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INTERNAL CONTROL AND STRATEGIC COMMUNICATION WITHIN FIRMS – EVIDENCE FROM BANK LENDING

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Internal Control and Strategic Communication within Firms – Evidence from Bank Lending

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Abstract

The allocation of authority affects the communication of information about clients within banks. We document that in small business lending internal control leads loan officers to propose inflated credit ratings for their clients. Inflated ratings are, however, anticipated and partly reversed by the credit officers responsible for approving credit assessments. More experienced loan officers inflate those parameters of a credit rating which are least likely to be corrected by credit officers. Our analysis covers 10,568 internal ratings for 3,661 small business clients at six retail banks. We provide empirical support to theories suggesting that internal control can induce strategic communication within organizations when senders and receivers of information have diverging interests. Our findings also point to the limits of the four-eyes principle as a risk-management tool in financial institutions.

Keywords: Internal Control, Authority, Information, Small Business Lending

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1. Introduction

The four-eyes principle is a cornerstone of governance and risk management in firms. For instance, international guidelines on licensing procedures for banks recommend checks to determine that "*the four eyes principle (segregation of various functions, crosschecking, dual control of assets, double signatures, etc.)*" will be followed.[1] The four-eyes principle –an instrument of preventive internal control - is expected to reduce operational risk by preventing fraud, and ensuring compliance with regulations and internal guidelines.[2] In addition, the four-eyes principle may improve decision making and mitigate financial risk by pooling knowledge (Blinder and Morgan, 2005) and ensuring timely and salient feedback (Christ et al., 2012).

But economic theory points to a potential dark side of the four-eyes principle: The authority of the decision proposer is inherently weak, as his proposal can be corrected or adjusted before it is executed. Theory suggests that weak authority can undermine the production of information in organizations when the interests of agents are not fully congruent (Aghion and Tirole 1997, Stein 2002). Moreover, diverging interests between information senders and receivers may lead to strategic communication within organizations (Crawford and Sobel 1982, Dessein 1992, Kartik 2009).[3]

In this paper, we examine how the allocation of authority affects the communication of information within banks. In particular, we study the internal credit assessment process for small business clients of retail banks. Small business lending is an ideal setting to study the effects of authority on information. First, information production is a core function of financial intermediaries. Indeed, efficient credit assessment and loan monitoring is widely

[1] Basle Committee on Banking Supervision: Core Principles of Effective Banking Supervision, 1997.

[2] The accounting / auditing literature distinguishes between measures of preventive control and detective control. See e.g. Romney and Steinbart (2009).

[3] Even when the interests of the proposer and approver are aligned information production may be undermined due to free riding (Holmström, 1992) or the crowding-out of intrinsic motivation (Falk and Kosfeld, 2006; Christ et al. 2008).

viewed as a raison d’être of banks (Diamond 1984). Second, in small business lending, the responsibility for producing information on the creditworthiness of borrowers is delegated to loan officers who typically have a substantial degree of discretion in their assessment. Third, in small business lending internal control is applied in a systematic and transparent manner: Credit assessments of loan officers are often subject to approval by risk managers (credit officers). Whether an assessment requires approval is determined by internal guidelines which are known by loan officers. Fourth, loan officers and credit officers have diverging interests. The compensation and promotion chances of loan officers are typically linked to loan volumes (Heider and Inderst, 2012). By contrast, the compensation and promotion chances of credit officers are not linked to lending volumes, but may be linked to loan performance. Loan officers thus have an interest in obtaining a more favorable credit assessment for their borrowers than credit officers.

We study administrative data covering 10’568 client ratings proposed by 580 loan officers at six different banks over the period 2006-2013. Due to bank-specific credit policies 78% of these ratings are subject to internal control, i.e. the rating proposed by the loan officer must be approved by a credit officer. Our analysis yields five main findings: First, weak authority does not undermine loan officers’ input to the credit assessment process: Loan officers are equally likely to use their discretion to influence ratings when a rating requires approval compared to when a rating does not require approval. Second, weak authority does lead to inflated credit assessments by loan officers: The rating proposed for a client is significantly higher when the rating requires credit officer approval. Third, rating inflation by loan officers is anticipated: Credit officers correct proposed ratings downwards. Fourth, we find that more experienced loan officers inflate those components of a rating which are least observable and hence least likely to be corrected by credit officers. Fifth, internal control does not improve the informational efficiency of the credit assessment process.

Our results provide empirical support to theories which point to strategic communication as a result of non-congruent interests between senders and receivers of information. In particular our findings are in line with Kartik (2009) who studies strategic communication in organizations when agents face lying costs. His analysis suggests that communicated information will be "inflated" but that this strategic communication will be anticipated by decision makers. This leads to an equilibrium in which information provided to decision makers is upward biased but they discount the received information when making their decisions. The degree of information inflation decreases as the (expected) costs of lying increases, e.g. due to a higher probability of being caught. Our findings broadly confirm these conjectures.

Our results contribute to a broader understanding of how internal control and incentives impact on behavior and decision making within banks. Hertzberg et al. (2010) study the impact of loan-officer rotation on the informational efficiency of the credit assessment process. The key difference between our analysis and that of Hertzberg et al. (2010) is that we examine the impact of preventive control (the four-eyes principle) as opposed to detective control (ex-post assessment due to rotation). Berg (2014) exploits thresholds in banks credit policies and shows that internal risk management reduces credit risk in mortgage lending. Compared to Berg (2014) we study a decision environment (small business lending) in which loan officers have considerably more discretion and may have more soft information relevant for credit assessments. Our evidence suggests that in such contexts risk management implemented through internal control may not improve the credit assessment process. Berg et al. (2014) show that volume incentives for loan officers in combination with minimum rating thresholds for loan approval, lead to the strategic manipulation of credit ratings by loan officers in consumer lending. We document that such strategic manipulation of information is likely to be anticipated by risk managers.[4] Cole et al. (2015) present experimental evidence documenting that incentive schemes which reward loan quality rather than just loan origination increase screening effort, reduce credit risk and improve bank profitability. Our evidence suggests that internal control may not be a good substitute for quality-based incentives in mitigating risk-taking, as loan officers are likely to react strategically to internal control mechanisms.

