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Discussion paper

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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 advantages that we can directly identify soft information in banks' lending decisions and that we observe ex post defaults of borrowers. Consistent with the previous literature, we find that smaller banks use more discretion in lending. We also show that borrowers self-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 relationship banks. Risky borrowers with negative soft information have the same chance to receive a loan from a relationship or a transaction bank. These selection effects are stronger in more competitive markets, as predicted by theory. However, while relationship banks have financially riskier borrowers, ex post default is not more probable compared to borrowers at transaction banks. As a consequence, relationship banks do not have higher credit risk levels. Loan officers at relationship banks thus do not use discretion in lending to grant loans to ex post riskier borrowers.

JEL Classification: G21, G28, G32

Key words: soft information, discretionary lending, relationship bank, bank risk

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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 four 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

[1] That is not to say that loan officer do never attempt to manipulate hard information (see Berg et 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

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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 transaction banks. 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.

may no longer be able or willing to correctly assess the risks facing the bank (e.g. Kane, 1990). 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).[5] 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 Section I 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. The third crucial advantage of the dataset is that it provides

[5] In addition, one could imagine that loan officers, especially those with long tenure, could suffer from overconfidence in their own ability to judge borrowers. In our context, we would not be able to distinguish loan officer capture from overconfidence.

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. We also show that these selection effects are stronger in more competitive banking markets.

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 officers rather seem to be 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. Overall, the results in this paper suggest that discretion in lending does not increase relationship banks' portfolio risk compared to 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.[6] 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*.

In much of the previous empirical literature, soft information is not directly observed and instead indirectly approximated. For instance, Cerqueiro et al. (2011) investigate the 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.[7] There are two recent notable exceptions that have access to a direct measure of soft information like this paper. 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. This paper differs from Degryse et al. (2011) in that we are able to analyze the selection of borrowers to relationship and transaction banks, respectively, because we have consistent data on the use of soft information for a cross section of banks. 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 this paper, we rather use data on the role of soft information in commercial borrower loan decisions. It is possible that the production

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

of soft information is more important for this type of borrower given the higher degree of information asymmetry between bank and borrower.

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.[8] The main focus so far has been on the effect that larger banks increase risk because of explicit or implicit public guarantees ("too big to fail") due to moral hazard (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, which is more common in small banks.

The reminder of the paper is organized as follows. The first section gives some institutional background on German savings banks. In Section II, we describe our dataset. Section III presents our empirical results. The last section concludes.

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[8] 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.

I. Institutional Background

Germany is an ideal laboratory to study the questions of this paper. The German banking market is almost evenly split between three types of banks: savings banks (the focus of this paper) and federal state banks[9], 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. Savings banks, hence, compete both with banks that can be characterized as "transaction" banks, such as the large commercial banks (Deutsche Bank, Commerzbank), as well as banks that are pure "relationship" banks, such as cooperative banks. Small savings banks typically have only one or two branches and flat hierarchies and seem excellent candidates for banks that are able to assign a large amount of discretion to loan officers, while large savings banks may operate much like transaction banks with numerous branches and many layers of hierarchy. Hence, we feel we have sufficient cross sectional variation in the use of soft information in lending decisions to study our question. At the same time, all savings banks that are members of the savings banks association use the same rating system. As we use the rating system to measure the use of soft information in lending decisions (explained in more detail below), we have a measure that is consistent across all banks in the sample.

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[9] 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).

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 no off-balance sheet operations.[10] Their main financing sources are customer deposits, which they transform into loans to households and firms. 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.[11] 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.

Savings banks in our sample are on average relatively profitable in the observation period 2002-2006: average pre-tax ROE is 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

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[10] 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.

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

UK. Overall, German savings banks look like a fairly typical small commercial bank in continental Europe.

II. Data

A. 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.[12] 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 verifiable. Soft information, on the other hand, is of subjective nature and difficult or impossible to verify. Specifically, we have 77,364 credit ratings for the years 2002-2006 of 60,696 borrowers.[13] 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

[12] There are seven savings banks in Germany that are not full members in the savings banks association. They are not covered in the dataset.
[13] Our observation period starts in 2002 because a new rating system was introduced in that year.

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 data also contain a final credit rating for each firm. The difference between the financial rating and the end rating reveals the non-financial (soft) information on the borrower that was used in the lending decision. The difference reflects qualitative information such as management quality, the firm's strategy, and perceived product or service quality, but also quantitative information complementary to financial statements, such as account activity and information from credit registries.

