Does Discretion in Lending Increase Bank Risk?

Borrower Self-selection and Loan Officer Capture Effects

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In this paper we analyze whether discretionary lending increases bank risk. We use a panel dataset of matched bank and borrower data. It offers the chief advantage that we can directly identify soft information in banks' lending decisions. Consistent with the previous financial intermediation literature, we find that smaller banks use more discretion in lending. We also show that borrowers optimally select to banks depending on whether their soft information is positive or negative. Financially riskier borrowers with positive soft information are more likely to obtain credit from small banks. Risky borrowers with negative soft information are equally likely to obtain a loan from a large or a small bank. However, while small banks have financially riskier borrowers, ex post default is not more probable compared to borrowers at large banks. As a consequence, smaller banks do not have higher credit risk levels. Loan officers at small banks thus do not use discretion in lending to grant loans to ex post riskier borrowers.

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In this paper we investigate whether discretion in lending affects bank risk. Discretionary lending is common in close bank-borrower relations that are typical for small banks. These "relationship banks" establish intense and long-term relations with their borrowers and thereby generate soft, and typically proprietary, information about the borrower that is hard to verify by other parties and subjective by nature (e.g., Stein, 2002). "Transaction banks" in contrast operate at arm's length to borrowers, base their lending decision on credit scoring models, and do not gather soft information. Their loan officers rely on information that is verifiable by third parties and is largely financial. Loan officers of transaction banks therefore have less or no discretion in their lending decisions.[1]

Discretionary lending and the use of soft information may increase or decrease a bank's portfolio risk. Based on the theoretical literature we would distinguish three main ideas. One, soft information is additional information that a bank can use when analyzing a borrower's credit risk (*information advantage hypothesis*). This should yield superior loan approval decisions compared to banks that cannot efficiently use such information. The empirical literature suggests that soft information indeed improves the accuracy of banks' screening (Grunert et al., 2005; Degryse et al., 2011). Second, recent theoretical models (Hauswald and Marquez, 2006; Inderst and Mueller, 2007) suggest that firms with positive soft information would tend to self-select to relationship banks that can take soft information into account, while firms with negative soft

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[1] That is not to say that loan officer do never attempt to manipulate hard information (see Berg at al. 2011).

information would tend to self-select to transaction banks that cannot.[2] This is a standard Akerlof-type adverse selection problem, in which transaction banks tend to receive applications from borrowers with on average negative soft information.[3] Transaction lenders still participate in the market for small business loans by requiring their borrowers to provide additional collateral (Inderst and Mueller, 2007) or because they have a cost advantages relative to relationship banks (Hauswald and Marquez, 2006). Both the *information advantage hypothesis* and the *selection hypothesis* would suggest that the ability to use soft information in lending decisions reduces the risk of banks.

Third and in contrast, the use of soft information may also increase risk taking. By assumption, soft information is not verifiable and leaves loan officers with more discretion in their decisions. Loan officers may obtain private benefits when lending to certain types of borrowers. For example, they may develop a close personal relationship to some borrowers, which could impair their judgment of the borrowers' risk.[4] This effect is similar to the one described in the regulatory capture literature: regulators working closely with bank management may no longer be able or willing to correctly assess the risks facing the bank (e.g. Kane, 1990).

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[2] In Inderst and Mueller (2007) and Hauswald and Marquez (2006), borrowers for whom the relationship bank's information advantage is large approach relationship banks, while borrowers for whom the relationship lender's information advantage is small borrow from the transaction bank. Thus, the probability that a borrower receives a loan offer from the transaction bank decreases in the information advantage of the relationship bank.

[3] Transaction banks may apply a negative adjustment to all their loan applicants taking into account this adverse selection. However, if they do this, even borrowers with slightly negative soft information may be better off obtaining a loan from a relationship bank, resulting in an even worse pool of loan applicants (with respect to soft information). Ultimately, in the absence of any offsetting factor, transactions banks would no longer participate in the market for small business loans. We do find weak evidence below that transactions banks apply such wholesale negative discounts to their customers.

[4] Hertzberg et al. (2010) show that loan officers are more likely to reveal negative information in the case of anticipated job rotations, which thus seem to alleviate moral hazard in communication.

This *loan officer capture hypothesis* would suggest that discretion and the use of soft information in lending decisions could increase bank risk taking. Fourth, insofar as relationship banks incur higher costs compared to transaction banks (Boot and Thakor, 2000; Hauswald and Marquez, 2006), their margins and charter values may be lower ("*cost hypothesis")*. Lower charter values may result in a greater willingness to accept riskier borrowers (e.g. Keeley, 1990; Hellman et al., 2000). Ultimately it is an empirical question whether the use of soft, non-verifiable, information in lending decisions decreases or increases bank risk.

We test these theoretical predictions using a matched bank-borrower dataset of German savings banks. German savings banks provide an ideal laboratory to test these questions, as they compete with pure transaction banks, such as Deutsche Bank or Commerzbank and with pure relationship banks, such as the large number of extremely small cooperative banks in Germany (see the next Section for more detail). At the same time, we document that there is sufficient variation within the savings bank sector in the degree to which banks incorporate soft information in their lending decisions. In addition, the dataset that we have access to includes a measure for soft information that permits a distinction between the case when positive soft information affected the lending decision of the bank versus the case when negative soft information affected the lending decision of the bank. We will describe the measure in more detail below. The third crucial advantage of the data set is that it provides information on creditor by creditor ex post defaults. Hence, we can link the ex-ante use of hard versus soft information in the lending decision to the ex post default probability of the borrower.

Using these rich data, we are able to provide direct evidence on the four hypotheses. We first confirm that the degree to which banks use soft information in lending decisions differs within our sample of savings banks. As predicted by theory (Stein, 2002) and consistent with prior empirical evidence (Cole et al., 2004; Berger et al., 2005; Liberti and Mian, 2009), smaller banks use more discretion in lending. The effect, however, is not symmetric, as predicted by the selection hypothesis. Borrowers with riskier financial characteristics are more likely to obtain credit from smaller banks if they have positive soft information. The converse is not true: firms with negative soft information are equally likely to obtain a loan from a small or a large bank. Hence, ex ante the customers of small banks appear riskier based on financial information alone.

At the same time, we do not find that firms that were upgraded based on soft information are ex post more likely to default. Loan officer rather seem to using soft information too cautiously: even when borrowers are upgraded based on positive soft information, they are less likely to default relative to the baseline and even when borrowers are downgraded based on negative soft information they are more likely to default relative to the baseline. Hence, we can reject the loan officer capture hypothesis in our sample. Finally, we show, consistent with theory, that the transaction banks' informational disadvantage is compensated for by greater cost-efficiency in lending and that borrowers can substitute collateral by positive soft information and vice versa. Overall, the results in this paper suggest that soft information is used efficiently in the sense that relationship banks' portfolio risk does not differ significantly from transaction banks' portfolio risk.

Our paper builds on a large body of literature on the role of relationships in banking. At a general level, relationship lending theory is based on the idea that financial intermediaries have a competitive advantage in the production of information about borrowers (Boyd and Prescott, 1986). In particular, Cole et al. (2004) and Berger et al. (2005) show that smaller banks have stronger borrower relationships than larger banks due to a smaller number of managerial layers between the loan officers and the bank management in small banks (Stein, 2002; Williamson, 1967). Liberti and Mian (2009) provide evidence that the greater the hierarchical distance, the less the importance of soft information on the borrower in the process of credit approval. Thus, smaller banks are better in producing soft information on the borrower than larger banks thanks to their organizational structure.