Our findings also contribute to the broader literature on organizational design and the use of information in financial institutions. In line with the theory of Stein (2002), Liberti and Mian (2009) and Agarwal and Hauswald (2010) show that "soft" information is less likely to be collected and also less frequently used in lending processes if the hierarchical or geographical distance between the information collectors (loan officers) and the loan approvers is large. Qian et al. (2014) show that "soft" information has a stronger impact on lending terms important when loan approval is delegated to the branches which are responsible for collecting this information. Our findings complement this literature by showing that the communication of soft information within banks may crucially depend on the internal control systems put in place. Gropp et al. (2013) examines how the degree of relationship lending affects the selection of business clients into retail banks in a competitive environment.

The remainder of this article proceeds as follows: The next section introduces the institutional setting of our study. Section 3 presents our data and clarifies our methodology. Section 4 presents our results. Section 5 concludes.

[4] Mosk (2014) finds that the removal of delegated decision making leads to less information manipulation by loan officers. However, he studies a setting in which formal authority lies in the hand of line-managers which have similar objectives to loan officers.

2. Institutional Background

Our analysis is based on internal credit ratings of small business clients by six Swiss retail banks. The banks in our sample are small to medium-sized regionally focused banks. These banks do not compete for small business clients. All banks use the same model for assessing the creditworthiness of small-business clients. [5] The rating model was developed and is currently maintained by an external provider which is jointly owned by the participating banks.[6]

2.1. Client Rating in Small Business Lending

In small business lending, credit analysis typically involves an internal client rating which (i) summarizes the financial conditions and repayment behavior of the firm and (ii) provides a qualitative assessment of the firms' managerial capacity and outlook. In addition to the client rating, small business credit analysis involves an assessment of the debt capacity of the client (cash-flow analysis) as well as an assessment of available collateral (e.g. property, movable assets, receivables).

At loan origination the client's rating, debt capacity and collateral jointly determine initial lending conditions (e.g. loan size or credit limit, maturity, interest rate, and amortization plans). During the course of a loan, periodical reviews of the client rating can trigger a re-pricing of the loan, the need for additional collateral or extra amortization payments, a recall of the loan, or the administration of the loan by the internal loan recovery department. For our sample of banks the precise influence of the client rating on lending terms varies. However, our review of the banks' internal credit guidelines and interviews with their credit managers

[5] In our sample small-business loans are classified as loans to firms with less than 10 million Swiss Francs (CHF; 1 CHF = 1.06 US Dollar) in annual turnover.

[6] This cooperation is typical of publicly owned and mutually owned regional retail banks (Hesse and Cihak, 2007).

reveal that the client rating has a significant effect on the terms which the bank can offer to the client.

Loan officers play a key role in the credit analysis of small business clients. In particular, loan officers have the discretion to complement "hard" information about the client's financial conditions and repayment history with "soft" information about the borrower's creditworthiness (Stein 2002). At the banks in our sample loan officers have substantial discretion to influence the client rating (see details below). While loan officers have strong influence on client ratings, their assessment is often subject to review and approval by internal risk or line managers. At the banks that we study, the client rating may be subject to internal approval by a credit officer who decides upon the final rating.

There are two institutional features of small business lending which are crucial to our analysis: First, there is a divergence in interests between loan officers and credit officers over the outcome of a client rating. Second, the allocation of authority over the client rating is systematic within a bank and therefore predictable for the loan officer.

While they play an important role in credit analysis, loan officers are primarily responsible for originating loans. As suggested by Heider and Inderst (2012) and documented recently by Cole et al. (2015), loan officer behavior in credit analysis will depend on the relative incentives provided for the volume of loans originated as opposed to loan performance. Important for our study, if loan officers have stronger incentives for originating loans than credit officers, then loan officers will be interested in generating a more favorable rating for their clients than the credit officer.

The determinants of compensation and promotion of loan officers varies across the six banks in our sample. However, at each bank the compensation of loan officers is either directly (volume-based bonus) or indirectly (via subjective performance evaluation) linked to the volume of lending in their loan portfolio. Moreover, the career concerns of loan officers are also determined by subjective performance evaluation which partly relies on lending volumes. By contrast, the compensation and career concerns of credit officers are not linked to lending volumes, but are (indirectly through performance evaluation) related to the quality of the loan portfolio.

At the banks which we study, the authority to approve client ratings is well defined and transparent: Whether the loan officer or a credit officer approves the client rating is based on internal guidelines which are made transparent through a credit policy. The precise internal guidelines which allocate authority over a client rating vary across the banks in our sample, but they do follow the same principle: Whether the loan officer can approve a client rating depends on the rank of the loan officer and the exposure of the bank to the client in question. Thus, whether the loan officer will have full authority over a particular client rating is predictable for the loan officer.

2.2 The Client Rating Process

Figure 1 provides an overview of the client rating process applied by the banks in our sample. First, a quantitative assessment is based on financial statement data as well as on the firm's age and its repayment history with the bank. The rating model combines this array of quantitative indicators to a *Quantitative Score* which ranges from zero (highest probability of default) to one (lowest probability of default). Second, a qualitative assessment of the client by the loan officer is based on seven questions which elicit information on the management quality as well as business and industry outlook. Each question must be answered on a scale from "below average" to "average" to "above average".[7] The ordinal assessments of the seven indicators are aggregated to a *Qualitative Score* which ranges from zero (low creditworthiness) to one (high creditworthiness).

[7] For each question there is an uneven number of (3 or 5) categories with the middle category labelled "average".

[Figure 1 here]

The rating model combines the quantitative score and the qualitative score of a client to a discrete *Calculated Rating*, which ranges from 1 (highest probability of default) to 8 (lowest probability of default). The relative weight of the qualitative score in determining the calculated rating depends on the quantitative score of a client: For low quantitative scores (below 0.775) the calculated rating results only from the quantitative score of a client. For medium-ranged quantitative scores the influence of the qualitative score on the calculated rating increases with higher quantitative scores of a client. For high quantitative scores (above 0.875), differences in the calculated rating can only be triggered by the qualitative score of a customer. Appendix I illustrates the relation between quantitative score, qualitative score and calculated rating.

Once the calculated rating is determined, the loan officer has the option to *Override* that rating. At all banks, overrides are possible in both directions, i.e. upgrades and downgrades, and are (technically) not restricted in the number of rating notches. In case a loan officer decides to override a calculated rating, she has to file a report stating the reasons for the override.[8] We label the rating proposed by the loan officer, after the override, the *Proposed Rating*.