We use five different proxies for soft information based on the rating information in the regressions below: 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 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.

In principal, the difference between the financial rating and the end rating may reflect three different items (Degryse et al., 2011): (i) private hard information from the transaction accounts of the firm and the firm's owner. This information is not publicly observable, but verifiable by senior management. (ii) Soft information that is not verifiable by senior management. (iii) Loan officer discretion. In the following we assume that relationship banks and transaction banks do not differ in the ability to take (i) into account and use the terms “soft information” and “discretion” interchangeably. This approach is supported by the findings in Degryse et al. (2011), who show for very detailed borrower information from one bank in Argentina that only non-verifiable soft information but not verifiable hard information guide 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.

In the previous literature, bank size is found to be a good indicator for tighter bank-borrower relationships (Cole et al., 2004; Berger et al., 2005). Berger et al. (2005) show that large banks tend to approve or reject loan applications primarily via credit scores, entirely based on financial information. Potential soft information on the borrower is not taken into consideration. The explanation is that, 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 (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.[14]

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 the strength of a relationship between a bank and a borrower (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.

In addition to the proxy for soft information, a central advantage of the dataset we use is the possibility to differentiate between *ex ante financial risk* and *ex post defaults* of the banks' commercial loan customers. We have two measures for a borrower's ex ante financial risk: One, the financial rating described above, which does not include the adjustment for soft information. Second, we use an Altman-type (1968) Z-Score, which is calibrated to the German market (Engelmann et al., 2003). A higher Z-Score indicates a lower risk associated with the borrower. For all commercial loan customers in the data we also have an ex post default measure, which

[14] 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.

equals 1 if the firm repaid principal or interest more than 90 days too late in the 12 months after the credit rating was assigned and 0 otherwise. 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. Furthermore, we use the borrowers' legal form to distinguish between closely held firms (OhG, Personengesellschaft) and incorporated firms (GmbH, AG etc.), as they have different accounting and transparency standards. We use a dummy variable, *Opaque borrower*, that equals 1 for the former and 0 for the latter type of firms.

We also 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).

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).[15] As savings banks do not compete with each other we can link the savings banks to different regions within Germany. We thus use a number

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

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.[16] 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.[17] The variable comes from the federal statistical office of Germany ("Destatis"). Refer to Table 1 for all variable definitions.

B. 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

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[16] The data covers the year 1996-2004. We assume that competition remained unchanged in 2005/2006 and use the 2004 data in these two years.

[17] 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). Both measures approximate financial risk from an ex ante perspective. On average, 4.8% of the borrowers in our sample default in the 12 months following the rating assignment. Sorting upgrades based on the financial rating reveals that upgrades are more likely for very risky ratings because these would not received loan offers without positive soft information. We observe the reverse pattern for downgrades.

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.

III. Results

A. Borrower Self-Selection

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 the 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 3 shows regression results with the five different measures for discretion in lending as dependent variables and the bank size measure as the main independent variable.[18] The first column of Panel B 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 evidence in favor of the self-selection hypothesis: borrowers with positive soft information are more likely to obtain a loan from small relationship lenders, borrowers with negative soft information are not.

Control variables also offer interesting insights. As expected, larger borrowers are less likely to be upgraded and any rating adjustments that are done are smaller.[19] Larger borrowers tend to be less opaque, because reporting quality is better on average, and, hence, soft

[18] We use OLS models throughout since differences to using Probit models for the binary dependent variables in columns two and three are negligible.
[19] 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.

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.

Unreported robustness checks further back 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 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 are strongest for the largest bank quartile (versus the smallest quartile). In further unreported robustness checks, we replace the macroeconomic controls (risk-free interest rate, change in ifo-Index) with year fixed effects. Our results are robust to these alternative specifications.[20]

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 Panel B 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

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

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 also find that larger banks tend to downgrade borrowers more often, although we do not obtain a statistically significant coefficient. We interpret this as weak evidence that large banks attempt to take the selection effect into account by downgrading borrowers across the board.

If firms with better soft information self-select towards smaller banks, that are more likely to take soft information into account, is this effect is stronger for firms with particularly weak financials? For firms with weak financials it should be particularly valuable if positive soft information is taken into account in the lending decision. We measure the extent of positive soft information by the upgrade probability, *Upgrade*, i.e. whether the bank improved the end rating compared to the financial rating. As a measure of the financial risk of a borrower we use the Z-Score, which is decreasing in risk. In addition, in the regressions below we use the borrowers' financial rating. Both measures are strictly limited to financial characteristics and do not include soft information.