Most of the previous literature bank-borrower relationships focused on their implications for the *borrowers*. Berger and Udell (1995) show that stronger relationships lead to lower collateral requirements and lower interest rates charged. Berger et al. (2005) and Cole et al. (2004) also show that smaller banks lend to more opaque clients while large banks focus on large firms with good accounting records. In addition, stronger bank-borrower relationships may increase the availability of credit for the borrower (Petersen and Rajan, 1994; Berger and Udell, 1995) even in situations of rating downgrades (Elsas and Krahnen, 1998). Jiménez and Saurina (2004) show that stronger bank-borrower relationships increase the willingness to lend to riskier borrowers.[5] We focus in our paper on the influence of discretionary lending, as an inherent characteristic of relationship lending, on bank risk taking. We thus shed light on the question how relationship lending affects *banks*.

Most empirical papers, the econometrician does not possess the soft information part and employs indirect ways to approximate it. For instance, Cerqueiro et al. (2011) investigate the

[5] Closer bank-borrower relationships can also create informational monopolies for the bank, which result in hold-up problems and deteriorating loan terms (see for instance Boot, 2000).

importance of discretion in loan rate setting. They use a heteroscedastic regression model to see which factors determine the dispersion in banks' loan rates to SMEs.[6] Two notable exceptions are also using direct measures of soft information. One, Degryse at al. (2011) use very detailed data from *one bank* and show that only soft information is explaining observed loan officer discretion. In addition, soft information is found to be important to determine the loan volume. In contrast to Degryse et al., we have access to a large number of different bank-borrower relationship intensity, which allows us the analysis of the borrower self-selection effect. Second, Puri et al. (2011) use *retail loan applications* and find that loan applications, that were rejected based on financial credit scoring, are more likely to be approved based on soft information in the case of existing borrowers and those of lower credit quality. In our paper, we rather use data on commercial borrowers because the production of soft information is more important for this borrower type given the higher complexity of overall firms compared with single individuals.

The relation of size and risk in banking is a long-discussed topic in finance. Especially in the wake of the financial crisis of 2007/2008 the debate about divestures of banks into smaller operational units in order to reduce risk was prominently pursued.[7] The main focus so far has been on deposit insurance literature, which predicts that larger banks increase risk because of explicit or implicit public guarantees ("too big to fail") and the subsequent moral hazard effects

[6] Garcia-Appendini (2011) and Agarwal and Hauswald (2010) are further examples for indirect approximations.

[7] In several countries the discussion about a break up of banks was initiated by the government, e.g., in the UK - compare for example Financial Times "Chancellor under pressure to break up banks" of June 13, 2010. Furthermore, there are cases where banks were actually broken up into a retail bank and a "toxic" wind-down bank; compare for example Financial Times "Dublin in move to split Anglo Irish Bank" of September 9, 2010.

(Merton, 1977; Bhattacharya et al., 1998). According to theory, large banks, which are perceived as "too big to fail", are more likely to be bailed-out and have therefore incentives to increase risk. These predictions have been empirically tested by many studies. For instance, Boyd and Runkle (1993) and Gropp et al. (2011) find evidence for a positive correlation between size and risk. In addition, most papers point towards higher failure probabilities at larger banks (e.g., De Nicoló, 2001). Our paper adds to this literature by trying to establish an empirical relationship between bank risk taking and discretionary lending.

The reminder of the paper is organized as follows. The first section gives some institutional background on German savings banks. In Section 2, we describe our dataset. Sections 3 and 4 present our empirical results. The last section concludes.

1 Institutional background

The German banking market is almost evenly split between three types of banks: savings banks (the focus of this paper) and federal state banks[8], credit cooperatives, and commercial banks. It is characterized by a low level of concentration with around 450 different savings banks, more than 1,000 credit cooperatives, and around 300 privately owned commercial banks.

Taken as a group, savings banks in Germany have more than Euro 1 trillion in total assets and 22,000 branches. German savings banks focus on traditional banking business with virtually

[8] Each savings bank is affiliated with one federal state bank ("Landesbank") and each federal state bank is affiliated with a state or group of states. The federal state banks facilitate the transfer of liquidity from savings banks with excess liquidity to those with liquidity shortfalls. In addition, the federal state banks secure market funding through the issuance of bonds. For an in-depth description of the German banking market see Hackethal (2004).

no off-balance sheet operations. Their main financing sources are customer deposits, which they transform into loans to households and small and medium sized enterprises (SME). Savings banks are owned by the local government of the community they operate in. For our research questions it is important to emphasize that the individual savings banks are relatively small compared to the well-known commercial banks in Germany. They act as a "house bank" for their customers with a strong focus on supply of savings products and loans (Elsas and Krahnen, 1998; Elsas, 2005). Due to the small size as well as the strong bonds with the city or region they operate in, savings banks can be seen as a textbook example for relationship banking. Another important difference between commercial banks and savings banks is that savings banks in Germany are obliged by law to serve the "common good" of their community by providing households and local firms with easy access to credit. They do not compete with each other, as a regional separation applies: each savings bank uniquely serves its local market (similar to the geographic banking restrictions that existed up to the 1990s in the U.S.). Finally, the savings banks make use of relatively similar compensation system for loan officers, which largely rely on fixed contracts.[9] In our dataset, the median commission payments over regular staff expenses, which approximate the loan officer bonus payments, is only around 2%. It thus seems very unlikely that any of our results are driven by loan officer incentive issues.

Despite their obligation to serve the common good, the savings banks in our sample are on average relatively profitable in the observation period 2002-2006: average pre-tax ROE is

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[9] Agarwal and Wang (2009) show that loan origination-based incentive compensation increases loan origination and the bank's credit risk.

8.9% while the average cost to income ratio is 80.6%. Notwithstanding the differences in governance, savings banks appear very similar to private commercial banks of comparable size in continental Europe. Pretax ROE of commercial banks is 9.8% in continental Europe and 8.2% in the UK (186 small banks, 2002-2004, data is from Bankscope). Similarly, cost to income ratios are 81.6% in continental Europe and 70.6% in the UK. Overall, German savings banks look like a fairly typical small commercial bank in continental Europe.

2 Data

2.1 Matching of bank and borrower information

Our main dataset consists of matched bank-borrower information. We start with an exhaustive dataset of commercial borrowers of the savings banks. It provides annual balance sheets and income statements of all commercial loan customers of the 452 German savings banks affiliated with the German Savings Banks Association.[10] The borrowers are largely small and medium size enterprises (SME), which strongly rely on bank loans.

This dataset's unique feature is its hard and soft information for each loan customer. Hard information consists of financial information, which is objective and easy to verify. Soft information, on the other hand, is of subjective nature and thus harder to verify. We thus use the soft information to approximate loan officer discretion. Empirical evidence by Degryse et al.

[10] There are seven savings banks in Germany that are not full members in the savings banks association. They are not covered in the dataset.

(2011) supports our approach. They have very detailed borrower information from one bank in Argentina and show that only soft information but not hard information guide loan officer discretion.

Specifically, we have 77,364 credit ratings for the years 2002-2006 of 60,696 borrowers.[11] The ratings are based on an internal and proprietary rating algorithm. All savings banks use the same rating algorithm, therefore the comparability of the rating is ensured. It produces a score from 1 to 21, where 1 equals AAA, 2 equals AA+, etc. until 21 equals C. Thus, the higher the numerical rating, the riskier is the borrower. The rating information is split into two components. The first consists of a financial rating that incorporates hard financial statement information on the borrower. The second component comes as a final credit rating. The difference between the financial rating and the end rating reveals the soft information on the borrower. According to the savings banks association, the second part accounts for around 50% of the final credit rating. It includes qualitative information such as management quality, the companies strategy, and perceived product or service quality and quantitative information such as account activity (Norden and Weber, 2010; Mester et al., 2007).