After the loan officer proposes a rating for a client, further procedures depend on the internal guidelines of the bank. If these guidelines imply that the loan officer has full authority over a rating then the rating proposed by the loan officer is identical to the *Approved Rating* and becomes relevant for lending decisions. Alternatively, the rating proposed by the loan

[8] Admissible reasons may be specific for example, “technical limitations of the rating tool”, but also very general like, for example, “bank-specific reasons”.

officer requires approval by a credit officer. In this case the credit officer reviews the entire application file and then either accepts the rating proposed by the loan officer or makes a *Correction,* i.e. adjusts the proposed rating upwards or downwards. The rating assigned by the credit officer is final. Thus, when a rating is subject to approval the credit officer has full authority over the rating.

3. Data and Methodology

3.1. Data

We observe 10,568 client ratings for 3,661 small businesses conducted by 580 loan officers at six banks over the period 2006-2013.[9] We hereby observe every client rating conducted by each bank after introducing the common rating model. Table 1 provides an overview of our sample.

For each client rating in our data set we observe the *Quantitative Score*. We further observe each of the seven components of the qualitative assessment as well as the resulting *Qualitative Score*. We observe the *Calculated Rating*, any *Override* made by the loan officer as well as the resulting *Proposed Rating*. For ratings which require credit officer approval, we observe any *Correction* by the credit officer. For all ratings we observe the *Approved Rating*.

[Table 1 here]

The dummy variable *Requires Approval* captures whether the proposed rating of the loan officer requires approval by a credit officer. Table 1 shows that within our sample 8,188 client

[9] Our data covers all client ratings until May 2013. This implies that the annual financial statement data for the most recent ratings refers to the year 2012 or 2013 (see Table 1).

ratings (77%) require approval. The share of ratings which require approval varies substantially across banks: At three banks (A, C, E), the internal guidelines imply that more than 90% of all observed ratings require approval. By contrast, at two other banks (D, F), the credit policy implies that almost none of the ratings require approval. Finally, at one bank (B) we observe a significant share of ratings which require approval as well as a significant share which do not.

We have unique identification numbers for each loan officer within each bank. The loan officer ID numbers together with the time stamp on each rating allow us to measure the *Experience* of loan officers with the client rating process (i.e. the number of previous ratings conducted). We also know the full name of each loan officer which allows us to derive the *Gender* of the loan officer.

With respect to the clients, we observe information on firm *Size* (total assets), and *Industry*. For each client we observe a unique identification number for each bank. The client ID numbers together with the time stamp on each rating allow us to measure the *Rating number* for a client, i.e. the bank's experience in rating a given client with this rating tool. Appendix II and Appendix III present definitions and summary statistics of all variables employed in our empirical analyses.

3.2. Methodology

Our objective is to study how the allocation of decision authority affects the behavior of loan officers during the credit assessment process. Our main analysis thus compares the behavior of loan officers for ratings which require credit officer approval to the behavior for ratings which do not require approval. We study two dimensions of loan officer behavior highlighted by economic theory.

First, theory suggests that weak authority may discourage loan officers from contributing information to the credit assessment process (e.g. Aghion & Tirole 1997). In this case we would expect that loan officers make less use of their discretion when they anticipate that a rating requires credit officer approval. From our data we derive two measures of the degree to which loan officers make use of their discretion: The variable *Neutral Qualitative* measures the number of qualitative indicators [0,7] which the loan officer ticks as "average" during his qualitative assessment of the client. Note that for each qualitative indicator the loan officer has to assess whether the client is below average, average or above average. Our indicator of the use of discretion by a loan officer thus assumes that loan officers which are discouraged from making an input to the credit assessment process will tick more qualitative indicators as average. Based on the same reasoning we employ the variable *No Override* as a second measure of the degree to which loan officers refrain from using their discretion.

Alternatively, weak authority may lead loan officers to use their discretion to inflate the ratings proposed for their clients (e.g. Kartik 2009). In this case we would expect loan officers to propose better ratings when the rating requires credit officer approval. We employ three measures of rating inflation: Our main measure $Discretion_{proposed}$ captures the degree to which the loan officer influences the proposed rating for the client. It is measured as the difference between the observed *Proposed rating* and a hypothetical proposed rating based on the assumption that the loan officer grades all qualitative indicators as average and makes no override. We further examine whether rating inflation occurs through an upward bias of qualitative scores or through positive overrides. Our measure of rating relevant upward bias of the qualitative score is the variable $Discretion_{qualitativ}$–. This is measured as the difference between the observed *Calculated rating* and a hypothetical calculated rating based on the assumption that the loan officer grades all qualitative indicators as average. Our measure of rating inflation via overrides is the observed *Override*.

Identification

We relate our dependent variables $D_{i,j,t}$ (*Neutral Qualitative, No Override, $Discretion_{proposed}$, $Discretion_{qualitativ}$, Override)* for the rating of client *j* in year *t* by loan officer *i* to the explanatory variable *Requires* $Approval_{j,t,}$. Equation [1] summarizes our empirical methodology:

[1] $D_{i,j,t} = \alpha_t + \beta_1 \cdot Requires\ Approval_{j,t} + \beta_2 \cdot X_{j,t} + \beta_3 \cdot Z_{i,t} + \varepsilon_i$

Given the non-experimental nature of our data we face several identification concerns. First, any observed correlation between required approval and loan officer behavior might be driven by reverse causality: Banks may have a policy of requiring credit officer approval if loan officers either make use of their discretionary power e.g. by making an override. We mitigate the concern of reverse causality by choosing a sample of banks for which we know (from their internal guidelines) that the requirement for credit officer approval is not triggered by the input of the loan officer.[10]

[Figure 2 here]

[Table 2 here]

Our analysis may further be plagued by omitted variable bias. One concern is that the true creditworthiness of clients may differ systematically between those ratings which require credit officer approval and those which do not. Mitigating this concern, Figure 2 and Table 2

[10] Our raw database includes information on 12 banks. We exclude 6 banks from our sample at which an override by the loan officer triggers credit officer intervention.

document that there is no difference in the *Quantitative score* for ratings which require credit officer approval compared to those that do not. Table 2 further shows that *Industry* affiliation of the firms does not differ for ratings subject to credit officer approval and those that are not. The table does however show that ratings which require approval involve substantially larger clients. This is in line with the credit policy of the banks which we study (see section 2). We control for observable measures of creditworthiness of the client with a vector $X_{j,t}$ of covariates including the *Quantitative score*$_{j,t}$, *Size*$_{j,t}$ and *Industry*$_{j}$ of the client. To account for the precision of the information which the bank has about the client, we control for the *Rating Number*$_{j,t}$, i.e. whether this rating is the first, second, third, etc. rating of that client by the bank. To account for the impact of broad economic conditions over our observation period we employ year fixed effects α_t.

