INFORMATION OR INSURANCE? ON THE ROLE OF LOAN OFFICER DISCRETION IN CREDIT ASSESSMENT.

MARTIN BROWN
University of St. Gallen

MATTHIAS SCHALLER
University of St. Gallen

SIMONE WESTERFELD
University of Applied Sciences Northwestern Switzerland

MARKUS HEUSLER
Risk Solution Network AG

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On the Role of Loan Officer Discretion in Credit Assessment

Martin Brown*, Matthias Schaller**, Simone Westerfeld***, Markus Heusler****

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Abstract

We employ a unique dataset of 6,669 credit assessments for 3,542 small businesses by nine banks using an identical rating model over the period 2006-2011 to examine (i) to what extent loan officers use their discretion to smooth credit ratings of their clients, and (ii) to assess whether this use of discretion is driven by information about the creditworthiness of the borrower or by the insurance of clients against fluctuations in lending conditions. Our results show that loan officers make extensive use of their discretion to smooth clients' credit ratings: One in five rating shocks induced by changes in the quantitative assessment of a client is reversed by the loan officer. This smoothing of credit ratings is prevalent across all rating classes, is independent of whether the borrower experiences a positive or a negative rating shock, and is independent of whether the shock is firm-specific or market-related. We find that discretionary rating changes have limited power in predicting future loan performance, indicating that the smoothing of credit ratings is only partially driven by information about creditworthiness. Instead, in line with the implicit contract view of credit relationships loan officers are more likely to smooth ratings when rating shocks have stronger implications for interest rates.

Keywords: Relationship banking, Asymmetric information, Implicit contracts, Credit rating
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* University of St. Gallen (e-mail: martin.brown@unisg.ch), ** University of St. Gallen (e-mail: matthias.schaller@unisg.ch), *** University of Applied Sciences Northwestern Switzerland (e-mail: simone.westerfeld@fhnw.ch), **** Risk Solution Network AG (e-mail: markus.heusler@rsnag.ch).

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1 Introduction

The theory of financial intermediation suggests that one key function of relationship banking is to overcome informational asymmetries between the lender and the borrower. Repeated interaction enables lenders to produce information about the creditworthiness of borrowers (Sharpe 1990, Petersen and Rajan 1994) and mitigates moral hazard by providing dynamic incentives for borrowers to choose safe projects, provide effort and repay loans (see e.g. Stiglitz & Weiss 1983).[1] This "information view" of relationship banking provides a strong rationale for the widely observed discretion of loan officers in credit assessments. The incorporation of "soft" information on a client's creditworthiness in the credit assessment requires a rating process in which loan officers can complement quantitative assessments of financial statement data with qualitative information about the client's creditworthiness, e.g. through the use of hybrid rating models.

The theory of implicit contracts (Fried and Howitt 1980)[2] provides an alternative explanation for the existence of long-term credit relationships: Repeated interaction may enable (risk-neutral) lenders to insure their (risk-averse) borrowers against fluctuations in lending conditions. This "insurance" view of relationship banking also provides a rationale for giving loan officers discretion in credit assessments: If credit assessments were purely based on quantitative indicators, fluctuations in aggregate economic conditions could trigger, e.g. through covenant breaches, sudden changes in the available loan volume, the interest rates or other non-price loan terms (e.g. maturity, collateral).

[1] A drawback to repeated interaction, i.e. "hold-up" of borrowers, is developed in the theories of e.g. Sharpe (1990) and Von Thadden (2004). Recent empirical evidence by Ioannidou and Ongena (2010) suggests that banks do, in fact, hold-up their borrowers in long-term lending relationships.

[2] The theory of implicit contracts was originally formulated in the context of the labor market in Bailey (1974) and Azariadis (1975).

In this paper, we employ a unique dataset on small business credit assessments to examine (i) to what extent loan officers use their discretion for smoothing shocks to credit ratings of their clients and (ii) to assess whether the use of discretion by loan officers is primarily driven by soft information about the actual creditworthiness of the client or by the loan officers' effort to insure their customers against shocks to their lending terms. Our analysis is based on 6,669 credit assessments for 3,542 small businesses by nine Swiss banks over the period 2006-2011. All of these banks employ an identical hybrid credit rating tool: A quantitative assessment of financial statement data is complemented by a qualitative assessment of the firm and its industry. In addition, loan officers at all banks have the discretion to override calculated credit ratings.

Our dataset allows us to analyze how loan officers react to shocks in the objective creditworthiness of their clients: Do loan officers make use of qualitative assessments and rating overrides to "smooth" changes to the credit ratings of their clients over time? Our data also allows analyzing the driving forces behind loan officer behavior. First, we analyze the information content of discretionary rating changes, i.e. to what extent rating changes induced by loan officers predict subsequent credit events. Second, exploiting differences in lending processes across banks, we study whether discretionary rating changes are driven by insurance considerations. Are loan officers more likely to smooth credit ratings when the bank explicitly links credit ratings to lending terms?

Our analysis yields three main results: First, loan officers make extensive use of their discretion to smooth clients' credit ratings. Roughly one in five rating changes which would be induced by changes in financial statement data of borrowers is reversed by loan officers. Smoothing of credit ratings is prevalent across all rating classes and is independent of whether the borrower experiences a negative rating shock (weaker financial statement data) or a positive rating shock (stronger financial statement data) to their rating. Smoothing is equally likely for rating shocks which reflect aggregate industry developments and shocks which are idiosyncratic to the firm. Second, the smoothing of credit ratings by loan officers is only partly related to soft information about the creditworthiness of borrowers. Discretionary rating changes predict credit events only for those clients which experience a negative rating shock (and are smoothed upwards), but not for those clients which experience a positive rating shock (and are smoothed downwards). Third, the smoothing of credit ratings is compatible with the insurance view of credit relationships: Loan offers are much more likely to smooth ratings at banks which link interest rates explicitly to rating classes than at banks which have no explicit link between client ratings and lending terms. Furthermore, within those banks which explicitly link rating changes to interest rates - through the use of an additional pricing tool - we find that loan officers are more likely to smooth ratings when a rating change implies a stronger price impact.

Overall, our results challenge the dominating “information” view of credit relationships in the financial intermediation literature. The widespread use of discretion by loan officers seems not only motivated by the objective of yielding more accurate assessments of the creditworthiness of borrowers. Loan officer discretion also plays a key role as banks insure their clients against changes in lending terms.

Our findings contribute to the empirical literature on insurance provision in long-term bank relations, i.e. implicit contracting. Berger and Udell (1992) and Berlin and Mester (1998, 1999) provide evidence that banks smooth loan rates to their clients in response to interest rate shocks and shocks to the aggregate credit risk. Petersen and Rajan (1995) show that banks smooth loan rates in response to changes in a firm-level credit risk. Elsas and Krahnen (1998) provide evidence that "Hausbank" relationships result in the provision of liquidity insurance to borrowers. However, as argued by Berlin and Mester (1998), the insensitivity of lending terms to interest rate shocks and firm-level credit risk may be driven by inefficient bank processes rather than risk-sharing. Our study mitigates this concern by providing direct evidence for active "smoothing" of credit ratings by loan officers. In addition we provide evidence that this smoothing is more frequent when credit ratings have direct implications for lending terms and that it is prevalent for both aggregate and idiosyncratic shocks to firms' creditworthiness.

We contribute to the recent literature on the use of "soft" versus "hard" information in bank lending and the role of loan officers in producing soft information.[3] Based on credit file data from four German banks, Grunert et al. (2005) provide evidence that the combined use of "hard" quantitative information and "soft" qualitative information leads to a more accurate prediction of future default events for medium-sized corporate clients. Scott (2006) provides evidence supporting the conjecture that loan officers play a key role in producing soft information within banks. Using survey evidence, he shows that loan officer turnover has a negative effect on the availability of credit to small US firms. Uchida et al. (2012) use survey data on Japanese firms to document that loan officer activity positively affects the soft information a bank produces on its small business clients. Using credit file data of a multinational bank in Argentina, Degryse et al. (2011) show that loan officers use their discretion in relationship lending for the incorporation of non-contractible soft information

[3] Several earlier studies suggest that relationship lending is particularly valuable to opaque, i.e. small and young, firms by providing better access to credit at more favorable price and non-price terms (e.g. Berger and Udell 1995 , Cole 1998, Harhoff and Körting 1998, Degryse and Van Cayseele 2000). However, these studies do not directly document the use of soft information in credit relationships.

into the lending decision. They show that the soft information gathered by loan officers affects the credit limit set for small business clients. Cerqueiro et al. (2011) provide evidence suggesting that soft information has a significant effect on lending terms to small US firms. They document a substantial degree of dispersion in lending terms to observably identical businesses and show that this variation in loan terms is stronger for small and young firms. Confirming these findings, Qian et al. (2010) find that internal “soft” information of a large Chinese bank has a more pronounced effect on price and non-price terms of loan contracts than public “hard” information. Our findings complement this literature by showing that information may not always be the primary driver of discretion in (small) business lending. Instead, our results suggest that loan officers may make extensive use of their discretionary power to insure their clients against shocks in lending terms.

Finally, we contribute to the literature on how the organizational structure and incentives within banks impact the behavior of loan officers. Stein (2002) suggests that hierarchical structures of banks, i.e. centralized as opposed to decentralized loan approvals may limit the production of soft information within banks. In line with this prediction, evidence by Berger et al. (2005) and Uchida et al. (2011) suggests that loan officers produce more soft information about their clients in small banks as compared to large banks. Liberti and Mian (2009) show that subjective information is used less frequently in lending processes if the hierarchical / geographical distance between the loan officer and the approver is large. Agarwal and Hauswald (2010a) show that the geographical distance between a bank and its clients affects the collection of relation-specific information, while Agarwal and Hauswald (2010b) show that bank branches with a more delegated authority in lending are more prone to collect such information. Hertzberg et al. (2010) examine the impact of anticipated loan officer rotation on the use of information in the lending process. They find that anticipated control leads to a more conservative assessment of clients. Our findings complement the above literature by documenting how the pricing policies of banks impact the way loan officers use their discretionary power in the credit assessment process. Our results suggest that when lending terms are sensitive to credit ratings loan officers are less likely to use their discretion to produce "soft" information and more likely to use this discretion to smooth loan terms.

The rest of the paper is organized as follows: Section 2 describes our data. Section 3 documents the smoothing of credit ratings in our dataset. Section 4 and 5 examine to what extent the observed smoothing of credit ratings is driven by information or insurance considerations. Section 6 concludes.

2 Data

Our dataset covers all credit assessments for small business clients conducted by nine Swiss banks during the period 2006 to 2011. Each bank in the sample is a regionally focused commercial bank. Measured by total assets, the size of the banks in our sample varies from roughly 3 to 39 Billion Swiss Francs (CHF; 1 CHF = 1.05 USD). Mortgage lending to households and small business lending are the major business lines for each bank. Small businesses are defined as corporate customers with an annual turnover of up to 10 million Swiss Francs. For clients in this segment, all nine banks employ a common credit rating tool which was developed and is currently serviced by an external service provider.