We use five alternative measures for soft information: i) the absolute difference between the financial and the end rating; ii) the probability of a rating upgrade because of the soft information; iii) the probability of a rating downgrade because of the soft information; iv) the strength of the rating upgrade in numerical rating notches; v) the strength of the rating

[11] Our observation period starts in 2002 because a new rating system was introduced in that year.

downgrade in numerical rating notches. Hence, in the empirical analysis below we can distinguish between downgrades based on soft information and upgrades based on soft information, which enables us to explicitly test for borrower selection based on privately observed soft information. Based on the findings in Degryse et al. (2011), we interpret the soft information as a proxy for loan officer discretion.

Merging borrower level with the bank level dataset comes at a cost: in order to ensure some degree of anonymity of customers, the matching of borrowers to savings banks is possible only aggregated in groups of 5-12 savings banks. In total, there are 62 savings bank groups with rating data available. The aggregation was done by the savings banks association and savings banks of the same region were lumped together, except, that larger savings banks were put into large bank groups. This helps in preserving enough heterogeneity with respect to average bank group size. Hence, while we have precise information on the individual bank and on the individual customer, we only know that the customer banked with any one of the group. We thus link the customer characteristics to the average of the group of savings banks, rather than to an individual savings bank.

We rely on bank size as an identifying variable for banks with tighter bank-borrower relationships.[12] This approach builds on Cole et al. (2004) and Berger et al. (2005) who find that smaller banks have stronger relationships to their borrowers. Berger et al. (2005) suggest that large banks tend to approve or reject loan applications primarily via credit scores. Potential soft

[12] Note that we do not have enough heterogeneity on the borrower level with respect to relationship length.

information on the borrower is not taken into consideration if it is not captured within the scoring system. In addition, if the number of hierarchy levels between the loan officer and the management is larger, decisions of the scoring system are overruled more often in management decisions or loan officers have fewer incentives to gather the soft information right away (Liberti and Mian 2009). The more branches for example a bank has the more disperse its geographical footprint and the farther the physical distance between the individual loan officers and the bank's management.[13]

Specifically, we use three measures for bank size: the natural logarithm of the average bank assets per group of savings banks, the number of bank branches, and the number of bank FTEs. Assets are very common in the literature and well-suited as they are relatively stable and not as much affected by the business cycle as a bank’s revenues or profits. However, when measuring how close borrowers and loan officers actually get (Williamson, 1967; Liberti and Mian, 2009), a more appropriate measure might be the number of branches or the number of employees of each savings bank. We throughout report results based on the bank assets and use the other two size measures as robustness checks. All results go through independently of the size measure used.

A borrower’s ex ante measure of credit risk is measured by Altman’s Z-Score (Altman, 1968) and the borrower’s financial rating. We use a Z-Score, which is calibrated to the German market (Engelmann et al., 2003). A higher Z-Score indicates a lower risk associated with the

[13] Degryse and Ongena (2005) show that loan rates decrease with the distance between the firm and the lending bank and increase with the distance between the firm and competing banks. However, the distance to the borrower is not available for our dataset.

borrower. We also control for borrower size (natural logarithm of total assets), as Stanton (2002) shows that managers are more efficient in monitoring fewer large loans.

We furthermore control for changes in the macroeconomic environment over time. We use the relative change in the ifo-Index, which is a nation-wide forward looking business climate index of the ifo institute. We also employ the average daily risk-free interest rate at the national level (Bundesbank data), in order to control for the relationship between interest rates and credit risk as there is a growing body of literature showing that low short-term interest rates may be related to softer lending standards and increased risk taking (Ioannidou et al., 2009; Jiménez et al., 2011). In unreported robustness checks, we include year fixed effects and drop the change in the ifo-Index and the risk-free rate. All results reported below are unaffected by this alternative way of modeling macro developments over time.

To investigate the relationship between bank size and screening / monitoring intensity we employ three different measures: i) sum of staff cost over average assets per bank group and year (in %); ii) number of bank branches (in hundreds) over the average assets per bank group (in billions) and year; iii) number of bank FTEs (in thousands) over the average assets per bank group (in billions) and year.

We further use several bank group level control variables. The number of mergers for the savings bank per year controls for potential effects that merged banks tend to weaken bank-borrower relationships (Di Patti and Gobbi, 2007).[14] As savings banks are regionally bounded

[14] However, Berger et al. (1998) provide evidence that reduced small business lending is offset by the reactions of other banks.

and do not compete with each other we can link the savings banks to different regions within Germany. We thus use a number of regional variables to control for bank level heterogeneity. We control for the regional level of competition (Boyd and De Nicoló, 2005) by using the ratio of branches of direct competitors (commercial banks and cooperative banks) to savings banks branches per group of savings banks and year. The data comes from the Bundesbank.[15] In line with Keeley (1990), we expect that banks lend more aggressively in more competitive markets which would result in higher risk. We also control by the average debt per capita of the community that the savings bank is located in. With this variable we attempt to control for differences in the financial strength of the savings banks' owners.[16] The variable comes from the federal statistical office of Germany ("Destatis"). Refer to Table 1 for all variable definitions.

2.2 Descriptive statistics

Table 2 provides descriptive statistics for the main variables. We first discuss variables, which are on the borrower level. The average absolute change in rating based on soft information on the borrower is 2.02 notches, which indicates a significant influence of soft information on the final rating decision. Upgrades, i.e. the final rating indicates a lower risk due to soft information than the financial rating, are observed with a frequency of 25% and have an average magnitude of 2.48 numerical rating notches. Downgrades are more frequently observed with 60% and on average slightly less strong with 2.37 notches. The rating remains unchanged for 15% of the

[15] The data covers the year 1996-2004. Thus, as the data ends too early, we assume that competition remained unchanged in 2005/2006 and use the 2004 data in these two years.

[16] Recall that all savings banks are at least in part owned by the local community it operates in.

borrowers. The average Z-Score for the borrower is 3.41 while the average financial rating is 12.4 (corresponding to a long-term credit rating of BB). On average, 4.8% of the borrowers in our sample default in the 12 months following the rating assignment. On the more aggregated bank group level for the ex post credit quality outcome, the average net charge off ratio (over bank assets) equals 0.46%.

Next we show the variables, for which we only present the bank group figures. The average assets of bank groups are Euro 2.28 billion. The dispersion of bank size is large. The 95% percentile of the bank assets is more than 14-fold the 5% percentile. Thus, the significant differences between the smallest and largest savings bank groups allow us to assume that bank-borrower relations are of different strength.

The number of direct competitors is less than one on average, indicating a rather low level of competition. On average, the savings bank groups were involved in a merger every third year. Local communities, the savings banks were operating in, were indebted by Euro 1,064 per capita on average. Looking at further national control variables, the change in the ifo-index is on average positive, which reflects Germany's healthy economic phase in 2004-2006. The risk-free interest rate was on average 2.28% indicating low interest rate levels in Germany in the analyzed time period. The average assets of the borrowers are Euro 616,000, which demonstrates that the savings banks mostly engage in SME lending.