Panel A of Table 4 shows the univariate results. We split the matched bank borrower dataset into quartiles, sorted according to the borrowers' Z-Score. The first quartile includes the riskiest 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 percent 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 percent 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 percent level.

Panel B of Table 4 shows the regression results.[21] We regress *Upgrade* on borrower risk, bank size measures, local competition and the controls. We form interaction terms to capture the bank size-borrower risk relationship that we discovered in the univariate analysis. We report results for two measures of firms' financial risk: Z-Score and the financial rating. We use the Z-Score in addition to the financial rating, because it is independent of the bank's assessment of the borrower. Specifically, the dummy variable *Risky borrower* equals 1 for borrowers in the riskiest Z-Score (financial rating) quartile and 0 otherwise. The dummy variables *Small bank* equals 1 for the smallest size quartile and 0 for the largest bank size quartile.

In addition, we check whether the selection effect is related to local competition. Hauswald and Marquez (2006) show that in more competitive markets banks will invest less in the acquisition of (soft) information. We can investigate this point in our sample. We use data from the Bundesbank that reveals the number of branches of other banks in the local market the savings bank operates in and define a dummy variable, *High competition*, that takes on the value of 1 if the bank operates in a market that is above median and 0 otherwise. We would then

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

interpret a negative relationship between higher competition and *Upgrade* as a reduction in the investment of banks in the generation of soft information. We furthermore interact *High competition* with bank size to analyze whether relationship banks maintain their investment in soft information compared to transaction banks. In addition, we interact *High competition* with the borrowers' risk to check whether banks concentrate their investment in soft information for riskier borrowers.

Columns 1 and 2 show the individual effects without the interaction terms. We find that riskier borrowers are more likely to be upgraded due to positive soft information. As suggested by the univariate analysis, smaller banks are more likely to upgrade their borrowers, but the effect is not robust to using the financial rating as a measure of the financial strength of the firm. In addition, smaller borrowers are upgraded more frequently. We obtain negative coefficients on the individual *High competition* dummy variable as predicted by Hauswald and Marquez (2006), although the coefficient is only statistically significant in column 2.

The specification of columns 3 and 4 also include the interaction term *Risky borrower * Small bank*. Smaller banks are 3.9% (that is -1.6% + 5.5%) more likely to upgrade ex ante financially risky borrowers compared to financially safe borrowers based on the Z-Score. The effect is even more pronounced for the financial rating. Both results are significant at the 1 percent level. Note that the unconditional probability to receive a rating upgrade is 24.5% (see Table 2). Concentrating on riskier borrowers we find an economically and statistically significant effect since riskier borrowers in column 3 are 7.3% (that is 1.8% + 5.5%) 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. The effect is about the same magnitude if we use the financial rating to sort the borrowers in column 4. This result is in line with the idea that riskier borrowers (based on financial characteristics) who have substantial positive soft (private) information have a stronger incentive to apply for a loan with a bank that takes the soft information into account.

In columns 1 and 2 we found an overall tendency to reduce investment into soft information in more competitive markets. If banks invest less in information acquisition in more competitive markets that may suggest that financially risky firms with positive soft information may no longer be able to obtain credit in these markets. We investigate this issue in more detail by including two way interaction terms between the competition level and bank size, and, in separate regressions, with borrower risk. First, we concentrate on the differential effect with respect to bank size. In columns 5 and 6 of Table 4 we show results in which we check whether relationship banks maintain their investment in soft information compared to transaction banks. In column 5 we find that smaller banks are slightly more likely to upgrade borrowers in more competitive markets (0.5%, that is 1.8% - 5.9% +4.6%) while large banks are less likely to do so (-5.9%). The difference between small and large banks is 6.4% and is significant at the 1 percent level. This difference is narrower for the financial rating in column 6 but still significant at the 5 percent level. Second, we focus on the differential effect with respect to the borrowers' ex ante risk level. In columns 7 and 8 we show results in which we analyze whether banks maintain their investment in soft information for riskier borrowers compared to safer borrowers. For the Z-Score as risk measure in column 7 we find banks are more prone to upgrade riskier borrowers in competitive markets (2.4%, that is 1.1% - 2.4% + 3.7%) while banks are less likely to upgrade safer borrowers in competitive markets (-2.4%). The difference is 4.8% and significant at the 1 percent level. The effect is even more pronounced in the case of the financial rating in column 8 of Table 4.