Table 1 provides a definition of all variables employed in our analysis. Table 2 provides summary statistics for these variables. Table 3 provides an overview of the available observations per bank as well as differences in the lending processes across banks. Our total sample contains information on 14,974 credit assessments for 6,934 firms. We cannot distinguish between new loans and the periodical review of existing loans. As shown by Table 3 the number of observations differs considerably across banks due to differences in bank size, but also due to the fact that not all banks introduced the rating tool at the same time. Four banks (labeled Bank B, C, D, E respectively) introduced the rating tool in 2006, one bank in 2007 (Bank A), three banks in 2008 (Banks G, H, I) and one bank in 2009 (Bank F).

2.1 The credit rating process

All banks in our sample employ the same hybrid credit rating process: The calculated rating class for a client depends on quantitative information as well as qualitative information. Loan officers can influence the calculated rating of a borrower through their qualitative assessment of the client. In addition, loan officers at all banks have the opportunity to override calculated ratings, i.e. to propose a rating class which differs from the one calculated by the rating model.

In the first step of a credit assessment, quantitative information based on seven financial ratios from the financial statement, plus past default behavior and firm age are aggregated to a quantitative score. The quantitative score ranges from zero (lowest score - highest probability of default) to one (highest score - lowest probability of default).

In a second step the loan officer provides a qualitative assessment of the firm and the industry in which the firm is active. This assessment is based on seven indicators each of which the loan officer grades on an ordinal scale, i.e. "bad", "average", "good". The scores on the seven questions are transformed to an overall qualitative score that ranges from zero (worst score - highest probability of default) to one (best score - lowest probability of default).

The quantitative score and the qualitative score are then weighted and transformed to a calculated rating on a scale of 1 (worst rating - highest probability of default) to 8 (best rating - lowest probability of default). For quantitative scores lower than 0.75 the rating relies solely on quantitative information. For borrowers in this range the calculated rating results from a transformation of the continuous quantitative score to the discrete rating classes. For quantitative scores higher than 0.75 and lower than 0.875, the relative weight of the qualitative score increases monotonously with quantitative scores.[4] For quantitative scores higher than 0.875, the relative weight of the qualitative score remains constant. Appendix I provides details about the rating process and the resulting rating classes depending on qualitative and quantitative assessment.

The loan officers in our sample do not know the rating model in detail, i.e. they are not instructed about the weighting of factors within the quantitative or qualitative scores or how these are transformed to the calculated rating classes. However, loan officers have the possibility to test different input parameters before the rating is actually saved and processed. This not only allows loan officers to adjust their qualitative assessment of a client iteratively. It also allows them to derive the mechanics of the rating algorithm and their scope to influence ratings. Appendix II provides a stylized illustration of the graphical user interface of the rating model.

[4] The exact weighting of soft and hard information depends not only on the initial quantitative score, but also whether the qualitative score is above or below 0.5.

At all banks, loan officers have the opportunity to override calculated ratings, i.e. to propose a rating class for a client which deviates from the calculated rating. Overrides may be done in either direction, i.e. upgrade or downgrade, and may encompass more than one rating step. If the loan officer decides to override a rating, he needs to state the underlying reasons for this decision. Permitted reasons include "existence of an alternative external rating", but also "bank-internal reasons" or "insufficient performance of the rating model".

Our data stems from the database of the external service provider of the rating tool and includes full information on all the input data and output data of the tool for all credit assessments. For the assessment of a firm at time t we observe the $QuantitativeScore_t$ obtained by the firm, the assessment of each qualitative indicator by the loan officer, as well as the resulting $QualitativeScore_t$. We further observe the calculated rating class $CalculatedRating_t$ as well as the rating class proposed by the loan officer ($ProposedRating_t$).

3 Smoothing of Credit Ratings

In order to identify the smoothing of credit ratings by loan officers we exploit the panel characteristics of our dataset: We analyze how qualitative assessments and rating overrides by loan officers react to changes in the quantitative score of a given client. Underlying our analysis is a decomposition of changes in the proposed rating ($ProposedRating_t$ - $ProposedRating_{t-1}$) for a client over time into two components: The first component $RatingShock_t$ measures the hypothetical rating change for the client based only on changes in his quantitative score. The second component $Discretion_t$ measures the rating change induced by changes in the qualitative assessment and/or override by the loan officer.

$$ProposedRating_t - ProposedRating_{t-1} = RatingShock_t + Discretion_t$$

whereby:

$$RatingShock_t = ProposedRating_{t,Qual(t-1)} - ProposedRating_{t-1}$$

$$Discretion_t = ProposedRating_t - ProposedRating_{t,Qual(t-1)}$$

We calculate $RatingShock_t$ as the difference between a hypothetical rating based on the current quantitative assessment and the previous qualitative assessment of the client ($ProposedRating_{t,Qual(t-1)}$) and the previous proposed rating of that same client ($ProposedRating_{t-1}$). Thus the variable *RatingShock* is positive or negative only if there is a rating-relevant increase or decline in the quantitative score of a client. As the quantitative score is a continuous function of the financial statement data, all borrowers experience changes in their quantitative score over time. We focus on the rating-relevant changes as we want to examine how loan officers react to changes in the quantitative score which may impact the lending terms or access to credit of their clients. Changes in the quantitative score of a client from one credit assessment to another are, from the point of view of the loan officer, largely exogenous: These changes are driven only by changes in financial statement ratios as well as changes in repayment behavior of the client and are not related to any kind of assessment by the loan officer.

The contribution of the loan officer to a rating change over time is captured by the variable $Discretion_t$. This variable measures the change in the rating which is the result of a change in the qualitative assessment between period t-1 and t and/or an override of the calculated rating by the loan officer in period t. In order to study how changes in quantitative scores of a client lead to new rating overrides by loan officers we limit our analysis to those firms which did not experience a rating override in period t-1.

As illustrated by model [1], in the first part of our empirical analysis we relate the endogenous component of a rating change for firm i $Discretion_{i,t}$ to its exogenous component $RatingShock_{i,t}$. At the firm-level, we include dummy variables for each initial rating class $\alpha_{PropRating,t-1}$ to control for heterogeneity in the level of credit risk. We further include industry dummies α_I to account for differences in the precision of the rating tool across industries. We control for the $Size_{i,t}$ of the firm (measured in log CHF), as theory and existing evidence suggests that qualitative credit assessments by loan officers may be particularly important for small, financially more opaque firms. We control for unobserved heterogeneity in bank policies and economic conditions over time with bank*year fixed effects $\alpha_{B,t}$. As we observe the identity of the loan officer responsible for the customer (captured by a bank-specific ID number), in robustness tests we replace the bank*year fixed effects $\alpha_{B,t}$ in model [1] with loan officer*year fixed effects.

In model [1] our key coefficient of interest is β_1 which measures the reaction of the loan officer in period t to an external rating shock for his or her client. We expect this coefficient to be negative if loan officers smooth credit ratings, i.e. use their discretion to compensate shocks to the quantitative score.

$$[1]\ Discretion_{i,t} = \alpha_{PropRating_{t-1}} + \alpha_I + \alpha_{B,t} + \beta_1 \cdot RatingShock_{i,t} + \beta_2 \cdot Size_{i,t} + \varepsilon_{i,t}$$

Our estimation of model [1] is based on a sample of 6,669 credit assessments for 3,542 different customers. As the empirical approach exploits the panel structure of our data we exclude from our original data set (14’974 observations) all firms with just one observation

(6,932 observations). We further exclude 1,368 observations in which loan officers had already made an override in period t-1, as loan officers might be inclined to repeat this kind of explicit discretionary exercise of influence in later rating applications. We further exclude five observations with missing information.

Figure 1 here

Panel A of Figure 1 presents a histogram of the variable *RatingShock*, i.e. the hypothetical rating changes which would have occurred to firms in our sample on the basis of changes in their quantitative score only. For 22% of all observations in our sample we observe a decline in the quantitative score that would have triggered a downgrade in their credit rating. For 23% of our observations, the rating shock would have implied an upgrade of the clients' credit rating. The figure shows that for those clients who experienced a rating-relevant increase or decrease of their quantitative score, the most common rating change is by one or two notches. For 55% of the observations, any changes in the quantitative score of the client were too small to trigger a shock to the client's credit rating.

Panel B of Figure 1 illustrates how loan officers use their discretionary power to smooth rating shocks. The graph plots the variable *Discretion* on the vertical axis against the variable *RatingShock* on the horizontal axis. The size of the bubbles in the graph reflects the frequency of observations conditioned on the value of *RatingShock*, i.e. bubble sizes sum to one when added vertically. The figure displays a strong negative correlation between *Discretion* and *RatingShock*. Loan officers raise the qualitative assessments or positively override calculated ratings of those customers whose rating would decline due to their quantitative score. They also lower the qualitative assessments or negatively override the calculated ratings of those customers whose rating would increase due to their quantitative score.

3.1 Baseline results

Table 4 presents our multivariate estimates of model [1] and confirms that loan officers make extensive use of their discretion to smooth clients' credit ratings. All reported coefficients are based on linear regressions with standard errors clustered at the bank*year level and reported in brackets. Our baseline results are presented in Panel A. Column (1) presents full sample results including bank and year fixed effects, while column (2) includes interacted bank*year fixed effects and column (3) includes loan-officer*year fixed effects. In line with the picture presented in Figure 1, all three columns report a significant and economically relevant negative coefficient for *RatingShock*. The estimates in columns (1-3) suggest that 18% of rating changes which would be induced by changes in quantitative scores are reversed by loan officers. This result is robust in both, statistical and economic terms to the inclusion of bank*year or loan officer*year fixed effects.

[Insert Table 4 here]

Columns (4-5) of Panel A show that loan officers smooth credit ratings independently of whether clients experience a negative or positive rating shock. Column (4) includes only observations with a *NegativeShock* (*RatingShock* < 0), while column (5) includes only observations with a *PositiveShock* (*RatingShock* > 0). The estimated coefficient of

RatingShock is almost identical in the *NegativeShock* sample and the *PositiveShock* sample. Unreported tests confirm that there is no difference in the magnitude of the estimated coefficient between the two subsamples. Thus, independent of whether clients' ratings are posed to increase or decrease, one out of five potential rating changes is reversed by loan officers.

3.2 Robustness tests

In Table 4, Panel B we report a range of robustness tests which confirm that our findings above are (i) not driven by outliers, (ii) are robust across rating classes, (iii) are independent of how long a bank has been using the rating tool, and (iv) are similar for crisis and non-crisis years. In column (1), we exclude any *RatingShock* larger than two notches (542 observations, or 8% of the sample) to rule out that our findings are driven by extreme changes in the quantitative scores. The reported coefficient for *Discretion* (-0.161***) confirms that our findings are robust in both economic and statistical terms to outliers. In columns (2-3) we divide our sample according to the initial credit rating of the borrower, i.e. $ProposedRating_{t-1}$ = 2, 3, 4 or $ProposedRating_{t-1}$ = 5, 6, 7.[5] The point estimates for *Discretion* in these columns (-0.178***, -0.182***) suggest that our main findings are robust across risk classes of borrowers.