3 Baseline Results

As a first cut of how discretion in lending affects risk taking, we present univariate results in Panel A of Table 3. We split the borrowers according to their bank groups' average assets. The last column shows the t-values of univariate regressions to test for differences of the smallest versus the largest savings banks. We find that the average absolute difference between financial rating and end rating, |Δ Rating|, is significantly higher for the smallest than for largest savings banks. Smaller banks thus seem to use more discretion in lending than larger banks. This is consistent with the previous literature that smaller banks produce more soft information (Berger et al., 2005; Uchida et al., 2012). More importantly, the effect is not symmetric for upgrades and downgrades. A rating upgrade is 3.7% more likely for small than for large savings banks. This accounts to around 15% of the unconditional upgrade likelihood (see Table 2). In addition, given they upgrade, the upgrade is by significantly more rating notches. In contrast, smaller banks do not use soft information to downgrade borrowers more often, nor do they downgrade by more notches compared to large banks. A rating downgrade is rather more likely for large than for small savings banks, however, the difference is not significant. Hence, we obtain first evidence for the hypothesis that borrowers with positive soft information self-select to smaller and more relationship oriented banks that are more likely to take this information component into account.

While we found the univariate results encouraging, it is possible, for instance, that the effects are due to regional differences across local markets. Panel B of Table e shows OLS regression results with the five different measures for discretion in lending as dependent variables and the bank size measure as the main independent variable.[17] The first column of Panel A shows that the absolute difference between the financial and the end rating, |Δ Rating|, is larger for smaller banks. As in the case of the univariate results, the effect is again not symmetric for upgrades and downgrades. Column 2 shows that smaller banks do seem to be significantly more likely to upgrade their borrowers based on soft information. In addition, given they upgrade, the upgrade is by significantly more rating notches (column 4). In contrast, smaller banks do not use soft information to downgrade borrowers more often (column 3), nor do they downgrade by more notches compared to large banks (column 5). We thus find again evidence for the self-selection effect of borrowers with positive soft information.

Control variables do also offer interesting insights. As expected, the rating of larger borrowers is likely to be adjusted based on soft information. Larger borrowers are less likely to be upgraded and experience smaller rating adjustments due to soft information in case of an upgrade or a downgrade.[18] Larger borrowers tend to be less opaque, because reporting quality is better on average, and, hence, soft information is less important in their assessment for a loan. In addition, upgrades based on soft information are less likely in years with a merger between two (or more) savings banks.

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[17] We use OLS models throughout since differences to using Probit models for the binary dependent variables in columns two and three are negligible.
[18] On the other hand, and to our surprise, they are more likely to be downgraded based on soft information than smaller borrowers. This finding is, however, not robust to using different size measures. These results are available from the authors upon request.

Unreported robustness checks further bank our results. One, using the number of bank branches and the number of bank employees yield qualitatively similar results. If we allow for non-linearities in size by using quartile dummies for bank size, we find unchanged evidence that the banks in the largest size category use less soft information, are less likely to upgrade their borrowers, and if they upgrade, the upgrade is by a smaller magnitude. The effects we find are strongest for the largest bank quartile (versus the smallest quartile). In further unreported robustness checks, we replace the national controls (risk-free interest rate, change in ifo-Index) with year fixed effects. Our results are robust to these alternative specifications.[19]

These results are important for two reasons. One, they relate our new proxies for the extent to which banks use soft information to bank size, which has been used in the previous literature (e.g., Berger et al., 2005; Cole et al., 2004). Column 1 of panels A shows that small banks use more discretion in lending. Second, columns 2 to 5 suggest that discretion is only used to upgrade firms (i.e. to improve upon the rating they would have received based on financial information alone), but not to downgrade firms (i.e. to decrease the rating firms would have received based on financial information alone). This is consistent with a selection effect emphasized in Inderst and Mueller (2007) or Hauswald and Marquez (2006): firms with positive soft information self-select to small relationship banks that are more likely to take this information into account, while borrowers with negative soft information self-select to larger banks that do not take the soft information component into account. We thus only observe

[19] We do the same robustness checks for all regressions below and all results carry over. They are available from the authors upon request.

empirically the impact of positive soft information, whereas we do not see any direct effect of negative soft information. If any, larger banks slightly tend (though this results is not significant) to downgrade borrowers more often. Hence it seems as if they anticipate their information disadvantage to more relationship oriented smaller banks.

The previous result leads us to the following question: If firms with better soft information self-select towards smaller banks, that are more likely to take soft information into account, is it the case that this effect is particularly strong for firms that look particularly risky purely based on financial information that both large and small banks can use to assess borrowers? We measure the extent of positive information by the upgrade probability, *Upgrade*, i.e. whether the bank improved the end rating compared to the financial rating because of positive soft information. As a measure of the financial risk of a borrower we use the Z-Score, which is decreasing in risk. In addition, we use the borrowers' financial rating. Both measures do not include soft information.

Panel A of Table 4 shows the univariate results. We split the matched bank borrower dataset according to the borrowers' Z-Score into quartiles. The first quartile includes the riskiest borrowers while the forth quartile contains the safest borrowers. The first and second columns show the upgrade probability for the smallest and the largest bank size quartile. Bank size is measured according to the sum of bank group assets in the respective year. We find that smaller banks are 3.7% more likely to upgrade their borrowers compared with larger banks (significant at the 10% level). This effect is more pronounced for the riskiest borrowers. The difference is 8.2% for the riskiest Z-Score quartile (significant at the 1% level) while the difference is only

2.0% for the safest Z-Score quartile (not significant). The differences-in-differences term is 6.2% and significant at the 1% level.

Panel B of Table 4 shows the multivariate OLS regression results.[20] We regress the upgrade probability based on soft information on borrower risk and bank size measures. We form interaction terms to capture the bank size-borrower risk relationship that we discovered in the univariate analysis. The dummy variable *Risky borrower* equals 1 for borrowers in the riskiest Z-Score (financial rating) quartile and 0 otherwise in columns 1 and 2 (in columns 3 and 4). The dummy variables *Small bank* equals 1 for the smallest size quartile and 0 for the largest bank size quartile. We restrict our sample to the smallest and largest bank size quartile and treat the large bank size quartile as reference category.

Columns 1 and 3 show that riskier borrowers are more likely to be upgraded because of positive soft information. Smaller banks are also more likely to upgrade their borrowers. In addition, smaller borrowers are upgraded more frequently. The specification of columns 2 and 4 also include the interaction term *Risky borrower* * *Small bank*. The positive coefficients tell us that smaller banks are more likely to upgrade risky borrowers. The effect is also economically significant since riskier borrowers in column 2 are 7.9% (that is 2.2% + 5.7%) more likely to receive a rating upgrade because of positive soft information at a small bank compared to the case of a risky borrower at a large bank. Note that the unconditional probability to receive a rating upgrade is 24.5% (see Table 2). The effect is about the same magnitude if we use the

[20] We again use OLS models since differences to using Probit models for the binary dependent variables are negligible.

financial rating to sort the borrowers in column 4 (7.4%). This result is in line with the selection effect that smaller banks more often lend to riskier borrowers (based on financial characteristics) who have substantial positive soft information.

That fact that small banks use soft information more frequently to upgrade risky borrowers suggests that smaller banks lend to riskier borrowers that appear riskier based on financial information alone. Next, we formally check whether this is the case. In the first step we analyze whether smaller banks extend more loans to riskier borrowers considering only their financial characteristics. The results of Table 5 demonstrate that smaller banks exhibit portfolios with significantly financially riskier borrowers. In additional unreported regressions, we test whether these results are robust for non-linearities in size. We use size quartile dummies for the average bank assets and find that the smallest bank size quartile has borrowers with riskier financials compared to the largest bank size quartile. We interpret these results as further evidence for the selection hypothesis, i.e. that smaller banks lend to riskier borrowers based on their financial characteristics alone.