A further identification concern is that the allocation of decision authority may be correlated with the skills, experience or attitudes of loan officers. If banks allocate authority based on the hierarchical rank of the loan officer then it is very likely that authority is correlated with loan officer skills. To disentangle any effects of authority from that of loan officer skills and experience we choose two strategies. First, in our full sample analysis we control for loan-officer characteristics $Z_{i,t}$. Most importantly, we control for loan officer *Experience* with the rating model. In addition, as recent evidence by Beck et al. (2013) suggests that female loan officers make better credit assessments in small business lending, we also control for the *Gender* of the loan officer. Our second strategy is to conduct robustness tests for a subsample of banks for which we know that loan officer authority can hardly be correlated with loan officer attributes. Table 1 shows that one bank in our sample almost always requires credit officer approval (Bank E) while two other banks (Bank D, Bank F) almost never require credit officer approval. The bank-wide implementation (or non-implementation) of the four-eyes principle implies that within these banks the requirement of credit officer approval is not correlated with loan officer attributes. We thus examine whether our full sample results are confirmed in the joint sample of these three banks.

A final identification concern is that the allocation of authority may be correlated with differences in incentives schemes as well as other institutional constraints on loan officer behavior. In particular, it is likely that the heterogeneous use of the four-eyes principle across banks (see Table 1) could be correlated with other differences in organizational design and incentive schemes across banks which influence loan officer behavior. One strategy to account for unobserved heterogeneity across banks would be to include bank fixed effects in our main specifications. However, as Table 1 indicates there is only limited within-bank variation in the allocation of authority within most of the banks in our sample. To mitigate the concern that our findings are driven by unobserved differences in other policies across banks we replicate our main analysis using only observations from Bank B. This is the one bank in our sample which displays a significant number of ratings subject to approval (2192 observations) as well as a significant number of observations not subject to approval (757 observations).

4. Results

4.1 Use of Discretion

In this section we provide evidence suggesting that weak authority does not reduce the degree to which loan officers make use of their discretion in the client rating process. Client ratings which require approval by a credit officer are not characterized by more neutral qualitative indicators, or by less overrides.

The summary statistics presented in Appendix III suggest that loan officers make moderate use of their discretion in the client rating process: On average, loan officers grade 4.7 qualitative indicators (out of 7) as “average” while 82% of the calculated ratings do not exhibit an override. Figure 3 displays the mean of our two indicators of (the absence of) loan officer discretion *Neutral Qualitative* (Panel A) and *No Override* (Panel B). Both panels show the means separately for ratings which require credit officer approval and ratings which do not require approval. If weak authority reduces loan officer input to the credit assessment process we would expect to see a higher mean of *Neutral Qualitative* and *No Override* for ratings which require approval. Figure 3 suggests that this is not the case.

[Figure 3 here]

[Table 3 here]

Table 3 presents results of a multivariate regression analysis in which we relate *Neutral Qualitative* and *No Override* to the dummy variable *Requires Approval*. In all specifications we include fixed effects to control for the quantitative score of each firm[11] and the *Year* of the financial statement data upon which a rating is based. We further control for client characteristics $X_{i,t}$ and loan officer characteristics $Z_{i,t}$. All estimates are based on linear regressions with standard errors clustered at the loan officer level.

Our full sample estimates (columns 1-2) do not support the hypothesis that weaker authority reduces loan officers’ use of discretion. The estimated coefficient for *Requires Approval* is negative and statistically insignificant in the regression for *Neutral Qualitative* (column 1) and *No override* (column 2). To rule out that our estimates are confounded by

[11] We include six fixed effects on the quantitative scores as the quantitative information non-linearly influences the calculated rating class.

heterogeneity in loan officer skills within banks we replicate our analysis using observations from Banks D, E, F which apply (or do not apply) the four-eyes principle to (almost) all client ratings (columns 3-4). To rule out that our estimates might be confounded by unobserved differences in credit policies and compensation policies across banks we replicate our analysis using observations from Bank B only in (columns 5-6). The estimated coefficients for *Requires Approval* in columns (3-6) confirm our full sample results.

4.2 Rating Inflation

The results above suggest that weak authority does not reduce the use of discretion by loan officers in the credit assessment process. Theory suggests that the driving force behind this result might be the divergence of interests between loan officers and credit officers. When a rating requires credit officer approval, loan officers might use their discretion to inflate the proposed ratings for their clients. If this is the case we should observe that the proposed rating is more positive when the rating requires approval. In this section we document that this is the case.

Figure 4, Panel A displays the distribution of the variable $Discretion_{proposed}$ for observations which require credit officer approval and those which do not. The figure shows that the influence of loan officers on the proposed rating is more likely to be positive for ratings which require approval. In our full sample, the mean values of $Discretion_{proposed}$ is 0.22 notches higher for ratings subject to approval (0.28) compared to ratings which are not subject to approval (0.06). Panel B of the figure shows that higher levels of $Discretion_{proposed}$ for ratings which require approval are found for clients with weak financial indicators (low quantitative scores), average financial indicators (intermediate quantitative scores) as well as for clients with strong financial indicators (high quantitative scores).

[Figure 4 here]

[Table 4 here]

The multivariate regression results presented in Table 4 confirm that loan officers propose significantly higher ratings when the rating requires credit officer approval. In this analysis we relate the variables $Discretion_{proposed}$, $Discretion_{qualitative}$ *and Override* to the dummy variable *Requires Approval*. We include fixed effects to control for the quantitative score of each client and the year of the latest financial statement data. We further control for observable characteristics of the client and the loan officer. Standard errors are clustered on the loan officer level. The full sample estimates in column (1) report a statistically significant and positive impact of *Requires Approval* on the $Discretion_{proposed}$ (0.197***). The point estimate is substantial given that the average of $Discretion_{proposed}$ in our sample is 0.23, suggesting that the large part of this positive bias in discretionary assessments stems from the observations that are subjective to approval. Roughly one in five client ratings which require credit officer approval, receives a proposed rating that is one notch higher than it would be if the four-eyes principle did not apply to the rating.