In columns (4-5) of Panel B we examine whether smoothing may be driven by the mistrust of the rating model by loan officers when it is first introduced. For this purpose we split observations into those which lie within a time frame of two years since the respective bank

[5] We exclude $ProposedRating_{t-1}$ 1 and 8 in order to make the samples identical for positive and negative shocks. For $ProposedRating_{t-1}$ of 1, a negative shock to rating is not possible, for $ProposedRating_{t-1}$ of 8, a positive shock to the rating is not possible.

adopted the rating model (column 4) and those which occur later than two years since the adoption of the rating model (column 5). Note that, as the nine banks adopted the rating tool at different points in time, we can still include year fixed effects in both specifications to account for changes in economic conditions over time. The estimated coefficients in columns (4-5) suggest that smoothing is not driven by mistrust of the rating tool in the introductory period.

Finally, as our sample period incorporates the recent financial crisis, we examine whether the smoothing behavior is more pronounced in the in crisis years (2008-2009) as opposed to the post-crisis years (2010-2011). The reported coefficients for *Discretion* in columns (6-7) suggest that this is not the case.

In Table 4, Panel C we present further robustness tests to our baseline regression to examine whether the loan officers' behavior deliberately aims at smoothing only those shocks to firms' quantitative credit scores which have an impact on the firm's credit rating. We exploit the fact that due to the discrete nature of the rating model employed by our banks a similar shock to the quantitative score of a firm may or may not induce a change in the rating class of the client. We divide our observations into subsets with similar changes in the quantitative score from the previous to the current credit assessment. As shown in Panel C we conduct subsample analyses for observations with changes in the quantitative score that range between [+/-0.1;+/-0.05], [+/-0.05;+/-0.02], and [+/-0.02;0].[6] Keeping the change in the quantitative information in these close ranges, we are able to assess whether, for equal shocks to the quantitative information, the loan officers' smoothing is driven by those changes in quantitative scores that actually trigger a change in the rating of a customer.

[6] For these intervals, the probabilities of experiencing a *RatingShock* are distributed symmetrically across positive and negative changes amount to roughly 70%, 35%, and 10%, respectively.

The results reported in Panel C suggest that a given shock to the quantitative score of a firm is much more likely to induce the use of *Discretion* by loan if it would trigger a change in the rating class of the firm. Confirming our results in Panel A and Panel B we find a significant negative coefficient of *RatingShock* in all six subsamples. The point estimates reported suggest that a change to the quantitative score of a client is 23% to 43% more likely to be smoothed if it induces a one-notch change in the rating class than if it has no impact on the rating class

In Appendix III we examine whether credit assessments which must be approved by a second staff member of the bank are less likely to be "smoothed" by loan officers. This robustness test is motivated by recent evidence suggesting that the hierarchical structure of a bank may affect the production and use of relation-specific information in lending (Liberti and Mian 2009, Hertzberg et al. 2010). For each credit assessment, our dataset provides information on whether the proposed rating of the loan officer was subject to approval by a colleague, i.e. a line manager or a credit officer. Three banks in our sample (Banks A, D, H) require internal approval for (almost) all credit assessments, three banks require almost no internal approvals (F, G, I), while the three remaining banks (B, C, E) have a significant share of both, approved and not approved loans. Bank internal policies referring to e.g. credit competences of loan officers, ratings, and the size of the underlying loan are the main determinants of whether an assessment is subject to approval or not. In order to avoid endogeneity issues we discard the observations from three banks (B, E, and F) in which control can be triggered by the subjective assessment of the loan officer, e.g. a rating override. We find that there is no robust relationship between (anticipated) internal approval and the subjective assessments of customers by loan officers. In particular, control has little impact on the smoothing of credit ratings. Our estimates suggest that internal approval leads to less smoothing of ratings only for those (few) firms which experience large positive rating shocks (larger than two notches).

3.3 Aggregate versus Idiosyncratic Shocks

Previous evidence on the smoothing of credit conditions suggests that banks smooth loan rates to their clients in response to aggregate shocks to interest rates and credit risk (Berger and Udell, 1992; Berlin and Mester 1998, 1999). However, there is scarce evidence on the "smoothing" of firm-specific shocks and whether banks are more likely to smooth aggregate as opposed to idiosyncratic shocks.[7] In Table 5 we exploit differences in aggregate rating shocks across industries and years in our sample to examine whether the smoothing of rating shocks differs for market shocks as opposed to firm-specific shocks.

To disentangle firm-specific rating shocks from aggregate rating shocks we calculate the average share of positive and negative *RatingShocks* for each industry in each year. We then divide our sample into three subsamples based on whether an observation is in an industry-year with a high share of negative rating shocks (Below-average market conditions), an industry-year with a high share of positive rating shocks (Above-average market conditions), or an industry-year with an average share of negative and positive rating shocks (Average market conditions).[8] Columns (1-3) of Table 5 present the results of our baseline regression

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[7] Elsas and Krahnen (1998) provide some evidence that "Hausbanks" insure their clients against firm-level rating shocks, but they do not distinguish between shocks which are driven by firm-specific conditions as opposed to aggregate market conditions.

[8] The allocation of industry-years to the Below-average, Above-average, and Average market condition subsamples is conducted so that we have 25% of our observations each in the Below and Above average samples.

for all observations in Average market conditions, Below-average market conditions and Above-average market conditions, respectively.

[Insert Table 5 here]

We capture positive firm-specific rating shocks by identifying those firms which experienced a positive rating shock (*PositiveShock*) while being in an industry-year with a high share of negative rating shocks i.e. Below-average market conditions. In column (2) of Table 5 (Below-average market conditions) we consequently identify differences in the smoothing of firm-specific as opposed to market shocks by adding the interaction term *RatingShock** *PositiveShock* to our baseline empirical model. Similarly, we capture negative firm-specific rating shocks by identifying those firms which experienced a negative rating shock while being in an industry-year with a high share of positive rating shocks i.e. Above-average market conditions. In column (3) of Table 5 (Above-average market conditions) we therefore identify differences in the smoothing of firm-specific as opposed to market shocks by adding the interaction term *RatingShock****NegativeShock* to our baseline empirical model.

The results reported in Table 5 indicate that the smoothing of rating shocks by loan officers is independent of whether these shocks are firm-specific or market related. The point estimates of *RatingShock** *PositiveShock* in column (2) and *RatingShock****NegativeShock* in column (3) are both insignificant at conventional statistical levels. Confirming our results in Table 4 we yield similar coefficients for the main term of *RatingShock* in all three subsamples in Table 5, suggesting that the smoothing of credit ratings is similar across market conditions.

4 Information

In this section we examine to what extent the smoothing of credit ratings documented in section 3 is related to “soft” information available to loan officers about the creditworthiness of their clients. To this end, we analyze how well discretionary rating changes by the loan officer predict subsequent loan performance.

Our measure of loan defaults $CreditEvent_{t+1}$ captures changes in the repayment behavior of the client from the current credit assessment in period t to the next credit assessment t+1. It is a dummy variable that takes the value one, whenever a customer’s credit file does not show a late, deferred, or failed payment in period t but does in the following period t+1. We focus our analysis on new credit events within a one-year period as – in line with the Basel II approach - the objective of this rating tool is to forecast default probabilities over a 12-month horizon.

Model [2] presents our empirical approach to examine the information content of discretionary rating changes. Our main coefficient of interest is β_1 which captures the relation between changes in loan performance of firm i $CreditEvent_{i,t+1}$ and discretionary rating changes $Discretion_{i,t}$. If discretionary rating changes are information driven we expect a negative estimate for β_1: Clients which experience a discretionary upgrade (downgrade) should be less (more) likely to default in the following 12 months. We include a full set of dummy variables $\alpha_{Prop.Rating,Qualt-1}$ to control for the initial level of credit risk prior to any discretionary rating change, i.e. the hypothetical proposed rating of a client $ProposedRating_{t,Qual(t-1)}$. As in model [1] we employ bank*year fixed effects $\alpha_{B,t}$ to control for heterogeneity in bank and economic conditions. We further employ industry fixed effects α_I and $Size_t$ to control for heterogeneity in the levels of creditworthiness across firms.

[2] $CreditEvent_{i,t+1}$=

$$\alpha_{B,t} + \alpha_I + \alpha_{Prop.Rat.,Qualt-1} + \beta_1 \cdot Discretion_{i,t} + \beta_2 \cdot Size_{i,t} + \varepsilon_{i,t}$$

In order to estimate model [2] we require at least three credit assessments for a given firm: We require the credit assessment in period t-1 and t to measure $Discretion_t$. Furthermore, we require information in period t and t+1 to measure changes in loan performance ($CreditEvent_{t+1}$). As a result, the number of observations available for this analysis is lower than for model [1]. The sample for this analysis covers 3,359 credit assessments for 1,986 different firms.

[Insert Figure 2 here]

On average, in our sample 4% of clients experience a new credit event between two credit assessments. Figure 2 suggests that discretionary rating changes by loan officers are only partly relevant in predicting such events. The figure displays the relation between $CreditEvent_{t+1}$ and $Discretion_t$ conditional on a borrower's initial credit rating. We hereby divide our observations into clients with low initial ratings ($ProposedRatings_{t,\mathrm{Qual(t-1)}}$ =2, 3, 4) and high initial ratings clients ($ProposedRatings_{t,\mathrm{Qual(t-1)}}$ = 5, 6, 7). As the underlying rating tool assumes a non-linear relation between rating classes and forecasted default probabilities we would expect to find a stronger relation between changes in rating classes and credit events among firms with a low initial credit rating than among firms with a high initial credit rating. For both samples of clients the figure shows the average of $CreditEvent_{t+1}$ depending on whether the loan officer upgraded the client ($Discretion_t > 0$), did not make a discretionary rating change ($Discretion_t$ =0) or downgraded the client ($Discretion_t$ <0).[9] Figure 2 suggests that there is a strong relation between discretionary rating changes and credit events among objectively risky clients. In the sample of clients with low initial ratings we find that clients which were upgraded by the loan officer are 3.5 percentage points less likely to experience a credit event in the next 12 months than clients which did not experience a discretionary rating change. As expected, in the sample of clients with low initial ratings there is a much weaker relation between discretionary rating changes and new credit events.

[Table 6 here]

Table 6 reports linear probability estimation results for model.[10] Column (1) reports full-sample estimates. In this column the estimated coefficient for *Discretion* is negative and significant suggesting that clients which were upgraded (downgraded) by their loan officers are less (more) likely to default in the following year. The reported point estimate implies that clients which received a discretionary increase in their rating by one notch were 1 percentage point less likely to default in the following period. This effect is sizeable in view of the fact that, overall, only 4% of the clients in our sample experience payment difficulties in-between two credit assessments.

