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HIDDEN GEMS AND BORROWERS WITH DIRTY LITTLE SECRETS

INVESTMENT IN SOFT INFORMATION, BORROWER SELF-SELECTION AND COMPETITION

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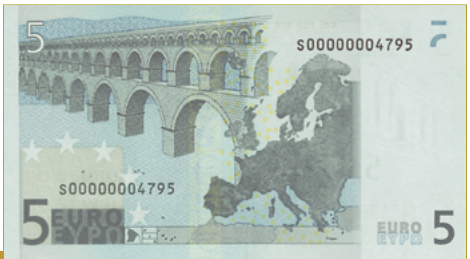

In 2013 all ECB publications feature a motif taken from the €5 banknote.

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ABSTRACT

This paper empirically examines the role of soft information in the competitive interaction between relationship and transaction banks. Soft information can be interpreted as a private signal about the quality of a firm that is observable to a relationship bank, but not to a transaction bank. We show that borrowers self-select to relationship banks depending on whether their privately observed soft information is positive or negative. Competition affects the investment in learning the private signal from firms by relationship banks and transaction banks asymmetrically. Relationship banks invest more; transaction banks invest less in soft information, exacerbating the selection effect. Finally, we show that firms where soft information was important in the lending decision were no more likely to default compared to firms where only financial information was used.

JEL Classification: G21, G28, G32

Keywords: soft information, discretionary lending, relationship lending, competition

EXECUTIVE SUMMARY

This paper empirically examines the competitive strategic interaction between relationship and transaction banks. "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, 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. Hence, soft information can be interpreted as a private signal about the quality of a firm that is observable to a relationship bank, but not to a transaction bank.

We focus on the difference between firms with positive soft information and firms with negative soft information. 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, because relationship banks can take the positive private signal into account in the lending decision. This creates an Akerlof-type adverse selection problem, in which transaction banks tend to receive applications from borrowers with on average negative soft information. In response, transaction banks may apply a negative adjustment to the rating of all their loan applicants. However, if they do, even borrowers with slightly negative private information may be better off obtaining a loan from a relationship bank, resulting in an even worse pool of loan applicants with respect to the private signal and so forth. Ultimately, in the absence of any offsetting factor, transactions banks would no longer participate in the market for small business loans and some positive NPV firms may no longer receive credit. The selection effect may explain why banks ultimately specialize in either relationship or transaction banking.

Furthermore, theory would predict that there are interaction effects with the degree of interbank competition. In particular, Boot and Thakor (2000) argue that there are two effects. When competition is introduced, banks' marginal rents from relationship lending are smaller and each bank thus reduces its investments in soft information. However, competition affects the bank's profits from both relationship and transaction lending asymmetrically. A relationship orientation helps to partially insulate the bank from pure price competition, so that an increase in competition from other banks hurts the bank's profits from transaction lending more than its profits from relationship lending. Thus, increased competition between banks may encourage banks to shift from transaction to relationship lending.

We use a matched bank-borrower dataset of German savings banks to test these predictions. These banks provide an ideal laboratory, as they compete with pure transaction banks, such as

Deutsche Bank and with pure relationship banks, such as the large number of extremely small cooperative banks in Germany. At the same time, there is sufficient variation within the savings bank sector in the degree to which banks incorporate soft information in their lending decisions. Most importantly, the dataset allows us to construct a proxy for the case when the private non-verifiable information about the firm was positive as opposed to when it was negative that is consistent across the banks in the sample. Using this consistent measure of soft information across banks, we show that firms are more likely to be upgraded by relationship banks. At the same time, transaction banks tend to adjust the rating downward more frequently, consistent with a broad downward ratings adjustment and adverse selection. We show that the effect is stronger for firms with weak financials and for firms that are more opaque, as for these firms positive soft information is more important compared to firms that are strong based on financials alone.

Our results regarding the effect of competition on banks' investment in soft information are also novel. We show that overall banks do tend to invest less in gathering soft information if markets are more competitive. However, there is evidence of specialization: smaller banks invest *more* in gathering soft information from risky borrowers, while larger banks reduce their investment. Hence, the selection effect is more pronounced in competitive markets. We find evidence that overall investment in gathering information is not necessarily reduced as competition increases. However, we do not observe a shift of transaction banks towards more relationship lending, as Boot and Thakor (2000) would predict. Rather, we find evidence of increasing specialization. We argue that the selection effect is at the root of this: As relationship banks invest more in discovering hidden gems, the likelihood that a customer approaching a transaction bank for a loan is a borrower with negative private information increases, exacerbating adverse selection and making small business lending less profitable for transaction banks.