In columns (2-4) we replicate our analysis for customers with different levels of quantitative scores. For the subsample of clients with quantitative scores below 0.75 we find the smallest impact (0.098**). For these ratings there is no influence of qualitative scores on the calculated rating (see appendix I) so that any inflation of the rating by the loan officer must be accomplished through an override. For clients with a quantitative score between 0.75 - 0.875 (where there is an increasing influence of the qualitative score on the calculated rating) the estimate more than doubles (0.220**). The estimate gains again in economic magnitude and statistical significance (0.261***) when we consider clients with quantitative scores exceeding 0.875 (i.e. clients with the highest influence of the qualitative score on the calculated rating).

The column (2-4) results suggest that loan officers with weak authority inflate the proposed rating of a client through higher qualitative scores and / or through positive overrides. In columns (5-6) of Table 4 we examine which of these two channels loan officers are more likely to use when both have a substantial influence on the proposed rating. To this end, we focus on those observations with quantitative scores of at least 0.875. In column (5) the dependent variable is the $Discretion_{qualitative}$ so that the estimate for *Requires Approval* indicates rating inflation through higher qualitative scores. In column (6) the dependent variable is the *Override* so that the estimate for *Requires Approval* indicates rating inflation by means of positive overrides. The estimates for *Requires Approval* in columns (5-6) are 0.208*** and 0.054 respectively, suggesting that when possible loan officers are much more likely to use higher qualitative scores rather than positive overrides to inflate client ratings. One reason for this behavior may be that manipulations of the qualitative score are less likely to be detected and reversed by credit officers than rating overrides. We examine the correction of proposed ratings by credit officers below.

[Table 5 here]

Table 5 presents robustness checks to our full sample results on rating inflation. In column (1) we replicate our main specification (Table 4, column 1) for the subsample of ratings from Banks D, E, F only. As mentioned above, these banks apply (or do not apply) the four-eyes principle to almost all client ratings. This subsample analysis allows us to rule out that our full sample results are driven by within-bank heterogeneity between loan officers which handle ratings that require approval and loan officers which have full authority over their client ratings. The Table 5 column (1) estimates for *Requires Approval* (0.237***) suggest that our full-sample results our not driven by unobserved heterogeneity across loan officers.

In columns (2-3) of Table 5 we replicate our main specification for ratings from Bank B only. This is the only bank in our sample which boasts a substantial within-bank variation in the use of the four-eyes principle. Subsample estimates for Bank B thus allow us to mitigate the concern that unobserved differences in credit policies and compensation policies across banks (which may be correlated with the bank-wide application of the four-eyes principle may drive our full sample results. The point estimate for *Requires Approval* in this subsample (0.093) is substantially smaller than in our full sample and imprecisely estimated. A closer look at the Bank B subsample reveals however that the weak estimate in column (2) is related to the fact that within Bank B the application of the four-eyes principle is inherently correlated with loan officer *Experience* (which we control for in this specification). In column (3) of Table 5 we replicate our subsample estimates for Bank B without loan officer controls $Z_{i,t}$ and again confirm our full-sample coefficient for *Requires Approval* (0.164**). A more detailed analysis on the impact of experience on loan officer behavior will be presented in a subsequent section.

In columns (4-5) of Table 5 we examine to what extent the relation between weak authority of the loan officer and rating inflation may be driven by the novelty of the common rating tool used by the banks in our sample. If the introduction of the rating tool is associated with a loss of authority among loan officers then they may inflate ratings predominantly in the introductory phase of the rating tool. To examine whether rating inflation occurs mainly during the introduction phase of the rating tool we split our sample into ratings which were conducted in the first year after introduction (column 4) and those in later years (column 5). As the banks in our sample introduced the rating tool at different points in time we can still account for changing economic conditions over time with year fixed effects. The column (4-

5) results suggest that the relation between loan officer authority and rating inflation holds beyond the introduction phase of the rating tool. The estimate for *Requires Approval* is almost identical to our full sample estimates in both columns.

4.3 Credit officer corrections

In line with economic theory our results above suggest that weak authority – as a consequence of the four-eyes principle – induces loan officers to inflate client ratings. Theory suggests that information receivers – in our case the credit officers which approve client ratings – will anticipate and counteract rating inflation. In the following we focus our attention on those client ratings which require credit officer approval and document that on average credit officers do correct proposed ratings downwards. However, significant downward corrections only occur after a positive override by the loan officer.

In Figure 5, we plot the frequency of the variable *Correction* against our main indicator of rating inflation $\text{Discretion}_{\text{proposed}}$. The former variable measures the difference between the rating approved by the credit officer and the rating proposed by the loan officer. The figure shows that the majority of ratings proposed by loan officers are not corrected by credit officers. Indeed, the mean of *Correction* for all observations which require approval is –0.12, implying that only one in eight client ratings is corrected downwards by one notch. However, in line with the theory of Kartik (2009), Figure 5 shows that credit officers do reverse inflated ratings proposed by loan officers: There is a negative relation between *Correction* and $\textit{Discretion}_{\textit{proposed}}$ for observations where the loan officer has "upgraded" the rating of the client, i.e. $\textit{Discretion}_{\textit{proposed}}$ is positive.

[Figure 5 here]

[Table 6 here]

In Table 6 we present a multivariate analysis of rating corrections by credit officers. In column (1) we regress *Correction* on $Discretion_{proposed}$. In column (2) we regress *Correction* on the $Discretion_{qualitative}$ in order to study how credit officers react to rating relevant variation in the qualitative score. In column (3) we regress *Correction* on the *Override* implemented by the loan officer. All specifications include year fixed effects, fixed effects for the quantitative score as well as our client and loan officer control variables. Importantly, in all specifications we control for unobserved heterogeneity across credit officers with credit-officer fixed effects.