Small banks lend to borrowers that exhibit ex ante weaker financial characteristics. However, these borrowers tend to be upgraded based on positive soft information that large banks are unable to use. Next we examine whether this use of soft information results in overall riskier outcomes ex post. Clearly, if banks use the soft information in an unbiased way, the customers with ex ante weaker financial information may not necessarily exhibit higher probabilities to default ex post. On the other hand, if loan officers use the discretion to provide loans to borrowers that entail a private benefit to them or are otherwise captured by their customers (*loan officer capture effect)*, banks using more discretion in lending would show higher risk also ex post. In order to differentiate the two possibilities we directly regress our proxy for the use of soft information on the default outcome of the borrower, which is either 1 in the case of a default in the following 12 months after the rating was assigned or 0 otherwise. Note that the unconditional default frequency is 4.8% (see Table 2).

Panel A of Table 9 shows results for this exercise. The first five columns exclude bank group fixed effects to see the effects of bank size and other bank related variables on the borrowers' default realization. We observe that soft information seems to matter for predicting the borrowers' default (this is in line with Degryse et al., 2011 and Grunert et al., 2005). In column 2, an upgrade based on soft information reduces the default likelihood by 0.9%. This is not only significant on the 1% level but also economically substantially given the reduction in the unconditional default likelihood of around one fifth. In case the borrower received a rating upgrade based on soft information, the upgrade strength is also negatively related to the default outcome (column 3). In contrast, a downgrade based on soft information increases the default likelihood by 1.0% (column 4) and the downgrade strength is positively related with the dependent variable (column 5). These results indicate that banks are too cautious in using soft information to adapt their view on the borrowers' credit risk that is formed by its financial characteristics. We thus do not find evidence for the *loan officer capture effect*.

The control variables provide additional insights. The financial rating enters the regression negatively, i.e. indicating that riskier borrowers are more likely to default. Double digits t-statistics show the very strong predictive power of the financial characteristics. On top of that, the borrowers' Z-Score also enters significantly negatively in some of the regressions. Larger borrowers exhibit larger default likelihoods. Larger banks have borrowers that are ex post less risky. Finally, banks operating in regions with higher bank competition have less risky borrowers.

We then include bank fixed effects in the last five columns of Table 6, Panel A, to control for unobserved time-invariant bank group characteristics. The main results go through as before, though the economic effect of the upgrade and downgrade variables decrease slightly. The time-variant bank level variables mostly lose significance, since there is not much variation over time in bank size and in particular with respect to the level of competition in our observation period. In Panel B of Table 6 we analyze whether the relation between our soft information proxies and the default outcome is stronger for borrowers with riskier financials by including interaction effects between the soft information proxy used and the borrowers' financial rating. In column 2 we indeed find evidence that upgrades based on soft information are indeed more negatively related to the default dummy in the case of riskier borrowers. In column 3 we see that downgrades are more positively related to the borrowers' default status for financially riskier borrowers. Overall, we find that banks are even more cautious to change the borrowers' financial rating based on soft information for borrowers with riskier financial characteristics.

We next use ex post credit risk proxies on the bank level to investigate the effect of discretion in lending on bank risk. As mentioned above, the problem is that when regressing soft information (which is available at the borrower level) on bank level risk, we are restricted to averages on the bank group level. Unfortunately, this reduces our sample size to 296 observations. We use the net charge off ratio (over average bank assets) as a measure for the bank level credit risk. This measures the credit risk of the commercial loan portfolio in a very direct way.[21] In our case, since we only analyze a very homogeneous group of banks with the same business model from one country, we do not face problems with respect to limited comparability of the loan loss provision data.

Table 7 shows that, no matter which proxy is used in columns 1-5, discretionary lending is not related to bank portfolio risk, as measured by the net charge off ratio. The control variables are in line with expectations. Larger banks, for reasons unrelated to the use of soft information, seem to have lower loan loss provisions.[22] Bank groups involved in mergers have higher provisions since these mergers are mostly undertaken to "rescue" problem banks by financially solid banks. In addition, provisions are lower in years with a solid business climate (outlook).

Overall, these results demonstrate that discretion in lending does not seem to increase a bank's portfolio risk. Neither does discretion in lending decrease bank risk. We find no evidence for the loan officer capture effect, but rather a tendency to cautiously using soft information. In particular, this is the case for financially riskier borrowers. It seems plausible that banks are aware of potential problems of giving too much discretion to loan officers and thus limit the use of soft information.

Even though we do not find any evidence on average, there still may be differential effects between savings banks with respect to loan officer capture. We thus analyze a potential channel that could cause loan officers to misuse their influence in interpreting soft information. Smaller

[21] Other sources of credit risk, such as consumer loans, are not important for German savings banks.
[22] We checked whether this effect is due to better diversified portfolios, but there is no relationship between sectoral concentration and bank size in our sample. The results are available from the authors upon request.

banks may be under larger political pressure in election years because they operate in smaller communities, which heavily rely on the savings banks’ loan supply (political lending effect). For example, Dinç (2005) shows that government-owned banks increase their lending in election years in emerging markets relative to private banks. We add local electoral data on Germany’s state level for this analysis. Germany has an important legislative layer below the national level, which is organized on the state level. Every four or five years, each of the 16 states has regional elections, which are not synchronized. The data comes from the regional statistical offices.

Since for this test we do not rely on borrower level data we can use the individual savings banks' balance sheets and income statements for all 452 savings banks individually, rather than bank group data. By using this proprietary dataset, the sample size is larger than by using public sources such as Bankscope. In addition it includes several non-publicly available data items as the number of employees, measured by full-time equivalents (FTEs), for each savings bank.

Table 8 provides results for this political lending effect. We regress the annual change in the commercial loan portfolio on the bank size measure. The interaction term between bank size and the election variable (equals 1 if there was a state-wide election in the respective year, 0 otherwise) is the main variable of interest. If small banks exhibit stronger political lending, we would observe a negative interaction term, i.e. smaller banks would increase their lending volume more in election years than larger banks would. The first two columns provides results for the full observation period 1996-2006. In line with Dinç (2005), the regression models in columns I and II show that commercial credit volume is increased in state-wide election years. Concentrating on the interaction term between the dummy variable *Election* and the bank size measure (column II), we find that credit volume is not expanded disproportionately by smaller banks in election years. The last two columns neither show any significant interaction effects for the restricted sample period 2002-2006. The *Election* dummy is still positive but lacks significance in the shorter observation period.

All in all, we do not find evidence for particular political pressure on smaller banks to extend loan supply. It does not seem as if loan officers were abusing their discretion in the lending process by misinterpreting soft information. This result is consistent with our overall finding that discretion in lending does not seem to increase ex post bank risk, despite ex ante financially weaker borrowers.

4 Additional results

4.1 Is there a trade-off between soft information and collateral?

In this section, we investigate the potential trade-off between soft information and collateral. This is based on Inderst and Mueller (2007) who propose that conditional on approaching the relationship bank, borrowers for whom this bank's information advantage is relatively smaller, face higher collateral requirements. In other words, potential borrowers can either provide more collateral or more positive soft information to the smaller and more relationship-oriented banks, while this trade-off is less important for larger and less relationship-oriented banks. We approximate collateral by the potential collateral a borrower is able to pledge. Specifically, we use a borrower's *Fixed assets* / *Total assets*.

