenarios, one in which capital requirements are binding, and one in which they are not. Start with the second, more interesting case. In the benchmark without CPM and, therefore, without further information on the correlation structure, the optimal buffer k^* is given by the first order condition (4),

$$\frac{c}{2\sqrt{2\pi}\,\sigma}\left(\rho^2\exp\left(-\frac{(2-k^*-2R)^2}{8\sigma^2}\right)+\sqrt{2}(1-\rho^2)\right.$$
$$\left.\exp\left(-\frac{(2-k^*-2R)^2}{4\sigma^2}\right)\right)=\phi k^*. \tag{10}$$

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 (10) 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

$$\frac{c}{2\sqrt{2\pi}\,\sigma}\exp\left(-\frac{(2-k^*-2R)^2}{8\sigma^2}\right)=\phi k_1^*. \tag{11}$$

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),

$$\frac{c}{2\sqrt{2\pi}\,\sigma}\sqrt{2}\exp\left(-\frac{(2-k^*-2R)^2}{4\sigma^2}\exp\right)=\phi k_0^*, \tag{12}$$

again with unique and strictly positive solution for k_0^*. Because (10) is a convex combination of (11) and (12), 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 it to k_0^*.

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

$$\Pi_{\mathrm{CRT}}=2R-2-\phi k^2/2-c\left[\rho^4\,\Phi\left(\frac{2-k-2R}{2\sigma}\right)+4\rho^3(1-\rho)\,\Phi\left(\frac{2-k-2R}{\sqrt{5/2}\,\sigma}\right)\right.$$
$$\left.+6\rho^2(1-\rho)^2\,\Phi\left(\frac{2-k-2R}{\sqrt{3/2}\,\sigma}\right)+(3\rho+1)(1-\rho^3)\,\Phi\left(\frac{2-k-2R}{\sigma}\right)\right] \tag{13}$$

The first order condition is

$$\frac{c}{\sigma\sqrt{\pi}}\left[\rho^4\frac{X^{8/8}}{\sqrt{8}}+\rho^3(1-\rho)\frac{X^{8/5}}{\sqrt{5}}+6\rho^2(1-\rho)^2\frac{X^{8/3}}{\sqrt{3}}+(3\rho+1)\right.$$
$$\left.(1-\rho^3)\frac{X^{8/2}}{\sqrt{2}}\right]=\phi k^*, \tag{14}$$

with X defined by (4). Again, the r.h.s. defines a bell-shaped curve with modal point at $k=2-2R<0$, 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 Fig. 3. The argument for an increase in ρ proceeds differently. For a small ρ, only the fourth constellation applies,

$$\begin{aligned} \Pi_{\text{CRT}} &\approx 2R - 2 - \phi k^2/2 - c\,\Phi\left(\frac{2-k-2R}{\sigma}\right) \quad \text{and} \\ \phi k^* &\approx \frac{c}{\sigma\sqrt{\pi}} \frac{X^{8/2}}{\sqrt{2}}. \end{aligned} \tag{15}$$

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 Fig. 3. Again, if capital requirements are binding, there is no the effect of CRT is smaller.

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

$$\begin{aligned} \Pi_{\text{ARM}} &= 2R - 2 - \phi k_4^2/2 - c\,\Phi\left(\frac{2-k_4-2R}{2\sigma}\right) \quad \text{and} \\ \phi k_4^* &= \frac{c}{\sigma\sqrt{\pi}} \frac{e^{-\frac{(2-k_4^*-2R)^2}{8\sigma^2}}}{\sqrt{8}}. \end{aligned} \tag{16}$$

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 Fig. 4. Again, if capital requirements are binding, there is no the effect of ARM is smaller.

Appendix B. Survey structure

The survey was conducted in April 2009 and was primarily answered by top management. 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%. For our analyses we used 249 responses (57%) because some banks returned the questionnaire without the front page containing the name of the bank. Banks involved in a merger since 2006 are excluded from the sample because historical data is not available for these new entities. Thus, comprising 57% of the banks participating in the survey, our sample is highly representative of all regions and asset classes.

In the survey, banks were asked to provide information on the instruments used in their daily corporate business. The respondents were asked to qualify the intensity of their use of different credit risk management tools as frequent, occasional or no use.

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?

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