As that the underlying rating tool assumes a non-linear relation between rating classes and forecasted default probabilities we should find a stronger relation between *Discretion* and

[9] *Discretion* < 0 does not include any observations that would receive the lowest possible rating based on their quantitative assessment only. Similarly, *Discretion* > 0 does not include any observations that would the highest possible rating due to their quantitative information. We therefore exclude any observations of the best and worst rating classes based on $ProposedRatings_{t,\mathrm{Qual(t-1)}}$.

[10] Due to the difficulty of interpreting marginal effects of interaction terms in non-linear models (Ai and Norton, 2003) we choose to report estimates from a linear probability model. Non-reported robustness tests for columns (1-5) using probit estimation yield qualitatively identical results.

CreditEvent among firms with a low initial credit rating than among firms with a high initial credit rating. Our column (2-3) estimates confirm that this is the case. Column (2) presents results for those clients with a low rating ($ProposedRatings_{t,\mathrm{Qual(t-1)}}$ = 2, 3, 4), while column (3) presents results for those with a high rating ($ProposedRatings_{t,\mathrm{Qual(t-1)}}$ =5, 6, 7). The estimated coefficient in column (2) is significant in both statistical and economic terms. For firms with low credit ratings a one-notch upgrade (downgrade) by the loan officer is associated with a 2 percentage point decrease (increase) in the probability of a future credit event. By contrast, in the subsample of clients with a high credit rating (column 3) the estimated coefficient of *Discretion* is four times smaller and is not statistically significant.

Our analysis in section 3 shows that loan officers are equally likely to smooth credit ratings independent of whether clients experience a positive or negative rating shock. Is the observed smoothing of credit ratings in both directions driven by information about "true" creditworthiness? The results in columns (4-5) suggest that this is not the case. In both columns we focus on the subsample of clients with low initial credit ratings ($ProposedRatings_{t,\mathrm{Qual(t-1)}}$ = 2, 3, 4) as in this sample we expect changes in ratings to be associated with stronger changes in loan performance. Column (4) reports estimates for those firms which experienced a negative rating shock (*RatingShock* < 0) while column (5) reports estimates for those that experienced a positive rating shock (*RatingShock* > 0). Our results suggest that discretionary rating changes are only valuable in predicting default for clients which experienced a negative rating shock. The column (4) estimate for *Discretion* suggests that for these clients a one-notch upgrade by the loan officer is associated with a 1.9 percentage point lower probability of a credit event in the following 12 months. By contrast, the point estimate of *Discretion* in column (5) is not significant.

Columns (6-8) present further robustness tests in which we examine whether the information content of discretionary rating changes is related to the informational opacity of firms. We expect the rating tool to be less accurate - and thus relationship-specific information to be more valuable - in assessing the creditworthiness of opaque firms. In line with the literature on relationship lending we employ firm *Size* and age (captured by the dummy variable *Young*) as measures of informational opacity. We also expect relation-specific information to be more accurate in predicting the creditworthiness of firms if the firm-loan officer relationship is more intense. As an indicator of intensity of the bank relationship we distinguish relations in which the loan officer is the *Same* in two subsequent credit assessments from those where the loan officer changed. In columns (6-8), we add the interaction terms *Discretion*Size*, *Discretion*Young* and *Discretion*Same* to our empirical model [2]. We again focus on the subsample of clients with low initial credit ratings ($ProposedRatings_{t,\mathrm{Qual}(t-1)}$ =2, 3, 4) as in this sample we expect changes in ratings to be associated with stronger changes in loan performance. The results suggest that the informational content of discretionary rating changes is not stronger for clients where relation-specific information should be more valuable.[11] The estimated coefficients for all three interaction terms are insignificant.

Overall, our Table 6 estimates suggest that the smoothing of credit ratings by loan officers is only partly related to information about the creditworthiness of their clients. The information content of discretionary rating changes seems limited to firms which experience negative rating shocks and are subsequently smoothed upwards by loan officers. By contrast,

[11] In unreported robustness tests, we also run regressions for the subsamples with the highest information content in discretionary rating changes (initially bad clients and clients with negative rating shocks). The results also yield insignificant estimates.

the downward smoothing of ratings for clients who experience positive rating shocks is not driven by information about the creditworthiness of clients. In the following section we examine whether insurance considerations provide a better empirical explanation for this smoothing behavior.

5 Insurance

The theory of implicit contracts suggests that loan officers may smooth the credit ratings of their clients in order to insure these clients against changes in lending terms. This theory would predict that the smoothing of clients' ratings is more likely to occur when lending terms, i.e. interest rates and credit limits, are sensitive to changes in rating classes. In this section we first exploit differences in loan pricing regimes across banks to examine whether smoothing of ratings is more common at banks where interest rates are more sensitive to rating changes. We then exploit non-linearities in loan pricing within pricing regimes to examine whether rating shocks which have a stronger impact on interest rates are more likely to be smoothed. We find evidence for both.

5.1 Smoothing across pricing regimes

While all nine banks in our sample employ the same rating tool for small business clients, they differ substantially with respect to how rating classes impact on loan terms. In particular, interest rates on loans are explicitly tied to rating classes at some banks, while they are unrelated to rating classes at other banks. Based on a questionnaire sent to all banks, as well as on expert interviews with the provider of the rating tool we classify each bank according to how sensitive their interest rates are to credit ratings.

The provider of the rating tool also offers a pricing tool to all banks which calculates risk-adjusted interest rates accounting for expected credit loss and capital costs. The dummy variable *Pricing tool-mandatory* indicates that a bank makes the use of the pricing tool mandatory for all rating applications. In our sample, this is the case for Bank C at which the pricing tool is used to calculate base rates for the negotiation of loan terms with the client. *Pricing tool – simulation* is a dummy variable which indicates that a bank uses the same pricing tool, but to simulate benchmark interest rates as opposed to calculating base rates. Two banks (Bank E and G) in our sample use the pricing tool in simulation mode. *Risk-adjusted pricing* is a dummy variable indicating that a bank uses the calculated rating class for the risk adjustment of interest rates, but that this adjustment is not based on the pricing tool offered by the provider of the rating tool. This is the case for the banks A, B, F, H and I. Finally as the benchmark case (and omitted category in our analysis) one bank in our sample (Bank D) reports that credit ratings have *No Influence* on interest rates.

If loan officers smooth credit ratings in order to insure their clients against changes in loan terms we expect to see the most smoothing at banks with *Pricing tool-mandatory*, followed by banks with *Pricing tool-simulation* or *Risk-adjusted pricing* and then by the bank at which ratings have *No influence* on interest rates. We test this hypothesis with empirical model [3], which expands upon our empirical model [1] examined in section 3. We interact our main explanatory variable $RatingShock_{i,t}$ with the dummy variables $Pricing\ tool\text{-}mandatory_B$, $Pricing\ tool\text{-}simulation_B$ as well as $Risk\text{-}adjusted\ pricing_B$ and add all three interaction terms to the empirical specification. Note that we do not include the main effect of the pricing regimes as they are already captured in the bank*year fixed effects $\alpha_{B,t}$.

$$[3]\ Discretion_{i,t} = \alpha_{PropRating_{t-1}} + \alpha_I + \alpha_{B,t} + \beta_1 \cdot RatingShock_{i,t} + \beta_2 \cdot Size_{i,t}$$

$$+\beta_3 \cdot RatingShock_{i,t} \cdot Pricing\ tool, mandatory_B$$

$$+\beta_4 \cdot RatingShock_{i,t} \cdot Pricing\ tool, simulation_B$$

$$+\beta_5 \cdot RatingShock_{i,t} \cdot Riskadjusted\ pricing_B + \varepsilon_{i,t}$$

Figure 3 suggests that banks at which interest rates are more sensitive to rating classes are characterized by more "smoothing" of ratings. The figure plots the mean value of *Discretion* against *RatingShock* for the four pricing regimes present in our sample: *Pricing tool-mandatory, Pricing tool-simulation, Risk-adjusted pricing, No influence*. If loan officers are more inclined to smooth credit ratings of customers when the pricing of loans is more sensitive to rating shocks, we should observe the strongest (negative) correlation between *Discretion* and *RatingShock* for the bank with *Pricing tool-mandatory* and the weakest correlation for the bank with *No influence.* This is exactly what we find: Loan officers appear to engage in distinctively more smoothing when rating shocks would have a stronger impact on interest rates.

[Figure 3 here]

Table 7, Panel A presents our multivariate estimates of model [3]. Column (1) presents full sample estimates. The estimated coefficients for the main effect of *RatingShock*, and the interaction terms *RatingShock*Pricing tool, mandatory, RatingShock*Pricing tool, simulation and RatingShock*Risk-adjusted pricing* suggest that smoothing of credit ratings is substantially stronger at banks where ratings have a stronger impact on interest rates. For example, the point estimates reported in column (1) suggest that at Bank D (no influence of ratings on interest rates) only 5% of rating shocks are reversed by loan officers. By contrast at those banks which employ risk adjusted pricing or apply the pricing tool in simulation mode 16%-19% of rating shocks are reversed by loan officers. Most strikingly at Bank C where loan officers are mandated to use the pricing tool we find that 32% of all rating changes are reversed by loan officers. Thus going from a pricing regime at which rating changes have no influence on interest rates to a regime where they automatically induce interest rate changes increases the smoothing of ratings six-fold.

Columns (2) and (3) present estimates for the subsample of clients with negative rating shocks (*RatingShock* < 0) and positive rating shocks (*RatingShock* > 0) respectively. Columns (4) and (5) present estimates for the subsample of clients with low initial ratings ($ProposedRating_{t-1}$=2, 3, 4) and high initial ratings ($ProposedRating_{t-1}$= 5, 6, 7) respectively. The results presented in all four columns confirm our full sample estimates. Across all subsamples the point estimate for *RatingShock* suggests that at Bank D - with no influence of ratings on interest rates – less than 10% of rating shocks are reversed. The interaction term *RatingShock * Pricing tool – mandatory* suggests that at Bank C – with strong price implications of rating changes – the share of rating shocks reversed by loan officers increases by between 20 and 33 percentage points. Thus independent of the initial credit rating of the firm or the direction of the rating shock experienced by the firm, loan officers are substantially more likely to smooth a rating shock if it induces a change in interest rates for their client.

The results presented in Table 7 strongly suggest that loan officers use their discretion in the credit assessment process to insure their clients against shocks to lending conditions. An alternative explanation for our findings could however be that loan officers smooth ratings (and thus interest rates) in order not to lose their clients to competing banks, especially when their own income is dependent on their loan volume under management. Note, however, that this reasoning only applies to clients which experience a negative rating shock. For these clients it is plausible that loan officers use their discretion to reverse the negative rating shock, so that interest rates need not be increased. However, our results in columns (2-3) of Table 7 show that the impact of a bank's pricing regime on smoothing of credit ratings is similar for clients which experience negative or positive rating shocks. As clients with positive rating shocks would benefit from improved lending conditions, it is not plausible that the observed discretionary rating changes are driven by the fear of losing clients.