I INTRODUCTION

This paper empirically examines the competitive strategic interaction between relationship and transaction banks. “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, 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.[1] Hence, soft information can be interpreted as a private signal about the quality of a firm that is observable to a relationship bank, but not to a transaction bank (Inderst and Müller, 2007).

In this paper we focus on the difference between firms with positive soft information and firms with negative soft information. 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, because relationship banks can take the positive private signal into account in the lending decision.[2] This creates an Akerlof-type adverse selection problem, in which transaction banks tend to receive applications from borrowers with on average negative soft information. In response, transaction banks may apply a negative adjustment to the rating of all their loan applicants. However, if they do, even borrowers with slightly negative private information may be better off obtaining a loan from a relationship bank, resulting in an even worse pool of loan applicants with respect to the private signal and so forth. Ultimately, in the absence of any offsetting factor, transactions banks would no longer participate in the market for small business loans and some positive NPV firms may no longer receive credit. The selection effect may explain why banks ultimately specialize in either relationship or transaction banking.[3]

Furthermore, theory would predict that there are interaction effects with the degree of interbank competition. In the literature, competition has an important effect on the degree to which banks will invest in gathering soft information, going back to Peterson and Rajan (1995). The

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

2 More precisely, 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 In the literature, one solution to the selection problem from the perspective of transaction banks is to require additional collateral from their borrowers (Inderst and Müller, 2007). However, firms without the ability to post such collateral would still be limited to borrowing from relationship banks. In addition, transaction banks may still participate, because due to automated screening procedures they have cost advantages relative to relationship banks (Hauswald and Marquez, 2006). These cost advantages tend to be largest, however, for firms that have sound financials and less so for firms where the soft information would be an important part of the decision to grant credit (Boot and Thakor, 2000).

literature is ambiguous as whether competition would increase or decrease banks' investment in gathering soft information. Boot and Thakor (2000), for example, argue that there are two effects. When competition is introduced, banks' marginal rents from relationship lending are smaller and each bank thus reduces its investments in soft information. However, competition affects the bank's profits from both relationship and transaction lending asymmetrically. A relationship orientation helps to partially insulate the bank from pure price competition, so that an increase in competition from other banks hurts the bank's profits from transaction lending more than its profits from relationship lending. Thus, increased competition between banks may encourage banks to shift from transaction to relationship lending.[4] Empirically, this effect may result in a greater specialization of banks, where relationship banks increase their investment in soft information further and transaction banks reduce their investment further, exacerbating the selection effect described earlier. However, it is also possible that in more competitive markets, transaction banks also start investing more in soft information, reducing the selection effect. Bharath et al. (2007) for example show that transaction banks may invest more in soft information in order to cross-sell other information-sensitive products.

The difficulty when attempting to test these theoretical predictions is that the empirical researcher needs a measure of the private signal of the firm and must be able to ascertain whether the soft information is positive or negative. Moreover, this information needs to be consistently available for a cross section of relationship and transaction banks. To the best of our knowledge, we are the first to have access to data that permit us to construct such variables. We use a matched bank-borrower dataset of German savings banks. These banks provide an ideal laboratory to test these questions, as they compete with pure transaction banks, such as Deutsche Bank 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, there is sufficient variation within the savings bank sector in the degree to which banks incorporate soft information in their lending decisions. In addition, we can measure direct competition to these banks well, as savings banks are restricted to operate locally only.

Most importantly, the dataset allows us to construct a proxy for the case when the private non-verifiable information about the firm was positive as opposed to when it was negative that is consistent across the banks in the sample. In our data, all banks use the same rating algorithm. Therefore, the comparability of ratings across banks is ensured. It produces two types of credit ratings for each firm. The first consists of a financial rating that incorporates hard financial

4 In Boot and Thakor (2000), higher competition from capital markets, rather than other banks has the opposite effect and unambiguously reduces investment in soft information. In our setup we are unable to test for this hypothesis.

statement information on the borrower only. The second is 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 final rating may be higher or lower than the financial rating, which gives us information about whether the private soft information of the firm was positive or negative and how important the soft information component is for a given borrower.