In the last two columns of the table we analyze a bank's investments into soft information in more competitive markets by using three way interaction terms between competition, the financial risk of the borrower, and the size of the bank. That way, we are able to estimate the probability of a financially risky firm to receive an upgrade from a small bank in a competitive market. Compared to a financially safe firm at a large bank in a competitive market, these firms are 9.3% more likely to receive an upgrade using Z-Score as a measure of financial risk in column 9 (significant at the 1 percent level).[22] For the financial rating as risk measure, the effect is again more pronounced and also highly significant (column 10). These results support Hauswald and Marquez (2006) in that we find that in more competitive markets overall the generation of information is reduced. However, we also find evidence in favor of specialization in more competitive markets: larger banks reduce their investment in information, while small banks do not. Hence, the selection effect of financially riskier borrowers selecting towards relationship banks is even more pronounced in more competitive markets.

To tackle the incentives to generate soft information from a different angle, we use the firms' legal form to distinguish between more and less opaque borrowers (Berger et al., 2005;

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[22] We need to sum up all displayed coefficients in column 9 of Table 4, Panel B, and to subtract -5.2%.

Cole et al., 2004).[23] Results are shown in Panel C of Table 4. Opaque borrowers are 6.5% more likely to receive a rating upgrade based on soft information (column 1). This individual effect is significant on the 1 percent level. Column 2 shows the interaction effect between bank size and opaqueness. We find that small banks are 3.4% more likely to upgrade opaque borrowers than large banks. This differential effect is significant on the 10 percent level. Column 4 includes the results for the interaction between the competition level and opaqueness. We find evidence that in highly competitive markets, opaque firms are 7.5% more likely to receive an upgrade than more transparent firms. The last column includes the three way interaction terms between competition, the opaqueness of the borrower, and the size of the bank. That way, we are able to estimate the probability of an opaque firm to receive an upgrade from a small bank in a competitive market. We find that in highly competitive markets, opaque firms at small banks are 11.6% more likely to receive an upgrade compared to more transparent firms at large banks. This effect is significant on the 1 percent level.

We thus find further support for our interpretation that smaller banks specialize on soft information production in more competitive markets; they not only do that for riskier firms (Panel B of Table 4) but also for more opaque firms. Hence, the selection effect of riskier *and* more opaque borrowers towards relationship banks is more pronounced in more competitive markets.

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[23] Our full set of covariates, for which we omit displaying results in Panel C of Table 4, includes the Z-Score to control for differences in ex ante financial risk. In Panel B of Table 4, we also include the *Opaque borrower* dummy variable.

That fact that small banks use soft information more frequently to upgrade risky borrowers suggests that smaller banks lend to 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. In further unreported regressions, we find that smaller banks more frequently lend to opaque borrowers. 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. In addition, they are more prone to lend to opaque borrowers.

B. Ex Post Credit Outcomes

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 hypothesis)*, 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).

Table 6 shows results for this exercise. Glancing at the results in the table as a whole, most soft information proxies tend to obtain significant coefficients, which suggests that soft information seems to matter for predicting the borrowers' default, even conditioning on financial information. This is consistent with the previous literature (Degryse et al., 2011 and Grunert et al., 2005). The financial rating enters the regression significantly positively as expected, indicating that riskier borrowers are more likely to default. Double digits t-statistics show the very strong predictive power of the financial characteristics.[24]

In column 1 we see that |Δ Rating| obtains a positive and significant coefficient, suggesting that if loan officers deviate from judging based on financial information alone, i.e. use soft information in their decision, these borrowers are more likely to default compared to those borrowers where loan officers only use financial information. This is evidence in favor of the "*loan officer capture hypothesis"*, i.e. the idea that loan officers use their discretion to grant loans to customers that ex post turn out to be riskier compared to those where loan officers did

[24] The full set of covariates that is omitted from being displayed in Table 6 also includes the borrowers' Z-Score as another measure of ex ante financial risk.