In unreported robustness checks we examine whether differences in the compensation regime for loan officers across banks affects the smoothing of credit ratings. Based on a questionnaire we elicited for each bank whether their loan officers are partly remunerated through volume-based compensation. This is the case for seven of the nine banks in our sample. We test whether discretionary rating changes are more common at those seven banks which employ volume-based compensation, compared to the two banks that do not. Our findings suggest that this is not the case.[12] This finding supports our interpretation that impact of pricing regimes on the smoothing of credit ratings is driven by concerns of insuring clients against price shocks as opposed to insurance loan officers against wage shocks.

5.2 Smoothing within pricing regimes

[12] Results are available on request from the authors.

Our analysis above suggests that loan officers are more likely to smooth credit ratings at banks where rating shocks have stronger price implications. This provides first evidence that the smoothing of credit ratings may be driven by the objective of insuring clients against fluctuations in credit terms. Unfortunately though, our analysis above cannot rule out that the pricing policy of banks is correlated with other (unobserved) bank policies (e.g. other aspects of compensation or promotion policy) which may affect loan-officers use of discretionary power.

In Table 7, Panel B we therefore check the robustness of our above findings by exploiting differential price implications of rating changes within banks. Our analysis focusses on Bank C which uses the pricing tool offered by the provider of the rating tool. For this bank we exploit (proprietary) information on the pricing tool to calculate the pricing implications of each $RatingShock_t$ to a client. We then examine whether rating shocks which induce stronger price changes are more likely to be smoothed.

The pricing tool employed by Bank C uses the probability of default, associated with a rating class, to calculate the required interest rate spread. In order to examine differential price impacts we can exploit the non-linear relation between the probability of default and rating classes: A given change in the rating class therefore, has a much stronger impact on interest rates if the initial rating of the client is low than when the initial rating of the client is high. For example, the price impact of a one-notch rating upgrade is 2.5 times higher if the initial rating of a client is in class three than when the initial rating is in class six. We capture this differential price impact of a rating shock by adding the interaction term $RatingShock*ProposedRating_{t-1} = 2,3,4$ to our empirical model [1]. We expect that at Bank C a given rating shock is more likely to be smoothed if the initial rating of the client is low as this induces a stronger price impact. Thus we expect a negative coefficient for the interaction term *RatingShock*ProposedRating*$_{t-1}$ *= 2,3,4.*

The estimates reported in column (6) of Table 7 confirm that at Bank C, a given rating shock is more likely to be smoothed when the initial rating of the client is low. The point estimate for *RatingShock* suggests that a one-notch rating shock has a 25% probability of being reversed at this bank if the initial rating of the client is high. The point estimate of the interaction term *RatingShock*ProposedRating*$_{t-1}$ *= 2,3,4* suggests that this probability of the rating shock being reversed increases to 38% if the initial rating of the client is low.

The results presented in column (6) may be driven by the fact that - for other reasons than the pricing impact - loan officers are more likely to smooth ratings for clients with low ratings than those with high ratings. If this is the case, though, we should find differential smoothing behavior for low and high rated clients at the other banks too. As a "placebo" test we therefore replicate this empirical exercise in columns (7-9) for the banks which do not use the pricing tool on a mandatory basis. Column (7) reports estimates for the two banks with the pricing regime *Pricing tool – simulation*. Column (8) reports estimates for the five banks with the pricing regime *Risk-adjusted pricing.* Finally, column (9) reports estimates for Bank D at with the rating changes have no influence on loan pricing. The estimated coefficients for the interaction term *RatingShock*ProposedRating*$_{t-1}$ *= 2,3,4* in these three columns are either positive (columns 7, 9) or weakly negative (column 8). This suggests that the strong additional smoothing of rating shocks for clients with low initial ratings only takes place at the bank where ratings shocks have the strongest differential pricing impact: Bank C.

6 Conclusions

In this paper we examine to what extent loan officers use their discretion to smooth shocks to the credit ratings of their clients. We find that 18% of all rating changes induced by changes in the quantitative scores of clients are reversed by loan officers - irrespective of the initial creditworthiness of the client, independent of whether a client experiences a positive or negative shock, and independent of whether this shock is firm-specific or market related.
We assess whether the widespread smoothing of credit ratings of discretion is driven by soft information on the creditworthiness of the client or aims at insuring the borrower against fluctuations in credit conditions. We find that the smoothing of credit ratings by loan officers is only partly driven by information about the creditworthiness of their clients. In particular the downgrading by loan officers of clients that experience a positive rating shock is unrelated to subsequent loan performance. Instead, we find that the widespread smoothing of credit ratings is compatible with an insurance view of credit relationships: Loan offers are more likely to smooth rating shocks when these have stronger price implications for the borrower.

Our findings provide support for the "implicit contracts" view of relationship banking as opposed to the "information" view which has arguably dominated the recent empirical literature. In addition, our results have practical implications for banks and regulators: The use of internal credit rating processes under Basel II (and Basel III) relies on the assumption that these processes make efficient use of the available information on clients' creditworthiness. If loan officers use their discretionary power in the credit assessment process to smooth clients' loan conditions rather than to improve the predictive power of the rating, the efficiency of rating models which provide strong discretion to loan officers may be questioned.

References

Agarwal, S. & R. Hauswald (2010a). “Distance and Private Information in Lending”, *Review of Financial Studies* 23, 2757-2788.

Agarwal, S. & R. Hauswald (2010b). “Authority and Information”, *Working Paper*.

Ai, C. & E. Norton (2003). “Interaction terms in logit and probit models”, *Economics Letters* 80, 123−129.

Azariadis C. (1975). “Implicit Contracts and Underemployment Equilibria”, *Journal of Political Economy* 83, 1183–1202.

Bailey, M. N. (1974). “Wages and Employment under Uncertain Demand”, *Review of Economic Studies* 41, 37–50.

Berger, A.N. & G.F. Udell (1992). “Some evidence on the empirical significance of credit rationing”, *Journal of Political Economy* 100, 1047-1077.

Berger, A.N.& G.F. Udell (1995). “Relationship lending and lines of credit in small firm finance”, *Journal of Business* 68, 351–381.

Berger, A., N. H. Miller, M. A. Petersen, R. Rajan & J.C. Stein (2005). “Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks”, *Journal of Financial Economics* 76, 237-269.

Berlin, M. & L. Mester (1998). “On the Profitability and Cost of Relationship Lending”, *Journal of Banking & Finance* 22, 873-897.

Berlin, M. & L. Mester (1999). “Deposits and relationship lending”, *Review of Financial Studies* 12, 579–607.

Cerquiero, G., H. Degryse, S. Ongena (2011). “Rules versus discretion in loan rate setting”, *Journal of Financial Intermediation* 20, 503-529.

Cole, R.A. (1998). “The importance of relationships to the availability of credit”, *Journal of Banking & Finance* 22, 959–977.

Degryse, H. & P. Van Cayseele (2000). “Relationship lending within a bank-based system: Evidence from European small business data”, *Journal of Financial Intermediation* 9, 90-109.

Degryse H., J. Liberti, T. Mosk & S. Ongena (2011). “The added value of soft information”, Working Paper.

Elsas, R. & J. P. Krahnen (1998). “Is relationship lending special? Evidence from credit-file data in Germany”, *Journal of Banking & Finance* 22, 1283-1316.

Fried, J. & P. Howitt (1980). “Credit rationing and implicit contract theory”, *Journal of Money, Credit, and Banking* 12, 471-487.

Grunert, J., L. Norden, L. & M. Weber (2005). “The Role of Non-Financial Factors in Internal Credit Ratings”, *Journal of Banking and Finance* 29, 509-531.

Harhoff, D. & T. Körting (1998). “Lending relationships in Germany: Empirical results from survey data”, *Journal of Banking and Finance* 22, 1317–54.

Hertzberg, A., J.M. Liberti & D. Paravasini (2010). “Information and Incentives Inside the Firm: Evidence from Loan Officer Rotation”, *Journal of Finance* 65, 795-828.

Ioannidou, V. & S. Ongena (2010). “Time for a Change: Loan Conditions and Bank Behavior when Firms Switch Banks”, *Journal of Finance* 65, 1847-1877.

Liberti, J. M. & A. R. Mian (2009). “Estimating the Effect of Hierarchies on Information Use”, *Review of Financial Studies* 22, 4057–4090.

Petersen, M. A & R.G. Rajan (1994). “The Benefits of Lending Relationships: Evidence from Small Business Data”, *Journal of Finance* 49, 3-37.

Petersen, M.A. & R.G. Rajan (1995). “The effect of credit market competition on lending relationships”, *Quarterly Journal of Economics* 110, 407-443.

Qian, J., P. E. Strahan, P. E. & Z. Yang, Z. (2010). “The Impact of Organizational and Incentive Structures on Soft Information: Evidence from Bank Lending”, Working Paper.

Scott, J.A. (2006). “Loan officer turnover and credit availability for small firms”, *Journal of Small Business Management*, 544–562.

Sharpe, S. A. (1990). “Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships”, *Journal of Finance* 45, 1069-87.

Stein, J. C. (2002). “Information Production and Capital Allocation: Decentralized vs. Hierarchical Firms”, *Journal of Finance* 57, 1891-1921.

Stiglitz, J. E. & A. Weiss (1983). “Incentive effects of terminations: Applications to the credit and labor markets”, American Economic Review 73, 912–927.

Uchida, H., G. Udell & N. Yamori (2012). “Loan Officers and Relationship Lending to SMEs”, Journal of Financial Intermediation 21, 97-122.

Von Thadden, E. (2004). “Asymmetric information, bank lending, and implicit contracts: The winner’s curse”, *Finance Research Letters* 1, 11-23.

Table 1. Definition of Variables

This table presents definitions for all variables used throughout our empirical analyses.