Table 9 shows the OLS regressions of the potential collateral ratio on our main proxy for positive soft information, *Upgrade*. This dummy variable equals 1 if the bank discovered positive soft information and 0 otherwise. In column 1, we restrict our sample to the smallest bank size quartile, measured by the average bank group assets. This specification thus conditions on borrowers at the most relationship-oriented banks. Our main variable of interest is *Upgrade*. Based on Inderst and Mueller (2007), we expect a negative relationship as a lack of sufficient collateral can be compensated with positive soft information, and vice versa. In column 1 we find that the upgrade coefficient is significantly negative. Borrowers with positive soft information thus seem to be able to have less pledgeable assets. We next analyze in the second column whether this negative relationship is more pronounced at smaller than at larger banks. We now use the smallest and the largest bank size quartiles. As in the case of Table 4, the dummy variables *Small bank* equals 1 for the smallest size quartile and 0 otherwise. We form interaction terms between *Upgrade* and the *Small bank* dummy variable and expect that the interaction effect is negative. We actually find a negative coefficient for the interaction term in column 2. A borrower with a rating upgrade needs a 2.4% lower pledgeable assets ratio at a smaller bank than a comparable borrower at a larger bank. Note that the unconditional *Fixed assets* / *Total assets* equals 33.4% (see Table 2). We further observe that our measure for the borrowers' credit risk, *Z-Score Borrower*, enter the regressions significantly negative, indicating a positive relationship between credit risk and pledgeable collateral.

Overall, we find empirical evidence for the postulated trade-off between a borrower's positive soft information and the available collateral. This effect is particularly pronounced at smaller banks.

4.2 Do smaller banks face higher screening and monitoring costs?

Having an informational advantage by gathering soft information should go hand in hand with higher screening / monitoring costs. Otherwise, transaction banks would end up with (too many) lemons relationship banks do not approve. The ideal measure for screening (monitoring) intensity would be the money spend per borrower to assess its creditworthiness (foster its repayment likelihood). Since we do not observe these borrower level expenditures we rely on three bank (group) level measures that come as close as possible to the ideal measure: i) sum of staff cost over average assets per bank group and year (in %); ii) number of bank branches (in hundreds) over the average assets per bank group (in billions) and year; iii) number of bank FTEs (in thousands) over the average assets per bank group (in billions) and year.

Table 10 shows the results for which we regress the three proxies on bank size (measured by the natural logarithm of bank assets). We further provide results for a longer observation period (columns 1 to 3) and the restricted time period spanning 2002-2006 for which we have rating data. The bank size coefficient enters significantly in the regressions for all three proxies. We find that smaller banks have higher staff cost, use more branches and have more employees (per unit of assets). This is consistent with a cost advantage for large banks in screening / monitoring that they use to offset the informational disadvantage and the associated selection problem.[23] Unreported robustness checks, which are available from the authors on request,

[23] In unreported regressions (available on request), we test whether these results are robust for non-linearities in size. We use size quartile dummies and find qualitatively similar effects.

further include bank fixed effects to control for unobservable time-invariant characteristics. The main results remain qualitatively unchanged.

A word of caution is needed with respect to the interpretation of these results. Given our indirect cost proxies, we cannot distinguish screening from monitoring. Both, more intense screening and more thorough monitoring drive up our cost proxies and enhance ex post financial quality, which we investigated in Tables 6 and 7. Although we have no means in distinguish the two lines of action, both intense screening and close monitoring characterize relationship lenders.

5 Conclusion

We document in this paper that discretionary lending does not influence bank risk taking. Despite lending to borrowers with riskier financial characteristics, smaller banks do not exhibit higher credit risk levels. This effect can be explained by the amount of positive soft information of these borrowers, which seems to offset their weaker financial prospects. Discretion in lending thus seems to be used in an efficient way.

Overall, firms with positive soft information tend to self-select to relationship banks that can take soft information into account, while firms with negative soft information are more likely to self-select to transaction banks that cannot. Smaller banks provide loans to borrowers with riskier financial attributes but positive soft information. These banks thus play an important part as financial intermediaries for SMEs with, at least on first sight, more difficult financial outlooks. We present new evidence on the role of relationship lenders as markets seem to deliver efficient results at the lower end of the bank size distribution.

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Table 1: Definition of variables

The table gives the definitions of all variables used in the empirical analysis. Destatis is the federal statistical office of Germany and Bundesbank is the German central bank.

Variable name	Description	Data source
Panel A: Dependent variables		
|Δ Rating|	Absolute difference in notches between financial rating and end rating. Both ratings range from 1 (AAA) to 21 (C).	Savings banks
Upgrade	Equals 1 for a positive change of the financial rating based on soft information, 0 otherwise	Savings banks
Downgrade	Equals 1 for a negative change of the financial rating based on soft information, 0 otherwise	Savings banks
Strength(Upgrade)	Strength of a positive change of financial rating based on soft information in notches	Savings banks
Strength(Downgrade)	Strength of a negative change of financial rating based on soft information in notches	Savings banks
Z-Score borrower	Altman's Z-Score calibrated to the German banking market (approximation of the credit risk of each individual loan customer), defined by Z-Score = 0.717*Working capital/Assets + 0.847*Retained earnings/Assets + 3.107*Net profits/Assets + 0.420*Net worth/Liabilities + 0.998*Sales/Assets	Savings banks
Financial rating borrower	A borrower's financial rating, numerical notches from 1 (AAA) to 21 (C)	Savings banks
Default borrower	Equals 1 if the borrower defaults up to one year after the rating was assigned, 0 otherwise.	Savings banks
Fixed / Total assets borrower	Fixed over total borrower assets approximates pledgeable collateral.	Savings banks
Net charge off ratio	Sum of net charge offs over savings bank group assets.	Savings banks
Credit volume change	Annual commercial credit volume change (in %) for each individual savings bank.	Savings banks
Staff cost / Bank assets (%)	Sum of staff cost over average assets per bank and year (in %)	Savings banks
Bank branches / Bank assets	Number of bank branches (in hundreds) over the average assets per bank (in billions) and year	Savings banks
Bank FTEs / Bank assets	Number of bank FTEs (in thousands) over the average assets per bank (in billions) and year	Savings banks
Panel B: Independent variables		
ln(Bank assets)	Natural logarithm of average average assets (in billion) of the savings bank (or savings bank group)	Savings banks
Direct competition	Branches of direct competitors (commercial banks and cooperative banks) to savings banks branches per group of savings banks	Bundesbank
Number mergers	Number of mergers within a group of savings banks per year	Savings banks
Regional debt per capita	Debt per capita of the community that the savings bank (or savings bank group) is located in	Destatis
Δ ifo-Index	Relative change in ifo business climate index at the national level	ifo institute
Risk-free interest rate	Average daily risk-free interest rate at the national level	Bundesbank
ln(Borrower assets)	Natural logarithm of total assets per borrower (in 1,000)	Savings banks
Industry specialization	Herfindahl-Index based on share of loan volumes per industry: Industry specialization = Σ_i (Loan volume industry$_i$/Total loan volume)	Savings banks
Election	Equals 1 if there was a state-wide election in the respective year, 0 otherwise	Destatis

Table 2: Descriptive statistics

This table shows descriptive statistics of the main variables. All variables are given on the borrower level except the last two variables in Panel A and the last two variable sin Panel B. The net charge off ratio is on the bank group level while the credit volume change, the three cost proxies (last three rows of Panel A), and the election dummy are on the individual bank level. The definitions of variables are given in Table 1.