Using this consistent measure of soft information across banks, we first establish that there is sufficient variation in the degree to which banks use soft information in lending decisions. 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 asymmetric, as predicted by the selection hypothesis. Firms are more likely to be upgraded by relationship banks. At the same time, transaction banks tend to adjust the rating downward more frequently, consistent with a broad downward ratings adjustment and adverse selection. We show that the effect is stronger for firms with weak financials and for firms that are more opaque, as for these firms positive soft information is more important compared to firms that are strong based on financials alone. Hence, ex ante, the customers of small banks appear riskier based on financial information alone.

In order to distinguish the idea that relationship banks are better at discovering hidden gems from other potential explanations for our findings (such as private benefits of loan officers), we examine whether ex post the probability of default of firms with positive soft information is higher than for other firms. Hence, we link the ex ante use of hard versus soft information by relationship and transaction banks in the lending decision to the ex post default probability of the borrower. Doing this, we do not find that firms that were upgraded based on soft information are ex post more likely to default. Hence, we can reject that loan officers simply use greater discretion to grant loans to worse customers, who provide, for example, greater private benefits to the loan officers. We also provide some evidence that the transaction banks' informational disadvantage is compensated for by greater cost-efficiency in lending.

Our results regarding the effect of competition on banks' investment in soft information are also interesting and novel. We show that overall banks do tend to invest less in gathering soft information if markets are more competitive. However, there is evidence of specialization: smaller banks invest *more* in gathering soft information from risky borrowers, while larger banks reduce their investment. Hence, the selection effect is more pronounced in competitive markets. The evidence is broadly consistent with the theoretical ideas in Boot and Thakor (2000). We find evidence that overall investment in gathering information is not necessarily reduced as competition increases. However, we do not observe a shift of transaction banks towards more relationship lending, as Boot and Thakor (2000) would predict. Rather, we find evidence of increasing specialization. We argue that the selection effect is at the root of this: As relationship banks invest more in discovering hidden gems, the likelihood that a customer approaching a transaction bank for a loan is a borrower with a dirty secret increases, exacerbating adverse selection and making small business lending less profitable for transaction banks.

The reminder of the paper is organized as follows. The first section sketches the previous literature. Section II presents some institutional background on German savings banks. In Section III, we describe our dataset. Section IV presents our empirical results. Section V presents some robustness checks and extensions. The last section concludes.

2 LITERATURE

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 on 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]

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.[6] There are three recent notable exceptions that have access to a direct measure of soft information like this paper. One, Degryse et 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

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).

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

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 of soft information is more important for this type of borrower given the higher degree of information asymmetry between bank and borrower.[7] The third paper is less related to our research question. Brown et al. (2012) analyze the role of loan officer discretion in credit assessment at nine banks. They show that loan officers use their discretion to smooth a borrower's credit rating. However, their smoothing behavior is unlikely to be driven by soft information.

7 Our paper also relates to the literature on the relation of size and risk. 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. 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).

3 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[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. 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.

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.[9] 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 a relatively similar compensation system for loan officers, which largely rely on fixed contracts.[10] 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.

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).

9 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.

10 Agarwal and Ben-David (2012) show that loan origination-based incentive compensation increases loan origination and the bank's credit risk.

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 UK. Overall, despite their unique governance structure, German savings banks look like a fairly typical set of commercial banks in continental Europe.

4 DATA

4.1 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.[11] 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. Specifically, the data set contains 77,364 credit ratings for the years 2002-2006 of 60,696 borrowers.[12] 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 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 such as management quality, the firm's strategy, and perceived product or service quality. We interpret this difference as a private signal that the borrower can send to a relationship bank but not to a transaction bank. Depending on whether the deviation from the financial rating is negative or positive, i.e. the end rating is higher or lower than the financial rating, we use this as a proxy for a firm's private information that is positive or negative and only observable to the bank to the degree it invests in gathering soft information.