The column (1) estimate for $Discretion_{proposed}$ (-0.123***) confirms that credit officers correct inflated proposed ratings downwards. One in eight proposed ratings which are inflated by one notch are reversed by credit officers. The column (2-3) results show that ratings which are inflated through the qualitative score are less likely to be corrected than ratings which are inflated through positive overrides. The estimated coefficient of $Discretion_{qualitative}$ in column (1) is small and lacks statistical significance. By contrast, the large, negative estimate for *Override* in column (2) confirms that credit officers are likely to reverse overrides by loan officers. The point estimate (-0.172***) suggests that credit officers reverse one out of six overrides by the loan officer.

In columns (4-5) of Table 6 we examine whether the corrections by credit officers differs according to the average use of discretion by loan officers. In particular we are interested in whether credit offers single out particular loan officers for corrections, i.e. those who loan officers who most often propose inflated ratings. We find that this is not the case, although there is considerable variation in the use of discretion across loan officers. For each loan officer we calculate the average of $Discretion_{proposed}$ across all observations in the sample. We find that in the cross-section of loan officers 14% have an average of $Discretion_{proposed}$ below 0. We then split our sample into ratings proposed by loan officers with Low Discretion (the average of $Discretion_{proposed}$ is below 0.28) and those with High Discretion (the average of $Discretion_{proposed}$ is at least 0.28). In columns (4-5) of Table 6 we examine credit officer corrections for these two subsamples respectively and find no difference in credit officer behavior. This suggests that credit officer corrections are targeted towards particular cases of ratings - those with positive overrides – rather than particular loan officers.

4.4 The role of experience

The Table 6 results suggest that credit officers do anticipate rating inflation by loan officers. However, credit officers are more likely to reverse positive overrides while they are not very likely to reverse positive qualitative scores. Loan officers who anticipate this behavior of credit officers are likely to adapt their credit assessments accordingly. In particular, we would expect that experienced loan officers influence qualitative scores rather than overrides to inflate their clients' ratings.

To examine how loan officer experience affects proposed ratings we replicate our analysis from Table 4 (columns 1, 4, 5) now splitting our sample by loan officer experience. We define a *High Experience* (*Low Experience*) observation as one where the loan officer has previously completed more (less) ratings than the median per loan officer in our sample.[12] We present the results of this subsample split in Table 7. Columns (1-2) present the results for the $Discretion_{proposed}$ as dependent variable, columns (3-4) for $Discretion_{qualitative}$ and columns (5-6) for *Override*.

[12] The median number of client ratings per loan officer in our sample is 22.

[Table 7 here]

The Table 7 results suggest that weak authority leads to a similar degree of rating inflation independent of the loan officers experience with the rating tool. The column (1-2) results show that the impact of *Requires Approval* on $Discretion_{proposed}$ (Low Experience: 0.205***; High Experience: 0.201***) is largely independent of loan officer experience. However, loan officers with more experience are more likely to influence the qualitative score, while less experienced loan officers are more likely to make positive overrides The column (3-4) estimate for *Requires Approval* on the $Discretion_{qualitative}$ is stronger for experienced loan officers (*Low Experience*: 0.0457**; *High Experience*: 0.129***). By contrast, the column (5-6) estimates for *Requires Approval* on *Override* are stronger for less experienced loan officers. (*Low Experience*: 0.159***; *High Experience*: 0.0722). Together, the Table 4 (column 5-6) and Table 7 results suggest that loan officers with weak authority not only strategically inflate client ratings, but do so by manipulating those parameters of a credit rating which are least likely to be detected and corrected. This finding is consistent with theory which predicts less information inflation when the expected costs of lying (and thus also of being caught lying) are higher (Kartik 2009).

Our results above suggests that loan officers adapt their behavior under internal control as they become more experienced. In Table 8 we examine how loan officers react when they are actually affected by internal control, i.e. when they experience a correction by a credit officer. To this end we relate our three main dependent variables $Discretion_{proposed}$ (column 1), $Discretion_{qualitative}$ *(column 2)* and *Override* (column 3) to a dummy variable which takes the value 1 if the previous rating of the same loan officer experienced a correction. We hereby include loan officer fixed effects in our specification to control for heterogeneity in the level of rating inflation across loan officers (which may trigger corrections). Surprisingly, we find no evidence of an immediate reaction of loan officers to previous corrections. The estimates for *Correction in Previous Rating* are very small and statistically insignificant in all three columns. Together with our previous results this finding suggests that loan officers anticipate correctly that credit officers may correct their proposed ratings downwards – and that they are not surprised when this actually happens.

[Table 8 here]

4.1 Informational Efficiency

Our results so far suggest that the allocation of authority leads to strategic behavior in the credit assessment process of retail banks. We conclude our empirical analysis by examining how the allocation of authority affects the informational efficiency of the rating process: Does the informational input of the loan officer (and credit officer) lead to a better or worse prediction of default when a rating requires credit officer approval.

For two banks in our sample (Bank A and Bank B) we can match our main dataset on client ratings to credit file information on loan defaults. We define a loan default as an incidence of 90 days failure to pay or an (earlier) write down on the loan. For each client rating we assign the variable *Default* the value 1 if the client defaults within 12 months after the rating. As we have information on defaults at Banks A and B from 2006 to 2013, we restrict our analysis to the client ratings made between 2006 and 2012. For this subsample of 3,889 client ratings we observe a total of 161 defaults implying an average default rate of 4.1%.

[Table 9 here]

Table 9 presents a multivariate analysis of the relation between loan default and the informational input of the loan officer / credit officer. We report marginal effects of probit estimations with *Default* as the dependent variable. Columns (1-2) report results for ratings which do not require credit officer approval. In these specifications our main explanatory variable $Discretion_{proposed}$ captures the informational input of the loan officer. Columns (3-4) report results for ratings which require credit officer approval. Here we relate default also to the informational input of the credit officers as captured by *Correction*. As the majority of defaults are concentrated among clients with low quantitative scores we present full sample estimates (columns 1,3) as well as estimates for the subsample of clients with quantitative scores below 0.75 (columns 2,4).

The estimates reported in columns (1-2) of Table 9 suggest that for ratings which do not require approval the informational input of the loan officer to the rating process is valuable in predicting default. In both specifications we yield a negative and significant coefficient for $Discretion_{proposed}$ suggesting that, conditional on the quantitative score, clients who are assigned a higher rating by their loan officer are less likely to default. The economic magnitude of this effect is substantial. For example the point estimate for $Discretion_{proposed}$ reported in column (2) suggests that clients which the loan officer upgrades by one notch are 4 percentage points less likely to default. This is one-third of the mean default rate in this sample of low quality clients (12.5%).