Variable	Observations	Mean	Std. dev.	5p	25p	Median	75p	95p
Panel A: Dependent variables								
$\|\Delta$ Rating$\|$	77,364	2.022	1.549	0.000	1.000	2.000	3.000	5.000
Upgrade (Dummy variable)	77,364	0.245	0.430	0.000	0.000	0.000	0.000	1.000
Downgrade (Dummy variable)	77,364	0.598	0.490	0.000	0.000	1.000	1.000	1.000
Strength(Upgrade)	18,982	2.475	1.626	1.000	1.000	2.000	3.000	6.000
Strength(Downgrade)	46,238	2.368	1.286	1.000	1.000	2.000	3.000	5.000
Z-Score borrower	77,364	3.399	3.008	0.523	1.654	2.786	4.353	8.093
Financial rating borrower	77,364	12.394	3.403	8.000	10.000	12.000	14.000	20.000
Default borrower	77,364	0.048	0.213	0.000	0.000	0.000	0.000	0.000
Fixed / Total assets borrower	74,585	0.334	0.274	0.013	0.093	0.263	0.535	0.864
Net charge off ratio (in %)	296	0.457	0.204	0.167	0.301	0.437	0.581	0.805
Credit volume change (in %)	4,668	0.517	10.072	-16.189	-3.503	1.053	5.573	13.656
Staff cost / Bank assets (%)	4,668	1.330	0.180	1.018	1.226	1.337	1.443	1.622
Number of bank branches / Bank assets	4,668	23.359	11.500	9.108	15.382	21.752	28.910	43.771
Number of bank FTEs / Bank assets	4,668	2.554	0.449	1.824	2.264	2.546	2.827	3.321
Panel B: Independent variables								
ln(Bank assets)	77,364	0.824	0.721	-0.130	0.360	0.681	1.051	2.528
Direct competition	77,364	0.841	0.252	0.461	0.667	0.823	0.945	1.361
Number mergers	77,364	0.364	0.696	0.000	0.000	0.000	1.000	2.000
Regional debt per capita (Euro thousands)	77,364	1.064	0.403	0.624	0.809	0.960	1.217	1.836
Δ ifo-Index	77,364	1.875	2.007	-2.583	0.125	2.200	3.642	3.642
Risk-free interest rate (in %)	77,364	2.276	0.360	2.048	2.048	2.090	2.318	3.278
ln(Borrower assets)	77,364	6.424	1.498	4.259	5.406	6.244	7.250	9.236
Industry specialization	77,364	20.728	3.739	15.797	18.101	20.197	22.834	26.761
Election (Dummy variable)	4,668	0.198	0.398	0.000	0.000	0.000	0.000	1.000

Table 3: Discretionary lending and bank size

Panel A shows the results of the univariate analysis on the impact of discretion in relationship lending. We split the borrowers into four groups depending on the savings banks groups' average assets, which approximates relationship strength. The first column provides the averages for borrowers of the smallest banks, while the forth column shows the averages for borrowers of the largest banks. Columns 5 gives the average differences between the smallest and the largest bank size quartiles. Panel B contains the results of OLS models regressing discretion in lending on bank size. We use the matched bank-borrower dataset including the five measures for discretion in lending of Panel A. The main independent variable are bank assets as a size-related proxy for relationship strength. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Univariate analysis

Soft information	Bank size, measured by average assets					t-value
measure	1, Small	2	3	4, Large	Small - Large	Small - Large
|Δ Rating|	2.039	2.106	1.994	1.951	0.088	-2.30**
Upgrade	0.249	0.272	0.249	0.212	0.037	-1.84*
Downgrade	0.593	0.582	0.590	0.626	-0.033	1.41
Strength(Upgrade)	2.519	2.625	2.474	2.230	0.289	-3.10***
Strength(Downgrade)	2.380	2.393	2.338	2.361	0.019	-0.41

Panel B: Multivariate analysis

	|Δ Rating|	Upgrade	Downgrade	Strength(Upgrade)	Strength(Downgrade)
ln(Bank assets)	-0.064***	-0.017*	0.011	-0.142***	-0.024
Direct competition	0.021	0.015	-0.011	-0.041	0.020
Number mergers	-0.008	-0.009*	0.007	-0.029	0.011
Regional debt per capita	0.060*	-0.010	0.023	-0.037	0.049
Δ ifo-Index	0.020***	0.003	-0.001	0.023**	0.016***
Risk-free interest rate	0.256***	0.030**	-0.007	0.227***	0.240***
ln(Borrower assets)	-0.134***	-0.038***	0.021***	-0.294***	-0.041***
Intercept	2.238***	0.430***	0.454***	3.894***	2.007***
Observations	77,364	77,364	77,364	18,982	46,238
Adj. R square	0.021	0.019	0.005	0.074	0.006

Table 4: Borrower self-selection

The table contains the results for the borrower self-selection with respect to bank size using the matched bank-borrower dataset. Panel A holds the univariate results. We split the sample according to the borrowers' Z-Score quartile. The first quartile includes the riskiest borrowers while the forth quartile contains the safest borrowers. The first and second column show the upgrade probability reflecting soft information for the smallest and the largest bank size quartile. Bank size is measured according to the sum of bank group assets in the respective year. The third column shows the difference between column one and two and the significance level. We use univariate regressions with standard errors clustered at the savings banks' group level. Panel B shows OLS regression results. We regress the upgrade probability on borrower risk and bank size. The dummy variable *Risky borrower* equals 1 for borrowers in the first Z-Score quartile in columns I and II and 0 otherwise. In columns III and IV, we use the financial rating instead. The dummy variables *Small bank* equals 1 for the smallest size quartile and 0 otherwise. The sample is restricted to the smallest and largest bank size quartile. We form an interaction terms between *Risky borrower* and the *Small bank* dummy variable. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Univariate results

	Bank size quartile		
Z-Score quartile	Smallest	Largest	Difference
1 (risky)	0.274	0.193	0.082***
2	0.216	0.175	0.041*
3	0.210	0.182	0.028
4 (safe)	0.291	0.273	0.018
Total	0.246	0.210	0.036*
1 – 4			0.064***

Panel B: Multivariate results

	I	II	III	IV
Risky borrower dummy (Z-Score)	0.020**	-0.010		
Risky borrower dummy (Financial rating)			0.482***	0.436***
Small bank dummy	0.036*	0.022	0.009	-0.009
Risky borrower (Z-Score) * Small bank		0.057***		
Risky borrower (Financial rating) * Small bank				0.083**
Direct competition	0.012	0.013	0.005	0.003
Number mergers	0.000	0.000	0.001	0.000
Regional debt per capita	-0.005	-0.005	-0.003	-0.003
Δ ifo-Index	0.002	0.002	-0.001	-0.001
Risk-free interest rate	0.009	0.009	-0.015*	-0.014*
ln(Borrower assets)	-0.033***	-0.033***	-0.025***	-0.025***
Intercept	0.395***	0.401***	0.315***	0.324***
Observations	38,665	38,665	38,665	38,665
Adj. R square	0.016	0.017	0.239	0.24

Table 5: Borrower financial characteristics and bank size

The table contains the OLS regression results with the borrower Z-Score (column I) and the financial rating (column II) as dependent and the savings banks' average assets as main independent variable. We use the matched bank-borrower dataset. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Borrower ex ante risk measure	
	Z-Score	Financial rating
ln(Bank assets)	0.226***	-0.303***
Direct competition	-0.132	0.096
Number mergers	0.011	-0.073*
Regional debt per capita	-0.139	-0.033
Δ ifo-Index	-0.019**	0.057***
Risk-free interest rate	-0.451***	0.803***
ln(Borrower assets)	-0.380***	-0.184***
Intercept	6.967***	11.869***
Observations	77,364	77,364
Adj. R square	0.040	0.017