	Definition
Discretion	Proposed rating minus the hypothetical rating based on the current quantitative assessment and the previous qualitative assessment of a customer.
RatingShock	The hypothetical credit rating of a client using his or her current quantitative and previous qualitative assessment minus his or her previous rating.
NegativeShock	Dummy variable which is 1 if RatingShock < 0, and 0 otherwise.
PositiveShock	Dummy variable which is 1 if RatingShock > 0, and 0 otherwise.
QuantShock	Difference between the current quantitative score and the quantitative score of the previous rating application.
RatingImpact	Dummy variable which is 1 if a change in the quantitative information of a customer results in a RatingShock of either direction.
CreditEvent	Dummy variable indicating whether the customer makes late payments or defaults between the current and next credit assessment (0: no, 1: yes).
Industry	Dummy variable (0,1), coding the industry into one of 21 industries.
ProposedRating_t	Rating proposed by the loan officer at the current credit assessment of this customer. Rating classes range from 1: worst to 8: best.
$\text{ProposedRating}_{t-1}$	Rating proposed by the loan officer at the previous credit assessment of this customer. Rating classes range from 1: worst to 8: best.
$\text{ProposedRating}_{t,Qual(t-1)}$	Hypothetical calculated rating based on the current quantitative score and the qualitative score in t-1.
Size	Natural logarithm of the balance sheet total in Swiss Francs (CHF).
Young	Dummy variable indicating the age of a customer (0: more than nine years, 1: less than nine years).
Same	Dummy variable indicating whether the loan officer is the same as at the previous credit assessment of the client (0: no, 1: yes).
No influence	Dummy variable indicating that rating classes have no impact on interest rates (0: no, 1: yes).
Risk-adjusted pricing	Dummy variable indicating whether the bank has an explicit rule relating rating classes to interest rates, but the bank does not use the pricing tool offered by the external rating provider (0: no, 1: yes).
Pricing tool - simulation	Dummy variable indicating that the bank employs the pricing tool offered by the external rating provider, but that the calculated interest rates serve only as benchmarks for loan officers (0: no, 1: yes).
Pricing tool - mandatory	Dummy variable indicating that the bank uses the pricing tool offered by the external rating provider and that loan officers are obliged to use the calculated interest rates as the basis for price negotiations (0: no, 1: yes).

Table 2. Summary statistics

The table shows the summary statistics of the variables employed in our empirical analysis. The summary statistics include the number of observations available, the mean values and standard deviations, as well as the minimum and the maximum values. See Table 1 for a detailed definition of all variables.

	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**
Discretion	6'669	0.03	0.62	-5	7
RatingShock	6'669	-0.03	1.30	-6	6
CreditEvent	3'359	0.04	0.19	0	1
$\text{ProposedRating}_{t-1}$	6'669	5.01	1.87	1	8
Size	6'669	7'262	1'335	2'398	15'888
Young	6'638	0.14	0.34	0	1
Same	6'669	0.43	0.49	0	1
No influence	6'669	0.13	0.33	0	1
Risk-adjusted pricing	6'669	0.25	0.43	0	1
Pricing tool - simulation	6'669	0.47	0.50	0	1
Pricing tool - mandatory	6'669	0.15	0.36	0	1

Table 3. Observations by bank

The table presents the number of rating applications across banks. Banks are labelled with consecutive letters A to I. Column (1) reports the total number of available observation in our data sample. Column (2) reports the number of observations that we actually employ in our analysis. We exclude any first observations of a customer in our data sample, as we focus our analyses on changes in rating data. Column (3) reports the relative share of each bank in our total sample, as based on actual values in the analyses. Columns (4) to (7) report the pricing regime of each bank, i.e. how sensitive interest rates are to credit ratings. See Table 1 for a detailed definition of all variables.

				Pricing regime			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank	Total Observations in Dataset	Observations employed in analysis	Share	No influence	Risk-adjusted pricing	Pricing tool - simulation	Pricing tool - mandatory
A	613	239	3.6%		1		
B	493	227	3.4%		1		
C	2'471	987	14.8%				1
D	1'402	850	12.7%	1			
E	5'319	3'121	46.8%			1	
F	1'778	292	4.4%		1		
G	112	28	0.4%			1	
H	2'296	817	12.3%		1		
I	490	108	1.6%		1		
Total	14'974	6'669	100%				

Table 4. Smoothing of credit ratings

The table reports estimates of linear regressions in which *Discretion* is the dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical signifcance of the coefficients at the 1%, 5% and 10% level respectively. See Table 1 for a definition of all variables.

Panel A: Baseline results

Panel A, Column (1) to (3) present our baseline regression on the full data sample using varying sets of fixed effects for the panel regressions. Column (4) and (5) restrict the analysis to customers whose change in objective information induced a negative or positive shock to the credit rating, respectively.

Dependent variable:	*Discretion*				
	(1)	(2)	(3)	(4)	(5)
Sample:	All	All	All	NegativeShock	PositiveShock
RatingShock	-0.182***	-0.182***	-0.178***	-0.210***	-0.227***
	[0.0207]	*[0.0207]*	*[0.0201]*	*[0.0358]*	*[0.0388]*
Size	0.189***	0.180***	0.186***	0.282*	0.0927
	[0.0556]	*[0.0554]*	*[0.0558]*	*[0.166]*	*[0.107]*
$\text{ProposedRating}_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	No	No	No
Year FE	Yes	No	No	No	No
Bank * Year FE	No	Yes	No	Yes	Yes
Loan officer * Year FE	No	No	Yes	No	No
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.154	0.149	0.150	0.112	0.135
Observations	6,669	6,669	6,669	1,515	1,478

Panel B: Robustness checks

Panel B presents robustness checks to our analysis in Panel A. In column (1), we exclude any RatingShocks larger than two rating steps to see whether our results are mainly driven by outliers. In column (2) and (3), we present our results for firms with bad proposed ratings (2,3,4) and good proposed ratings (5,6,7) in the prior period respectively. Column (4) and column (5) split our sample into observations where the bank uses the rating model for less and more than two years. Column (6) presents the results for observation in the years 2008 and 2009, while column (7) reports the results for observation in 2010 and 2011.

Dependent variable:	*Discretion*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:	Excludes Shocks Larger than 2	ProposedRating$_{t-1}$ = 2, 3, 4	ProposedRating$_{t-1}$ = 5, 6, 7	Time Since Adoption < 2yr	Time Since Adoption > 2yr	2008 & 2009	2010 & 2011
Rating Shock	-0.161***	-0.178***	-0.182***	-0.159***	-0.203***	-0.181***	-0.176***
	[0.0175]	*[0.0317]*	*[0.0215]*	*[0.0279]*	*[0.0274]*	*[0.0313]*	*[0.0293]*
Size	0.142***	0.0752	0.232***	0.243***	0.120	0.240***	0.105
	[0.0446]	*[0.100]*	*[0.0718]*	*[0.0702]*	*[0.0840]*	*[0.0562]*	*[0.0820]*
ProposedRating$_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.101	0.175	0.133	0.146	0.165	0.172	0.147
Observations	6,127	2,120	3,887	3,018	3,651	2,916	3,596

Panel C: RatingShocks vs. Shocks to the Quantitative Information

Panel C presents estimates of the use of *Discretion* for different ranges of shocks to the quantitative score of a customer. Columns (1-3) present estimates for negative shocks to the quantitative score of a customer. Column (1) includes only observations with shocks to the quantitative score that range between -0.1 and -0.05. Column (2) includes all changes from -0.05 to -0.02, column (3) includes changes from -0.02 to 0. Columns (4-6) present identical sample splits for positive shocks to the quantitative score.

Dependent variable:	*Discretion*					
	(1)	(2)	(3)	(4)	(5)	(6)
	Change in Quant. Score	Change in Quant. Score	Change in Quant. Score	Change in Quant. Score	Change in Quant. Score	Change in Quant. Score
Sample:	∈ [-0.1;-0.05]	∈ [-0.05;-0.02]	∈ [-0.02;0]	∈ [0;0.02]	∈ [0.02;0.05]	∈ [0.05;0.1]
RatingShock	-0.233***	-0.273***	-0.436***	-0.414***	-0.381***	-0.314***
	[0.0358]	*[0.0438]*	*[0.0679]*	*[0.0520]*	*[0.0551]*	*[0.0541]*
Size	0.244	0.151	0.220**	0.202***	0.284***	-0.188
	[0.169]	*[0.143]*	*[0.0979]*	*[0.0692]*	*[0.0683]*	*[0.138]*
$\text{ProposedRating}_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.108	0.133	0.165	0.129	0.190	0.170
Observations	628	845	1,085	1,214	922	694

Table 5. Smoothing of firm-specific vs. aggregate shocks

The table reports estimates of linear regressions in which *Discretion* is the dependent variable. We split our sample according to the share of positive and negative rating shocks within each industry in each year. Column (1) presents the results for observations with average market conditions, i.e. those industry-years that did not experience an exceptionally high share of negative or positive rating shocks. Column (2) includes the observations from Below-average market conditions, i.e. those industry-years with the highest share of negative rating shocks. Column (3) includes the observations from Above-average market conditions, i.e. those industry-years with the highest share of positive rating shocks. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5% and 10% level respectively. See Table 1 for a definition of all variables.

Dependent variable:	*Discretion*		
	(1)	(2)	(3)
Sample:	Average market conditions	Below-average market conditions	Above-average market conditions
Rating Shock	-0.166***	-0.184***	-0.149***
	[0.0192]	*[0.0374]*	*[0.0417]*
Rating Shock * NegativeShock			*-0.0543*
			[0.0446]
Rating Shock * PositiveShock		*-0.0418*	
		[0.0438]	
Size	0.343***	-0.0971	0.0247
	[0.0515]	*[0.142]*	*[0.127]*
ProposedRating$_{t-1}$ FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes
Method	OLS	OLS	OLS
R-squared	0.134	0.214	0.181
Observations	3,425	1,706	1,790

Table 6. Information content of discretionary rating changes

This table reports estimates of linear regressions with CreditEvent as dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical signifcance of the coefficients at the 1%, 5% and 10% level respectively. See Table 1 for a definition of all variables. Column (1) presents our baseline regression. Column (2) and (3) reports the results for firms with high credit risk (*Proposed rating* $_{t,\,Qualt-1}$ = 2,3,4) and low credit risk(Proposed ratingt, Qualt-1 = 5,6,7) respectively. For the subsample of firms with high credit risk columns (4) and (5) provide estimates for those firms which experienced negative rating shocks and positive rating shocks respectively. Column (6) to (8) each include three different sets of interaction terms, using size, young, and same interacted with discretion.