not use such discretion. In column 2, we distinguish between upgrades and downgrades. This permits a distinction between higher defaults, because loan officers upgraded firms too much based on positive soft information and higher defaults because loan officers downgraded firms too little based on negative soft information. It turns out that if a firm was upgraded it is as likely to default as a borrower whose rating was not changed due to soft information (the coefficient is -0.003 and insignificant). In contrast, firms that were downgraded are 0.7% *more* likely to default (significant at the 1 percent level) relative to firms that received a loan purely based on financial information. If we compare firms that were upgraded to firms that were downgraded we find that downgraded firms are 1% more likely to default relative to firms that were upgraded, controlling, as before, for the financial rating. A similar picture emerges from the regression where we consider the strength of the upgrade and the strength of the downgrade, given the firm was upgraded or downgraded, respectively (columns 3 and 4 of Table 6). Firms that received a higher upgrade (by more notches in the rating system) were significantly *less* likely to default (by 0.3%) and firms that received a stronger downgrade were significantly *more* likely to default (also by 0.3%). 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. Ultimately, we thus do not find evidence for the *loan officer capture hypothesis*.

In columns 5 to 8 of Table 6 we analyze whether the relation between soft information and default is stronger for borrowers with riskier financials. To ascertain this we include interaction terms between the soft information proxy used and the borrowers' financial rating. The evidence is consistent with banks investing more in soft information where the pay-off may be greatest:

financially risky borrowers. Comparing upgraded and downgraded borrowers that are risky based on financials, we find that upgraded borrowers are 1.1% (that is 0.6% - 1.1% - 0.9% + 0.3%) less likely to default compared to downgraded risky borrowers (column 6). This difference is significant at the 1 percent level. On the other hand, borrowers that received a financial rating in the top three quartiles of the distribution and were upgraded are more likely to default ex post (0.6%). We interpret this evidence to suggest that banks invest in generating soft information about borrowers where the pay-off is largest, namely borrowers that have ex ante very weak financial characteristics.

In further unreported regressions, we check the robustness of our results with subsamples for which two-year and three-year risk outcome measures (the maximum we can go with our data) are available. This way we test the "evergreening" effect that banks have incentives to grant credit to their financially weakest borrowers in order to delay the borrowers' defaults and the realization of losses on their own balance sheets (e.g., Peek and Rosengren, 2005). In our setup, the loan officer capture effect could be offset in the short run by evergreening, while becoming visible in the mid to long run. We thus use two-year and three-year default measures and still find that upgraded borrowers are significantly less likely to default than downgraded borrowers. We also test the potential reverse causality of discretion on the probability to default. Defaults may become less likely if upgrades based on soft information increase access to credit and improve loan terms such as interest rates and maturity. We exclude borrowers without further lenders and postulate that the reverse causality bias should be less influential for the remaining firms with multiple lenders. We find qualitatively unchanged results for this subsample. Reverse causality thus seems to play no role in explaining our findings of Table 6.

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.

C. Political Lending

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 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 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.[25] 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 mergers for each savings bank.

Table 7 provides the results.[26] We regress the annual change in the commercial loan portfolio on bank size. 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. In line with Dinç (2005), we find 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 2), we find that credit volume is not expanded disproportionately by smaller banks in election years.

[25] Local elections on the county / city level are often organized at the same dates as the state wide elections.
[26] We use a sample with a longer time series (1996-2006 instead of 2002-2006), as we do not rely on the rating data, which are available only for the shorter time period. We also estimated the model for 2002 to 2006 and also do not obtain a political lending effect. The results are available from the authors upon request.

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.

D. Cost of Relationship Lending

Having an informational advantage by gathering soft information may go hand in hand with higher screening / monitoring costs at relationship banks (Boot and Thakor, 2000; Hauswald and Marquez, 2006). Otherwise, transaction banks would end up with (too many) lemons relationship banks do not approve. Compared to transaction banks, margins and charter values may be lower at relationship banks ("*cost hypothesis")*, which may result in a greater willingness to accept riskier borrowers (e.g. Keeley, 1990; Hellman et al., 2000).

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 percent); 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 8 shows the results for which we regress the three proxies on bank size (measured by the natural logarithm of bank assets). 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. Unreported robustness checks, which are available from the authors on request, further include bank fixed effects to control for unobservable time-invariant characteristics. We also test whether the results in Table 8 are robust for non-linearities in size by using size quartile dummies. This should alleviate concerns about any mechanical correlation between ln(*Bank assets*) and the three dependent variables, which use bank assets as denominator. The main results remain qualitatively unchanged.