We construct five different variables based on the rating 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 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

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

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

observed soft information. Our dataset also enables us to link the use of soft information with ex post defaults to address any biased use of soft information by loan officers

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 its 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.[13]

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 employees in terms of full time equivalents (FTE). Assets are very common in the literature and well-suited as they are

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.

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), another 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 further variable of particular interest in this paper is competition. As we emphasized in section I, savings banks are regionally restricted in the operations. Hence, we can 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 in their region.[14] The data comes from the Bundesbank.

We also use other regional control variables. The number of mergers for the savings bank per year is intended to control for weakening bank-borrower relationships in the wake of a merger (Di Patti and Gobbi, 2007).[15] 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 heterogeneity in local public finances, which may be reflected in the operations of the local banks. The variable comes from the federal statistical office of Germany ("Destatis").

An important advantage of the dataset is the possibility to relate the *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 equals 1 if the firm repaid principal or interest more than 90 days 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, soft information should be more important for opaque firms. We use the borrowers' legal form to distinguish between closely held firms (OhG, Personengesellschaft) and incorporated firms (GmbH, AG etc.), as closely held firms have much lower accounting and accounting standards. We use a dummy variable, *Opaque borrower*, that equals 1 for the former and 0 for the latter type of firms.

14 „Region“ here refers to a county („Kreis“) or a municipal area („Stadt“).

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

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). Please refer to Table 1 for all variable definitions.

[Table 1]

4.2 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, indicate 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 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 have received loan offers without positive soft information. We observe the reverse pattern for downgrades.

[Table 2]

Next we show bank group descriptive statistics. Average assets of bank groups are Euro 2.28 billion. The dispersion of bank size is large. The 95th percentile of the bank assets is more than 14 times the 5th percentile. This suggests that we may have sufficient within savings bank variation in the use of soft information to assume that bank-borrower relations are of different strength, but we will test for whether large savings banks adjust the ratings of their customers less based on soft information compared to small savings banks formally below. The number of direct competitors is less than one on average, indicating a rather low level of competition. Merger activity was extensive during our sample period. On average, the savings bank groups were involved in a merger every third year.

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.

5 RESULTS

5.1 BORROWER SELF-SELECTION

As a first step, we check whether small savings banks deviate more from financial ratings than large savings banks. This would suggest that we indeed observe cross-sectional variation in the use of soft information in our sample. 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, which 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 into account.

[Table 3]

Encouraged by the univariate results we now present some regressions. It is possible, for instance, that the univariate 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.[16] 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,

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

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 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 rating adjustments are smaller.[17] 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, consistent with some loss of soft information of merged banks and the previous literature (see e.g. most recently Ogura and Uchida, 2012).

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 small banks use additional discretion 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: 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.[18] 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 tentative evidence that large banks attempt to take the selection effect into account by downgrading borrowers across the board.

5.2 FINANCIALLY RISKY AND OPAQUE BORROWERS

If firms with better soft information self-select towards smaller banks that are more likely to take soft information into account, is this effect stronger for firms with particularly weak

17 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.

18 It is possible that loan officers of small banks use their discretion inefficiently to upgrade borrowers that provide loan officers with greater private benefits. This is investigated below.

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.

[Table 4]

Table 4 shows the univariate results. We split the matched bank borrower dataset into quartiles, sorted according to the borrowers' Z-Score. We use the firm's Z-Score instead of the financial rating, because it is independent of the bank's assessment of the borrower. The first row includes the riskiest borrowers, while the fourth row 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.

[Table 5]

Table 5, columns I to IV, shows the regression results.[19] We regress *Upgrade* on borrower risk, bank size, 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. 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.

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

Columns I and II show the individual effects or firm financial risk without interaction terms. We find that riskier borrowers are more likely to be upgraded due to positive soft information. The specification of columns III and IV 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% 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.

Selection would also predict that large banks should be more likely to adjust the rating of borrowers downward, because they are concerned that the borrowers with negative private soft information are particularly likely to apply for a loan at a large bank. This effect should be particularly strong for financially risky borrowers. In Panel B of Table 4 we show that this is indeed the case: The borrowers in the riskiest two quartiles of the distribution are 6-8 percentage points more likely to be downgraded by a large bank than by a small bank. The difference between the downgrade probability of safer borrowers between large and small banks is not significant, although negative. We concede, of course, that we cannot fully distinguish between the situation in which the large bank actually observes negative soft information versus that case that we have focused on, in which the bank simply downgrades because it cannot observe the private signal, but knows that it is likely to be negative, as those with positive signals would be better off getting credit from a relationship bank that can observe the signal.