Dependent variable	*CreditEvent*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	All	Proposed Rating$_{t,Qual(t-1)}$: 2, 3, and 4	Proposed Rating$_{t,Qual(t-1)}$: 5, 6, and 7	Proposed Rating$_{t,Qual(t-1)}$: 2, 3, and 4; NegativeShock	Proposed Rating$_{t,Qual(t-1)}$: 2, 3, and 4; PositiveShock,	Proposed Rating$_{t,Qual(t-1)}$: 2, 3, and 4	Proposed Rating$_{t,Qual(t-1)}$: 2, 3, and 4	Proposed Rating$_{t,Qual(t-1)}$: 2, 3, and 4
Discretion	-0.0107**	-0.0201***	-0.00525	-0.0191**	-0.0579	-0.463	-0.0202***	-0.0128**
	[0.00473]	*[0.00441]*	*[0.00912]*	*[0.00775]*	*[0.0603]*	*[0.353]*	*[0.00456]*	*[0.00491]*
Discretion * Size						0.0497		
						[0.0395]		
Discretion * Young							0.00213	
							[0.00961]	
Discretion * Same								-0.0219
								[0.0154]
Size	-0.0150	-0.0129	-0.0288	0.0545*	-0.0321	-0.0269	-0.0126	-0.0125
	[0.0156]	*[0.0300]*	*[0.0216]*	*[0.0298]*	*[0.110]*	*[0.0388]*	*[0.0301]*	*[0.0299]*
ProposedRating$_{t,Qual(t-1)}$ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.020	0.021	0.014	0.046	0.061	0.022	0.021	0.022
Observations	3,359	1,038	1,971	526	216	1,038	1,036	1,038

Table 7. Pricing regimes and the smoothing of credit ratings

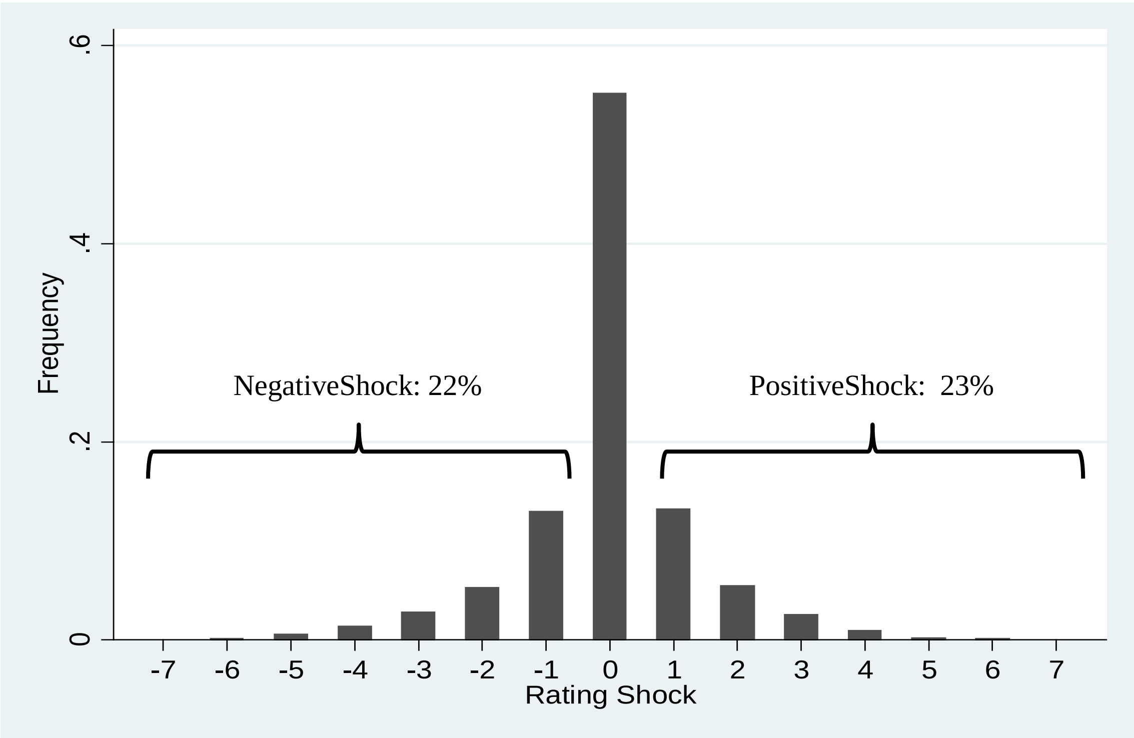
This table reports estimates of linear regressions with *Discretion* as the dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical signifcance of the coefficients at the 1%, 5% and 10% level respectively. See Table 1 for a definition of all variables. Column (1) presents full sample estimates. Columns (2-3) present subsample estimates for those firms which experience negative and positive rating shocks, respectively. Column (4) reports results for firms with low initial credit ratings (*ProposedRating* $_{t-1}$ = 2, 3, 4) while column (5) reports results for firms with high initial credit ratings (*ProposedRating* $_{t-1}$ = 5, 6, 7). Columns (6-9) report separate estimates according to the pricing regime (*Pricing tool - mandatory, Pricing tool - simulation, Risk-adjusted pricing, No influenc* e) of each bank.

Dependent variable:	*Discretion*								
	Panel A. All banks					Panel B. By pricing regime			
Sample:	All	NegativeShock	PositiveShock	ProposedRating$_{t-1}$ = 2 , 3, 4	ProposedRating$_{t-1}$ = 5, 6, 7	Pricing tool - mandatory (Bank C)	Pricing tool - simulation (Bank E, G)	Risk-adjusted pricing (Bank A,B, F, H, I)	No influence (Bank D)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RatingShock	-0.0521***	-0.0860***	-0.0939***	-0.0375**	-0.0528***	-0.251***	-0.236***	-0.143***	-0.0484***
	[0.00693]	*[0.0289]*	*[0.0251]*	*[0.0151]*	*[0.00812]*	*[0.0473]*	*[0.0167]*	*[0.0240]*	*[0.00751]*
RatingShock * Risk-adjusted pricing	-0.111***	-0.0873	-0.161**	-0.176***	-0.0867***				
	[0.0292]	*[0.0628]*	*[0.0709]*	*[0.0481]*	*[0.0271]*				
RatingShock * Pricing tool - simulation	-0.139***	-0.137***	-0.110*	-0.0744**	-0.188***				
	[0.0127]	*[0.0453]*	*[0.0630]*	*[0.0293]*	*[0.0184]*				
RatingShock * Pricing tool - mandatory	-0.270***	-0.303***	-0.321***	-0.332***	-0.205***				
	[0.0164]	*[0.0556]*	*[0.0505]*	*[0.0188]*	*[0.0457]*				
RatingShock * ProposedRating$_{t-1}$ = 2 , 3, 4						*-0.128***	*0.129****	*-0.0687**	*0.0184*
						[0.0451]	*[0.0356]*	*[0.0368]*	*[0.0165]*
Size	0.166***	0.294*	0.0849	0.0425	0.231***	-0.292**	0.369***	-0.0732	0.128
	[0.0571]	*[0.163]*	*[0.105]*	*[0.0954]*	*[0.0712]*	*[0.0724]*	*[0.0444]*	*[0.0952]*	*[0.0682]*
ProposedRating$_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.176	0.124	0.157	0.237	0.151	0.359	0.160	0.175	0.080
Observations	6,669	1,515	1,478	2,120	3,887	950	2,787	1,496	774

Figure 1. Exogenous and Discretionary rating changes

Panel A of Figure 1 presents the frequency distribution of *RatingShock* . A negative rating shock indicates worsening objective information. Positive rating shocks indicate improved objective information. Panel B of Figure 1 shows the distribution of discretionary rating changes in response to rating shocks. Positive *Discretion* indicates an increase in the qualitative assessment or a positive overide of the calculated rating. Negative *Discretion* indicates a reduction of the qualitative assessment or a negative overide of the calculated rating. Sizes of bubbles indicate relative frequencies and sum to 100% across each value of *RatingShock.*

Panel A. Distribution of RatingShocks



Panel B. RatingShocks and discretionary rating changes

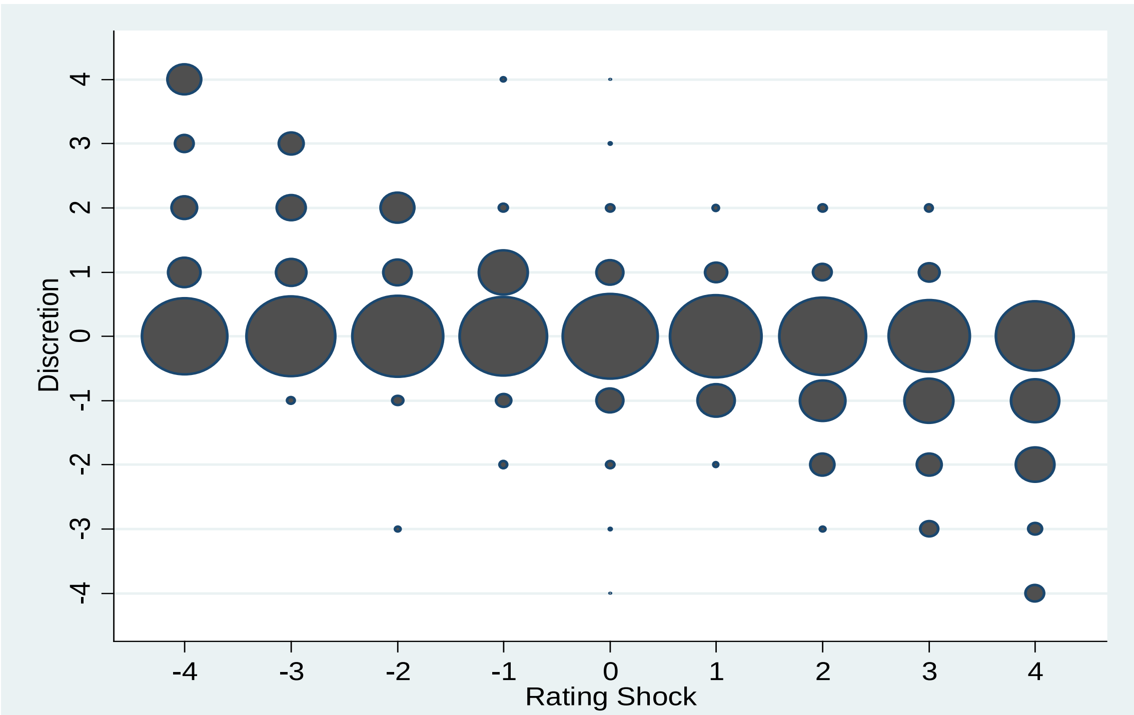


Figure 2. Information content of discretionary rating changes

Figure 2 shows the mean values of *CreditEvent* depending on whether the loan officer smoothed the client upwards (*Discretion* >0), downwards (*Discretion* <0) or did not make a discretionary rating change (*Discretion* =0). The figure presents separate means for firms with low hypothetical credit ratings ($ProposedRating_{t,\,Qual\,(t-1)}$ =2,3,4) and firms with high hypothetical credit ratings ($ProposedRating_{t,\,Qual\,(t-1)}$ =5,6,7) in the absence of discretion.