The results reported in columns (3-4) for ratings which require credit officer approval are surprising. First, the magnitude of the point estimates for $Discretion_{proposed}$ in columns (3-4) are similar to those estimated in columns (1-2). Thus the higher ratings proposed by loan officers under the four eyes principle do not translate into less accurate default predictions. This finding suggests that loan officers do not inflate the proposed ratings across the board, but rather do so for clients which are more likely to warrant a higher rating. Second, we find no relation between credit officer corrections and incidences of default. The point estimates for Correction in columns (3-4) are very small and statistically insignificant. This result suggests that risk managers do not contribute directly to better credit risk assessments. However, the finding is consistent with our estimates for $Discretion_{proposed}$ and the correction behavior of credit officers displayed in Figure 5. First, we observe in Figure 5 that credit officers are most likely to correct proposed ratings which have been upgraded by loan officers. Second, our estimates for $Discretion_{proposed}$ suggest that the clients which are upgraded (downgraded) by loan officers are substantially less (more) likely to default. Thus it seems that – in our context of small business lending – front office loan officers rather than risk managers contribute valuable soft information to the credit assessment process.

5. Conclusions

In this paper, we provide evidence supporting the conjecture that the allocation of authority can trigger strategic communication of information within firms. Our analysis is based on administrative data covering 10,568 internal credit ratings for 3,661 small business clients at 6 retail banks. We document that in small business lending the four-eyes principle leads loan officers to propose inflated credit ratings for their clients. These inflated ratings are, however, anticipated and corrected by the credit officers responsible for approving credit assessments. Overall, the allocation of decision authority to the credit officers does not improve the informational efficiency of the credit assessment process

Our findings provide empirical support to economic theories which highlight the importance of decision authority and congruency of objectives for the production and communication of information within organizations. Our results also point to the limits of internal control systems in firms. Preventive control systems - such as the four-eyes principle

- may not only undermine employee effort due to free riding or a crowding-out of intrinsic motivation. Our findings suggest that preventive control may also trigger strategic information communication within firms.

Finally, our results cast doubt on the effectiveness of the four-eyes principle as a risk management tool in financial institutions. The presumption that the four-eyes principle may improve decision making and reduce risk may not always be warranted. As suggested by theory, the allocation of decision authority within firms should depend on the degree to which agents possess soft information and the extent to which interests of the involved parties within financial institutions coincide.

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Figure 1. The Client Rating Process

This figure illustrates the client rating process. The hybrid credit rating model uses quantitative and qualitative information for generating a calculated rating. The loan officer is allowed to override the calculated rating, resulting in the proposed rating. If the rating does not require approval the proposed rating equals the approved rating. If the rating does require approval, the credit officer can correct the proposed rating and determines the approved rating.

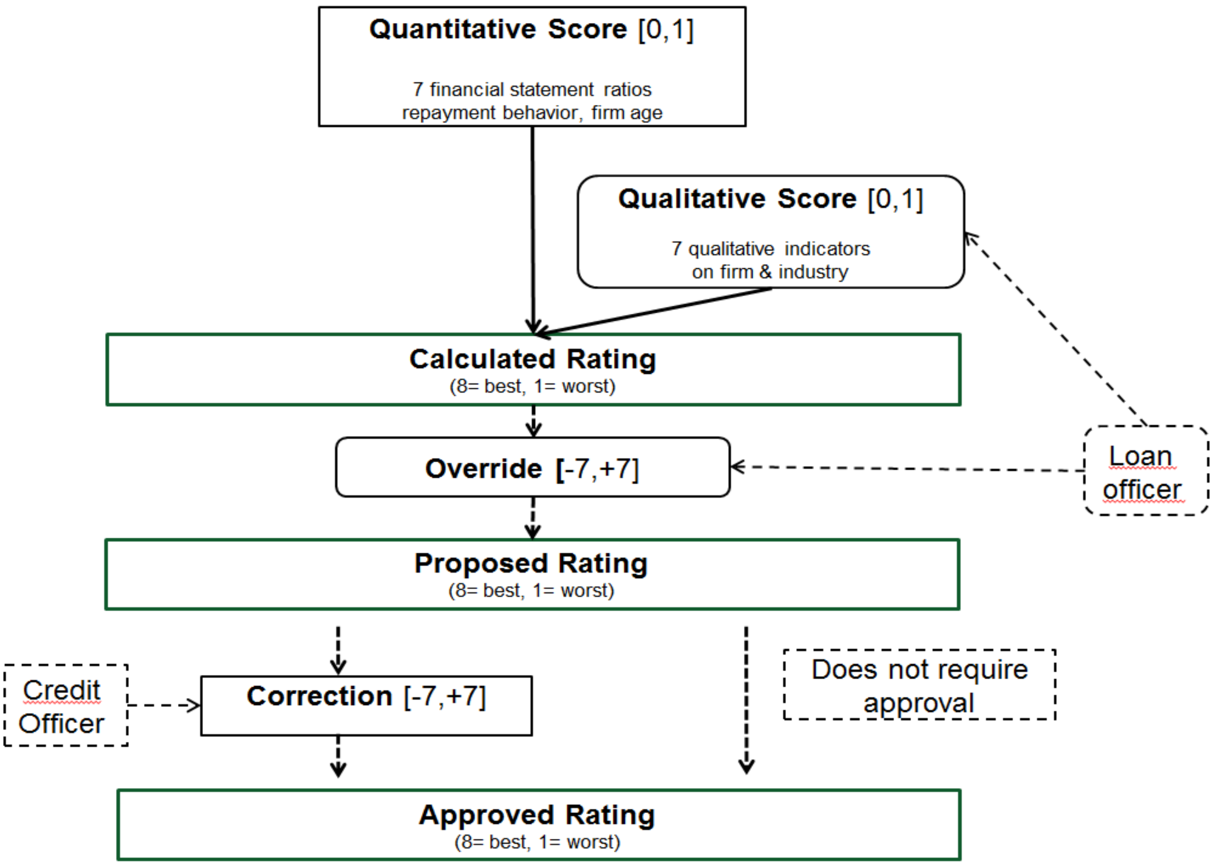


Figure 2. Quantitative Score and Internal Control

This figure plots the distribution of observations in our full sample across different buckets of quantitative rating scores. The sample is divided into client ratings which require approval by a credit officer and those that do not.