IV. Conclusion

Discretionary lending and the use of soft information may increase or decrease a bank's portfolio risk. We propose and empirically test four hypotheses that are derived from the theoretical literature: (i) *information advantage hypothesis, (ii) the selection hypothesis, (iii) loan officer capture hypothesis* and (iv) *cost hypothesis.* We use a matched bank-borrower dataset of German savings banks. 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 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 also have information on creditor by creditor ex post defaults.

Using these rich data, we find that smaller banks use more discretion in lending, but that the effect 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. We also show that these selection effects are stronger in more competitive banking markets and for more opaque borrowers.

Even though the customers of relationship banks are financially riskier, we do not find that the customers of relationship banks are more likely to default ex post. Loan officers rather seem to be using soft information too cautiously. Hence, we can reject the loan officer capture hypothesis. Overall, the results in this paper suggest that discretion in lending does not increase relationship banks' credit risk compared to transaction banks' credit risk. They also emphasize that relationship banks provide credit to firms that based on financial information alone may not have had access to outside funding. The ability to take soft information into account in lending decisions, hence, may play an important role in the supply of credit to small, financially risky and opaque firms. We show that competition, while overall reducing the production of soft information, does not reduce the willingness of relationship banks to invest in the generation of this information. Rather, in more competitive banking markets, banks tend to specialize more, i.e. relationship banks increase their investment in soft information while transaction banks focus increasingly on purely transaction based lending.

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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 12 months after the rating was assigned, 0 otherwise	Savings banks
Credit volume change	Annual commercial credit volume change (in percent) for each individual savings bank	Savings banks
Staff cost / Bank assets	Sum of staff cost over average assets per bank and year (in percent)	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 total 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 (in percent)	Bundesbank
ln(Borrower assets)	Natural logarithm of total assets per borrower (in 1,000)	Savings banks
Opaque borrower	Equals 1 for closely held borrowers that are more opaque, 0 otherwise	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 variables in 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								
|Δ 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
Credit volume change (in percent)	4,668	0.517	10.072	-16.189	-3.503	1.053	5.573	13.656
Staff cost / Bank assets (in percent)	2,140	1.355	0.187	1.007	1.246	1.368	1.482	1.637
Number of bank branches / Bank assets	2,140	20.291	9.291	8.148	13.606	19.494	24.769	36.171
Number of bank FTEs / Bank assets	2,140	2.404	0.401	1.719	2.161	2.404	2.675	3.046
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 percent)	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
Opaque borrower (Dummy variable)	77,364	0.515	0.500	0.000	0.000	1.000	1.000	1.000
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 bank 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. Column 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 natural logarithm of bank assets approximates 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 columns 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 riskiest Z-Score (financial rating) quartile. The dummy variables *Small bank* equals 1 for the smallest size quartile. We use a *Mid size bank* dummy for the second and third bank size quartile while *Large bank* serves as the omitted category. *High competition* is a dummy variable that equals 1 if the competition level is above the median and 0 otherwise. We omit the individual effects for *Mid size bank*, all interaction terms with that variable, and the other covariates for space considerations. Panel C shows OLS regression results for which we use the *Opacity borrower* dummy variable instead of the ex ante financial risk measures to form interaction terms. 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: Probability of receiving an upgrade, related to ex ante financial risk and bank size

	Bank size quartile		
Z-Score quartile	Smallest	Largest	Difference
1 (risky)	0.277	0.195	0.082***
2	0.217	0.179	0.039*
3	0.213	0.184	0.029
4 (safe)	0.294	0.274	0.020
Total	0.249	0.212	0.037*
1 - 4			0.062***

Table 4 continued

Panel B: Probability of receiving an upgrade, related to ex ante financial risk, bank size, and competition

	I	II	III	IV	V	VI	VII	VIII	IX	X
Risky borrower dummy (Z-Score)	0.030***		-0.016**		0.030***		0.011		-0.01	
Risky borrower dummy (Financial rating)		0.505***		0.432***		0.504***		0.498***		0.461***
Small bank dummy	0.031*	0.005	0.018	-0.012	0.018	-0.004	0.031*	0.005	0.009	-0.017
Risky borrower (Z-Score) * Small bank			0.055***						0.043***	
Risky borrower (Financial rating) * Small bank				0.085**						0.062*
High competition dummy	-0.014	-0.017*	-0.014	-0.018*	-0.059***	-0.052***	-0.024*	-0.020**	-0.052***	-0.027*
High competition * Small bank					0.046*	0.033			0.034	0.014
High competition * Risky borrower (Z-Score)							0.037***		-0.023***	
High competition * Risky borrower (Financial rating)								0.012		-0.147***
High competition * Risky borrower (Z-Score) * Small bank									0.040**	
High competition * Risky borrower (Financial rating) * Small bank										0.126***
Full set of covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,364	77,364	77,364	77,364	77,364	77,364	77,364	77,364	77,364	77,364
Adj. R square	0.026	0.267	0.026	0.268	0.026	0.267	0.026	0.267	0.027	0.269