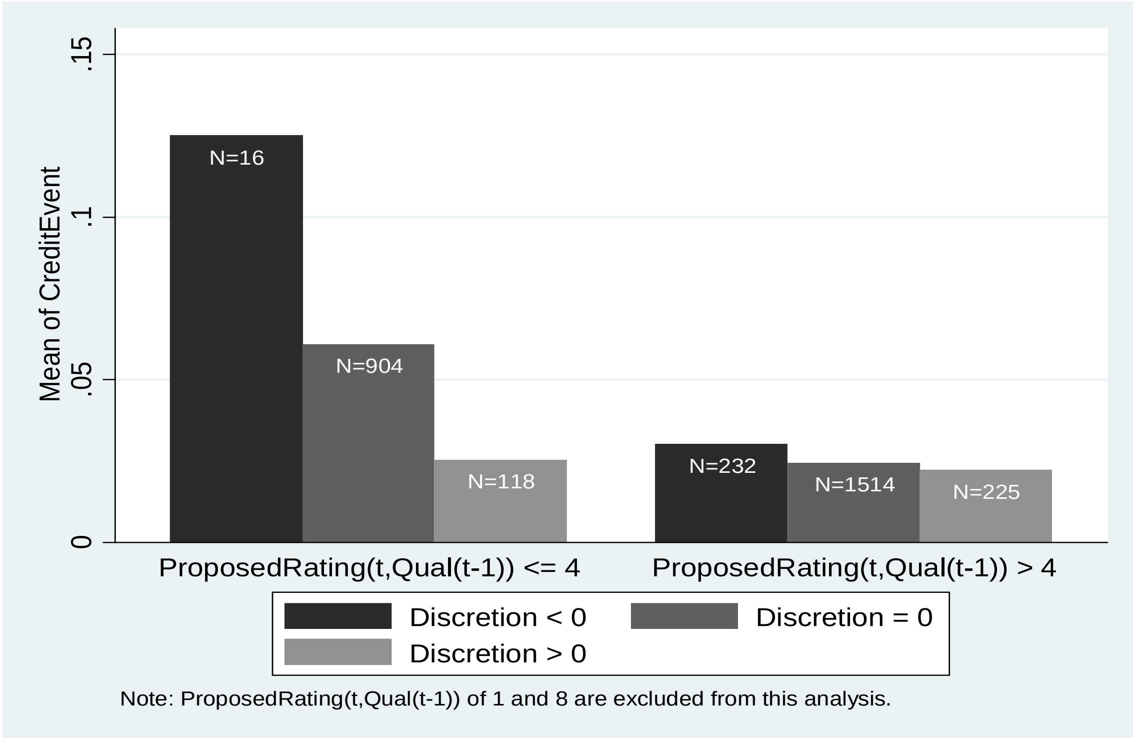
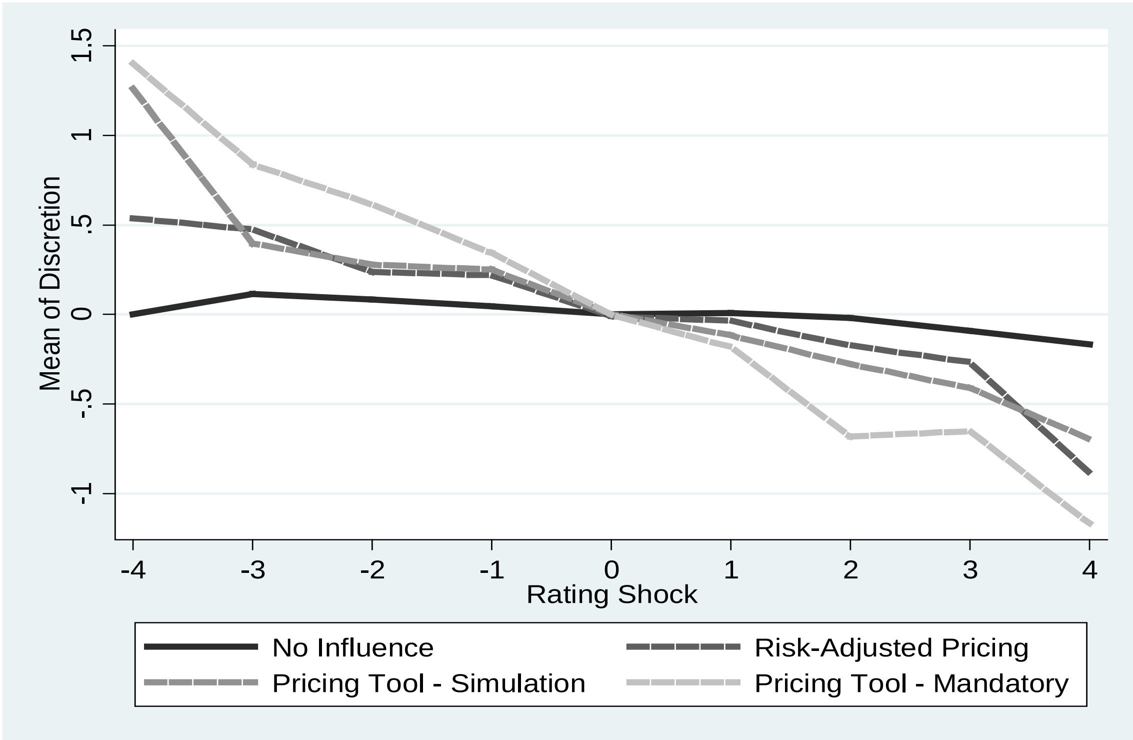


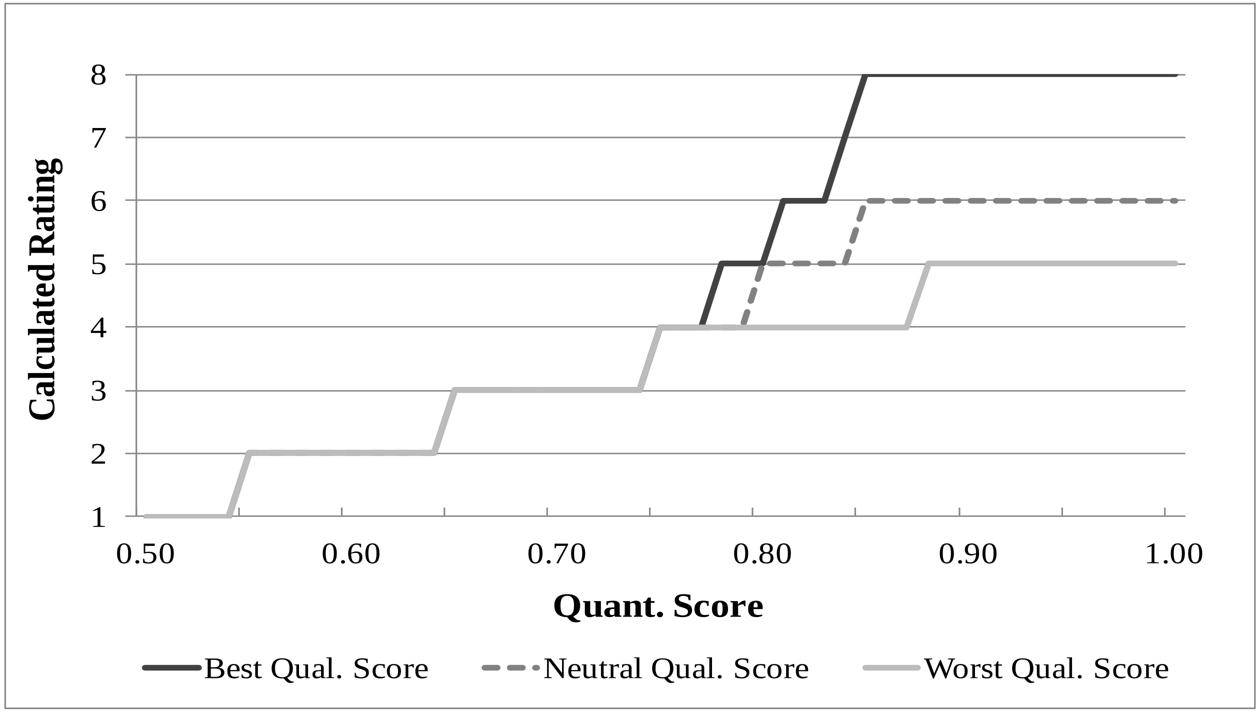
Figure 3. Pricing regime and discretionary rating changes

This figure presents the mean values of discretion across different RatingShocks for the different levels of pricing implication. Additionally, below the figure, the number of available observations for each mean value. For detailed definitions of all variables, see Table 1.



Appendix I: Calculated Rating as a function of Quantitative Score and Qualitative Score

Appendix I presents the conversion mechanics from the quantitative scores to the calculated rating. The different lines represent the rating results for a hypothetical rating with a best, worst and neutral qualitative assessment. Quantitative scores below 0.5 result in a calculated rating of one, irrespective of the qualitative score. For a detailed definition of the variables, see Table 1.



Appendix II: Exemplary Rating Application Form

Appendix II presents a stylized design for the graphical user interface of the rating tool for SMEs used at the banks in our data sample. The first section includes basic information on the customer and the date of the application and the underlying data. This section also reports the calculated credit score and the resulting calculated rating. The second section requires the relationship manager to input the relevant quantitative information on the customer. For each of the seven different ratios, the quantile of the customer is displayed immediately. Besides the ratios, the rating model also includes additional quantitative information on three items that need to be answered categorically. The following section processes the qualitative information on the customer. Each question is designed to choose between three and four categorical assessments. In the final section, the relationship manager may calculate the rating, and potentially redo his / her assessment, before proceeding and saving the results.

Credit Rating Application for SMEs

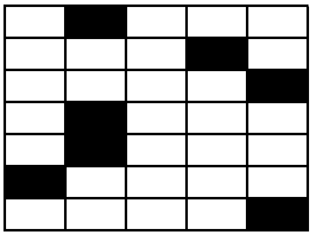
Customer:	XXX
Date of Financial Statement:	MM/DD/YYYY
Date of Rating:	MM/DD/YYYY
Calculated Rating	
Calculated Score	

Input for Quant. Score

Quantile

1 2 3 4 5

Ratio 1	x%
Ratio 2	x%
Ratio 3	x%
Ratio 4	x%
Ratio 5	x%
Ratio 6	x%
Ratio 7	x%



Additional Information 1	category 1 / category 2 / category 3
Additional Information 2	category 1 / category 2 / category 3

Input for Qual. Score

Qual. Score 1	good / average / weak
Qual. Score 2	good / above average / average / below average / weak
Qual. Score 3	very good / good / average / weak
Qual. Score 4	good / average / weak
Qual. Score 5	good / average / weak
Qual. Score 6	good / average / below average / weak / very weak
Qual. Score 7	very good / good / average / weak

Calculate Rating

Save & Proceed

Appendix III: Impact of Control on Discretionary Rating Changes

This table reports estimates of linear regressions with Discretion as dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5% and 10% level respectively. "Control" is a dummy variable taking the value one if a second person is responsible for reviewing and approving the rating proposed by the loan officer and zero otherwise. Regressions only include observations of banks that do not assign control based on a potential override. Column (1) reports the results for the complete sample. Column (2) uses only observations that experienced a negative shock to the objective credit information. Column (3) uses only observations with a positive shock. See Table 1 for a definition of all variables.

Dependent variable:		*Discretion*	
Firms:	All	NegativeShock	PositiveShock
	(1)	(2)	(3)
RatingShock	-0.229***	-0.236**	-0.475***
	[0.0635]	*[0.105]*	*[0.130]*
Control	0.128***	0.110	-0.236
	[0.0374]	*[0.179]*	*[0.171]*
RatingShock * Control	0.0374	0.00246	0.253**
	[0.0616]	*[0.118]*	*[0.115]*
Size	0.0222	-0.261*	0.0936
	[0.0583]	*[0.135]*	*[0.130]*
ProposedRating$_{t-1}$ FE	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Method	OLS	OLS	OLS
R-squared	0.194	0.243	0.169
Observations	3,029	736	741