[Table 6]

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; Cole et al., 2004).[20] Results are shown in Table 6. 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% 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 at the 10% level.

Overall, we find a striking asymmetry: Small, relationship banks are much more likely to adjust the credit rating of borrowers upward. We observe the exact opposite for large, transaction banks, who are much more likely to adjust the credit rating of borrowers downward. Both of these effects are especially operative for firms that are financially risky and opaque. Hence, the investment in soft information of relationship banks is important for financially risky firms that have positive private information only available to the relationship bank, as they in the absence of relationship banks may be unable to obtain credit at the same terms.

5.3 BORROWER SELF-SELECTION AND COMPETITION

We next check whether the selection effect is related to local competition. Hauswald and Marquez (2006) argue that banks will invest less in the acquisition of (soft) information in more competitive markets, because they have to share rents with the borrowers. In contrast, the predictions in Boot and Thakor (2000) are more differentiated: While they acknowledge the existence of the effect of increased rent sharing with borrowers and they also argue that banks may invest more in gathering soft information in competitive markets in order to avoid direct price competition. We can investigate these arguments in our sample. We use data from the Bundesbank on 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 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.

20 Our full set of covariates, for which we omit displaying results in Table 6, includes the Z-Score to control for differences in ex ante financial risk. In Table 5, we also include the Opaque borrower dummy variable.

In columns I and II of Table 5 we document an overall tendency to reduce investment into soft information in more competitive markets. 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 II. 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 Table 7 we show results, in which we check whether relationship banks adjust their investment in soft information differently from transaction banks. In column I 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% level. This difference is smaller for the financial rating in column II but still significant at the 5% level.

[Table 7]

Second, we focus on the differential effect with respect to the borrowers' ex ante risk level. In columns III and IV of Table 7, we show results in which we analyze whether banks maintain their investment in soft information for financially riskier borrowers compared to financially safer borrowers. For the Z-Score as risk measure in column III, 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% level. The effect is even more pronounced when using the financial rating as a control in column IV of Table 5.

In the last two columns of the table we analyze a bank's investments in 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

V (significant at the 1% level).[21] For the financial rating as risk measure, the effect is again more pronounced and also highly significant (Table 7, column VI).

Columns IV and V of Table 6 include 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% 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 (Table 7) but also for more opaque firms (Table 6). Hence, the selection effect of riskier *and* more opaque borrowers towards relationship banks is more pronounced in more competitive markets.

These results support the idea 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.

5.4 EX POST CREDIT OUTCOMES

Relationship banks lend to borrowers that exhibit ex ante weaker financial characteristics. However, these borrowers tend to be upgraded based on positive soft information that transaction 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, these borrowers would show a higher ex post default frequency compared to other borrowers. In order to differentiate between the two possibilities, we directly regress our proxy for the use of soft information on the default outcome of the borrower, which

21 We need to sum up all displayed coefficients in column V of Table 7 and to subtract -5.2%.

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 8]

Table 8 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; Grunert et al., 2005). The financial rating enters the regression significantly positively as expected, indicating that financially riskier borrowers are more likely to default.[22]

In column I 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 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 not use such discretion. In column II, 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% 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 III and IV of Table 8). 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

22 The full set of covariates that is omitted from being displayed in Table 8 also includes the borrowers' Z-Score as another measure of ex ante financial risk.

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 strong evidence for loan officers using soft information in a biased way.

In columns V to VIII of Table 8 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 1.0% (that is 0.6% - 1.1% - 0.8% + 0.3%) less likely to default compared to downgraded risky borrowers (column VI). This difference is significant at the 1% 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 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, a biased use of soft information 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 (Degryse et al., 2011). While banks use soft information ex ante to predict defaults, the latter 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 that borrow exclusively from savings banks because any reverse causality bias should be less influential for the remaining firms with multiple lenders as the savings banks is only one of several banks in these cases. We find qualitatively unchanged results for this subsample. Reverse causality thus seems to play no role in explaining our findings of Table 8. In addition, we split our sample with respect to the level of local bank competition. Results remain qualitatively unchanged in both samples.