Table 4 continued

Panel C: Probability of receiving an upgrade, related to opacity, bank size, and competition

	I	II	III	IV	V
Opaque borrower dummy	0.065***	0.054***	0.065***	0.054***	0.060***
Small bank dummy	0.033**	0.035*	0.021	0.033**	0.027
Opaque borrower * Small bank		-0.001			-0.011
High competition dummy	-0.013	-0.013	-0.057***	-0.024*	-0.045**
High competition * Small bank			0.045*		0.026
High competition * Opaque borrower				0.021**	-0.029**
High competition * Opaque borrower * Small bank					0.043**
Full set of covariates	Yes	Yes	Yes	Yes	Yes
Observations	77,364	77,364	77,364	77,364	77,364
Adj. R square	0.025	0.026	0.026	0.026	0.026

Table 5: Borrower ex ante financial characteristics and bank size

The table contains the OLS regression results with the borrower Z-Score (column 1) and the financial rating (column 2) 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)	0.207***	-0.263***
Direct competition	-0.083	-0.007
Number mergers	0.013	-0.078*
Regional debt per capita	-0.124	-0.063
Δ ifo-Index	-0.021**	0.061***
Risk-free interest rate	-0.436***	0.771***
ln(Borrower assets)	-0.426***	-0.087***
Opaque borrower	-0.441***	0.927***
Intercept	7.417***	10.922***
Observations	77,364	77,364
Adj. R square	0.045	0.033

Table 6: Discretionary lending and borrowers' ex post default 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. *Risky borrower* equals 1 for borrowers of the riskiest quartile according to the Z-Score and 0 otherwise. We conduct Wald tests in columns 2 and 6 for *Upgrade* = *Downgrade* and in column 6 also for the interaction effects *Upgrade* * *Risky borrower* = *Downgrade* * *Risky borrower*. See Table 1 for the definitions of the list of covariates that are omitted from being displayed in the table. 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	VI	VII	VIII
|Δ Rating|	0.001*				0.003***			
Upgrade		-0.003				0.006*		
Downgrade		0.007***				0.008***		
Strength(Upgrade)			-0.003**				0.000	
Strength(Downgrade)				0.003***				0.003***
Financial rating	0.008***	0.009***	0.018***	0.008***	0.010***	0.010***	0.018***	0.008***
|Δ Rating| * Risky borrower					-0.005***			
Upgrade * Risky borrower						-0.011***		
Downgrade * Risky borrower						-0.003		
Strength(Upgrade) * Risky borrower							-0.004	
Strength(Downgrade) * Risky borrower								0.000
Wald tests								
Upgrade = Downgrade		-0.010***				-0.002		
Upgrade * Risky borrower = Downgrade * Risky borrower						-0.008***		
Full set of covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,364	77,364	18,982	46,238	77,364	77,364	18,982	46,238

Table 7: 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 for the years 1996-2006. 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)
Election	1.428***	1.262***
ln(Bank assets)	-0.300	-0.474***
Election * ln(Bank assets)		0.860
Direct competition	-0.336	-0.322
Number mergers	-0.876	-0.878
Regional debt per capita	1.115***	1.121***
Δ ifo-Index	0.335***	0.335***
Risk-free interest rate	0.056	0.058
Intercept	-1.054	-1.046
Observations	4,668	4,668
Adj. R square	0.027	0.028

Table 8: 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 (in percent)	Number of bank branches / Assets	Number of bank FTEs / Assets
ln(Bank assets)	-0.080***	-3.465***	-0.180***
Direct competition	0.046	8.613***	0.168*
Number mergers	0.053***	1.190	0.085**
Regional debt per capita	0.000	0.003**	0.000**
Δ ifo-Index	0.002***	-0.099***	-0.009***
Risk-free interest rate	-0.035***	0.367**	0.030***
Intercept	1.438***	9.665***	1.995***
Observations	2,140	2,140	2,140
Adj. R square	0.163	0.164	0.206