Table 6: Discretionary lending and the borrowers' ex post risk

The table contains marginal effects from Probit regressions with the borrowers' default dummy variable (1 equals default, 0 otherwise) as the dependent variable and the five discretionary lending proxies as the main independent variables for the matched bank-borrower dataset. Panel B also includes interaction terms formed between the discretionary lending proxies and the financial rating. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A

	I	II	III	IV	V	VI	VII	VIII	IX	X
|Δ Rating|	0.001					0.001*				
Upgrade		-0.009***					-0.007***			
Downgrade			0.010***					0.008***		
Strength(Upgrade)				-0.004**					-0.003**	
Strength(Downgrade)					0.003***					0.003***
Financial rating	0.009***	0.009***	0.009***	0.018***	0.009***	0.008***	0.009***	0.009***	0.017***	0.008***
Borrower Z-Score	-0.002***	-0.001***	-0.001***	-0.001	0.000	-0.001***	-0.001***	-0.001***	0.000	0.000
ln(Borrower assets)	0.003***	0.003***	0.003***	0.012***	0.001	0.002***	0.002***	0.002***	0.010***	0.000
ln(Bank assets)	-0.006***	-0.006***	-0.006***	-0.007*	-0.006***	-0.004	-0.005	-0.005	-0.269**	0.001
Industry specialization	0.000	0.000	0.000	-0.001	0.000	0.000	0.000	0.000	0.002	0.000
Direct competition	-0.023***	-0.023***	-0.023***	-0.054***	-0.017***	0.001	0.001	0.001	-0.005	-0.006
Number mergers	0.001	0.001	0.001	0.002	0.000	0.001*	0.001	0.001	0.002	0.001
Regional debt per capita	0.003	0.003	0.003	0.005	0.002	0.008	0.007	0.008	0.020	-0.025
Δ ifo-Index	0.000	0.000	0.000	-0.003	0.000	0.000	0.000	0.000	-0.003	0.001
Risk-free interest rate	0.013**	0.013**	0.013**	0.014	0.012*	0.014**	0.014**	0.014**	0.019	0.011*
Bank group fixed effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,364	77,364	77,364	18,982	46,238	77,364	77,364	77,364	18,982	46,238

Table 6 continued

Panel B

	I	II	III	IV	V
|Δ Rating|	0.014***				
|Δ Rating| * Financial rating	-0.001***				
Upgrade		0.028***			
Upgrade * Financial rating		-0.002***			
Downgrade			-0.015***		
Downgrade * Financial rating			0.002***		
Strength(Upgrade)				0.015	
Strength(Upgrade) * Financial rating				-0.001**	
Strength(Downgrade)					-0.001
Strength(Downgrade) * Financial rating					0.000
Financial rating	0.010***	0.010***	0.008***	0.019***	0.008***
Full set of covariates	Yes	Yes	Yes	Yes	Yes
Bank group fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	77,364	77,364	77,364	18,982	46,238

Table 7: Discretionary lending and the banks' ex post risk

The table contains the OLS results with the net charge off ratio as the dependent variable and the five discretionary lending proxies as the independent variables for the bank group level dataset. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	I	II	III	IV	V
|Δ Rating|	0.008				
Upgrade		-0.019			
Downgrade			0.014		
Strength(Upgrade)				0.016	
Strength(Downgrade)					0.002
ln(Average bank assets)	-0.057**	-0.057**	-0.057**	-0.054*	-0.057**
Herfindahl Index	0.400	0.394	0.396	0.422	0.414
Direct competition	-0.069	-0.067	-0.068	-0.068	-0.065
Number mergers	0.061***	0.061***	0.061***	0.062***	0.061***
Regional debt per capita	0.024	0.025	0.024	0.020	0.024
Δ ifo-Index	-0.017***	-0.017***	-0.017***	-0.014***	-0.017***
Risk-free interest rate	-0.028*	-0.027	-0.027	-0.022	-0.024
Intercept	0.614***	0.630***	0.618***	0.568***	0.607***
Observations	296	296	296	264	291
Adj. R square	0.165	0.165	0.165	0.105	0.153

Table 8: Political lending effect

The table contains the results for the analysis of the political lending effect. We regress the annual change in the commercial loan portfolio on the savings banks' assets using the dataset on the individual bank level. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	(I)	(II)	(III)	(IV)
Election	1.428***	1.262***	0.200	0.251
ln(Bank assets)	-0.300	-0.474***	0.072	0.118
Election * ln(Bank assets)		0.860		-0.231
Direct competition	-0.336	-0.322	0.074	0.073
Number mergers	-0.876	-0.878	1.672	1.672
Regional debt per capita	1.115***	1.121***	0.070	0.069
Δ ifo-Index	0.335***	0.335***	-0.007	-0.007
Risk-free interest rate	0.056	0.058	1.532***	1.532***
Intercept	-1.054	-1.046	-5.917***	-5.925***
Sample	1996-2006	1996-2006	2002-2006	2002-2006
Observations	4,668	4,668	2,140	2,140
Adj. R square	0.027	0.028	0.016	0.016

Table 9: Discretion in lending and collateral

The table contains the results for the analysis of the relationship between discretion in lending and a proxy for potential collateral. The latter is measured by the borrowers' *Fixed Assets* / *Total assets*. We regress the potential collateral ratio on our main proxy for positive soft information, *Upgrade*; the latter equals 1 if the bank discovered positive soft information and 0 otherwise. The dummy variables *Small bank* equals 1 for the smallest average assets quartile and 0 otherwise. In column 1, the sample is restricted to the smallest bank size quartile, while in column 2 the sample consists of the smallest and largest bank size quartile. We form an interaction terms between *Upgrade* and the *Small bank* dummy variable. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	(I)	(II)
Upgrade	-0.026***	-0.004*
Small bank		0.080***
Upgrade * Small bank		-0.024***
Direct competition	-0.026	0.009
Number mergers	-0.006	0.004
Regional debt per capita	0.027	0.054***
Δ ifo-Index	-0.002	-0.002
Risk-free interest rate	-0.015	-0.022***
Z Score Borrower	-0.025***	-0.020***
ln(Borrower assets)	0.015***	0.015***
Intercept	0.386***	0.250***
Observations	19,116	37,238
Adj. R square	0.081	0.088

Table 10: Screening and monitoring intensity

The table contains the results for the analysis of the relationship between the screening / monitoring intensity and banks size. We regress three proxies of screening / monitoring intensity on bank size. See Table 1 for the definitions of all variables. Standard errors are clustered at the savings banks' group level. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Screening / monitoring intensity					
	Staff cost / Assets (%)	Number of bank branches / Assets	Number of bank FTEs / Assets	Staff cost / Assets (%)	Number of bank branches / Assets	Number of bank FTEs / Assets
ln(Bank assets)	-0.072***	-3.821***	-0.187***	-0.080***	-3.465***	-0.180***
Direct competition	-0.015	9.677***	0.041	0.046	8.613***	0.168*
Number mergers	0.030**	0.624	0.063*	0.053***	1.190	0.085**
Regional debt per capita	0.000	0.003	0.000**	0.000	0.003**	0.000**
Δ ifo-Index	0.001***	-0.085***	-0.006***	0.002***	-0.099***	-0.009***
Risk-free interest rate	-0.023***	1.536***	0.090***	-0.035***	0.367**	0.030***
Intercept	1.437***	8.027**	2.040***	1.438***	9.665***	1.995***
Sample	1996-2006	1996-2006	1996-2006	2002-2006	2002-2006	2002-2006
Observations	4,668	4,668	4,668	2,140	2,140	2,140
Adj. R square	0.139	0.154	0.194	0.163	0.164	0.206