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 that discretion is used in a biased way, but rather a tendency to using soft information too cautiously, in particular for financially riskier borrowers.

6 ROBUSTNESS AND EXTENSIONS

We perform a number of robustness checks and extensions. One, we use different measures of banks size and account for non-linearities of the size of the bank in the investment in soft information. We also introduce time dummies in place of macro economic control variables. We furthermore check the relationship between savings bank (group) size and the level of local bank competition. Second, we examine whether political lending ahead of local elections may have driven our result of a higher probability of upgrades by small banks. And finally, we check whether larger banks indeed have lower cost per loan ratios.

We start with checking whether the selection result is robust to using different measures of bank size. For space limitations, we do not report these regressions, but they are available from the authors upon request. We find that using the number of bank branches or the number of bank employees yields qualitatively similar results in Section III. 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). This is consistent with the univariate results reported earlier. In further 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. We furthermore analyze the relationship between savings bank (group) size and the level of local bank competition to address concerns that our results may be driven by omitted regional characteristics. We apply a double sort on bank group size (quartiles) and the level of local bank competition (below and above the median). Table A1 in the appendix shows that there is no evidence that larger savings banks operate in more competitive markets. In particular, the largest banks are located in banking markets that exhibit below average competition.

Even though loans that benefited from a discretionary upgrade were not more likely to default, political lending could still drive part of our results. 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.[23] 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 9]

Table 9 provides the results.[24] 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. Hence, we do not find evidence for particular political pressure on smaller banks to extend loan supply.

Next, we examine whether there are differences in costs between small and large banks in granting loans. 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). Compared to transaction banks, margins and charter values may be lower at relationship banks, which may result in a greater willingness to accept riskier borrowers (e.g. Keeley, 1990; Hellmann et al., 2000).

[Table 10]

23 Local elections on the county/city level are often organized at the same dates as the state wide elections.

24 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.

We rely on three bank (group) level measures for costs per loan: 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 10 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 may 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 10 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.

7 CONCLUSION

We start from the idea that soft information can be viewed as private information about a borrower that is observable to a relationship bank but not to a transaction bank (Inderst and Müller, 2007), resulting in a Akerlof-type adverse selection effect: Firms with positive soft information optimally self-select to relationship banks, firms with negative soft information to transaction banks. Transaction banks therefore face disproportionately many borrowers with negative soft information and adjust their lending behavior accordingly. The interaction between relationship and transaction banks is also affected by the competitive environment, which from a theoretical perspective may result in more or less investment in gathering soft information by both types of banks.

We use a matched bank-borrower dataset of German savings banks that has three distinct advantages: One, we observe whether the lender used positive or negative soft information in the lending decision. Second, due to restrictions on the geographic operations of the banks in our sample, we can accurately measure their competitive environment. Third, we have information on borrower ex post defaults and therefore can check whether soft information was used efficiently.

Using these unique data, we are able to uncover two empirical results that to our knowledge have so far not been documented in the literature. One, we find that borrowers with riskier financial characteristics are more likely to obtain credit from relationship banks than from transaction banks if they have positive soft information. In contrast, financially riskier firms with negative soft information are more likely to turn to a transaction bank. This evidence supports adverse selection in the market for small business loans. Second, we show that competition affects relationship banks' and transaction banks' investment in gathering soft information asymmetrically. Relationship banks tend to increase their investment in gathering soft information, while transaction banks reduce it. An increase in competition results in a further specialization of banks, but does not necessarily reduce the overall investment in gathering soft information. Hence, interbank competition may not reduce the availability of credit to firms with weak financials but strong soft information, as some previous theory has suggested (e.g. Hauswald and Marquez, 2006). All of these results are more pronounced for firms where soft information can ex ante to be expected to play a greater role in the lending decision: firms with weak financials and more opaque firms.

Further, our results suggest that discretion by loan officers is used efficiently in the sense that firms with upgrades in their rating based on soft information are not more likely to default than other firms. Taking soft information into account may reduce credit constraints for financially weak or opaque firms.

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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
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	Bundes bank
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
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)	Bundes bank
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. The definitions of variables are given in Table 1.

Variable	Observatio	Mean	Std.	5p	25p	Media	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
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	-	-	1.053	5.573	13.65
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	2,140	20.29	9.291	8.148	13.60	19.49	24.76	36.17
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
Z-Score borrower	77,364	3.399	3.008	0.523	1.654	2.786	4.353	8.093
Financial rating borrower	77,364	12.39	3.403	8.000	10.00	12.00	14.00	20.00
Number mergers	77,364	0.364	0.696	0.000	0.000	0.000	1.000	2.000
Regional debt per capita (Euro	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	20.72	3.739	15.79	18.10	20.19	22.83	26.76
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 provides the average differences between the largest and the smallest bank size quartiles and the significance level. We use univariate regressions with standard errors clustered at the savings banks' group level. 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 measure	Bank size, measured by average assets 1, Small	2	3	4, Large	Large - Small
|Δ Rating|	2.039	2.106	1.994	1.951	-0.088**
Upgrade	0.249	0.272	0.249	0.212	-0.037*
Downgrade	0.593	0.582	0.590	0.626	0.033
Strength(Upgrade)	2.519	2.625	2.474	2.230	-0.289***
Strength(Downgrade)	2.380	2.393	2.338	2.361	-0.019

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 selection and financial risk: univariate analysis

The table contains the univariate results for the borrower selection with respect to bank size using the matched bank-borrower dataset. Panel A shows the probability of receiving an upgrade based on soft information, while Panel B shows the probability of receiving an downgrade based on soft information. We split the samples 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. 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***

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

	Bank size quartile		
Z-Score quartile	Smallest	Largest	Difference
1 (risky)	0.633	0.714	-0.081***
2	0.649	0.713	-0.064***
3	0.607	0.649	-0.042
4 (safe)	0.465	0.475	-0.011
Total	0.593	0.626	-0.033
1 - 4			-0.070***

Table 5: Borrower selection and financial risk: regressions

Table 5 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. 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
Risky borrower dummy (Z-Score)	0.030***		-0.016**	
Risky borrower dummy (Financial rating)		0.505***		0.432***
Small bank dummy	0.031*	0.005	0.018	-0.012
Risky borrower (Z-Score) * Small bank			0.055***	
Risky borrower (Financial rating) * Small bank				0.085**
High competition dummy	-0.014	-0.017*	-0.014	-0.018*
High competition * Small bank				
Full set of covariates	Yes	Yes	Yes	Yes
Observations	77,364	77,364	77,364	77,364
Adj. R square	0.026	0.267	0.026	0.268

Table 6: Borrower selection, opacity and competition

Table 6 shows OLS regression results. We regress the upgrade probability on borrower opacity and bank size. 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. The dummy variable *Opaque borrower* equals 1 for the former and 0 for the latter type of firms. 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. 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
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 7: Borrower selection and competition

Table 7 shows OLS regression results. The dependent variable is the upgrade probability. 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. 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	VI
Risky borrower dummy (Z-Score)	0.030***		0.011		-0.01	
Risky borrower dummy (Financial rating)		0.504***		0.498***		0.461***
Small bank dummy	0.018	-0.004	0.031*	0.005	0.009	-0.017
Risky borrower (Z-Score) * Small bank					0.043***	
Risky borrower (Financial rating) * Small bank						0.062*
High competition dummy	-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
Observations	77,364	77,364	77,364	77,364	77,364	77,364
Adj. R square	0.026	0.267	0.026	0.267	0.027	0.269

Table 8: Discretionary lending and borrowers' ex post default risk

The table contains marginal effects from Probit estimates 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						-0.008***		
Downgrade * Risky borrower								
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 9: Political lending

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 10: Costs per loan

The table contains the results for the analysis of the relationship between the costs per loan 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.

	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

APPENDIX

Table A1: Additional sample characteristics

The table shows the number of observations sorted by bank size and bank competition. See Table 1 for the general data definitions and Table 5 for the bank competition measure.

	Bank competition		
Bank size quartile	Below median	Above median	Total
1 (Smallest)	14,138	5,507	19,645
2	6,648	12,506	19,154
3	3,463	16,082	19,545
4 (Largest)	14,925	4,095	19,020
Total	39,174	38,190	77,364