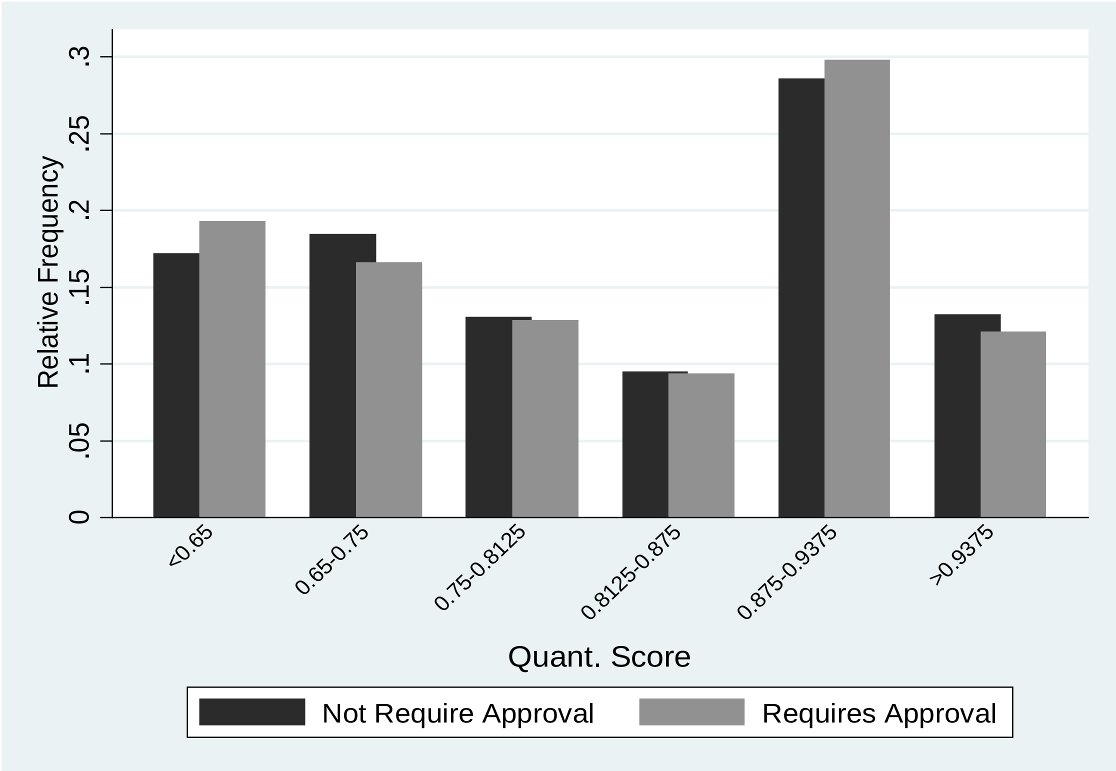
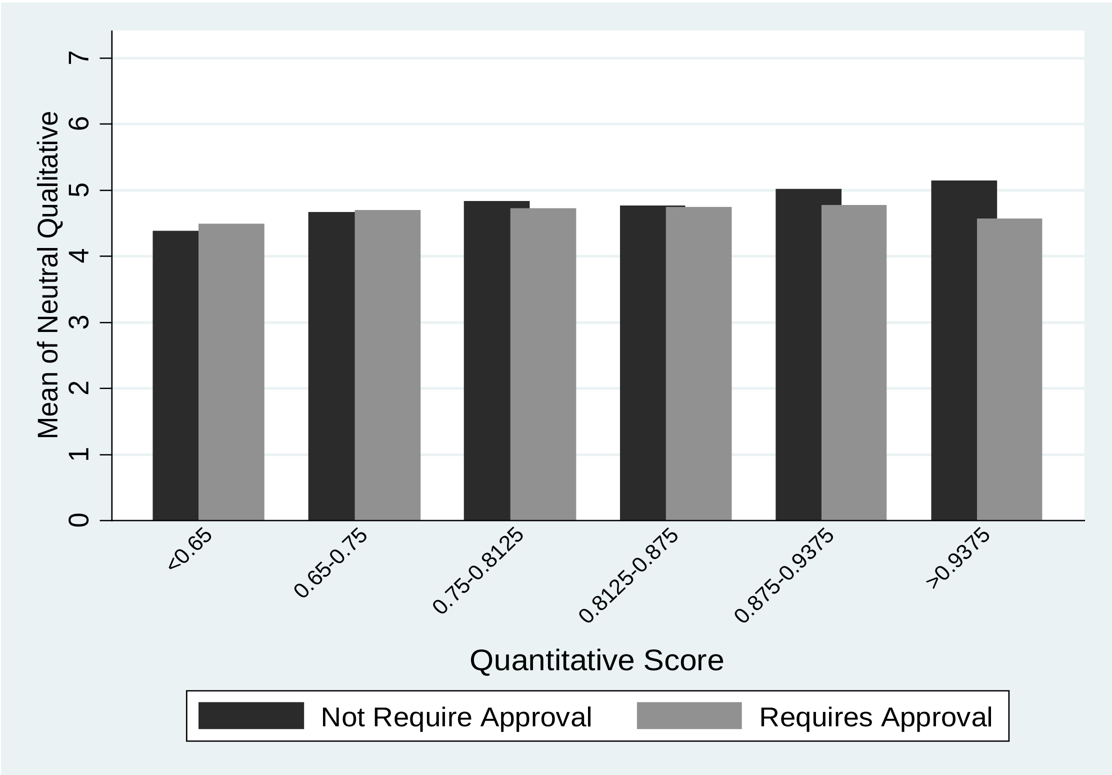


Figure 3. Use of Discretion

This figure plots the means of *Neutral Qualitative* (Panel A) and *No Override* (Panel B). Observations are clustered by quantitative score. Means are displayed separately for ratings that are require credit officer approval and ratings that do not require approval. See Appendix II and III for definitions and summary statistics of all variables.

Panel A. *Neutral Qualitative*



Panel B. *No Override*

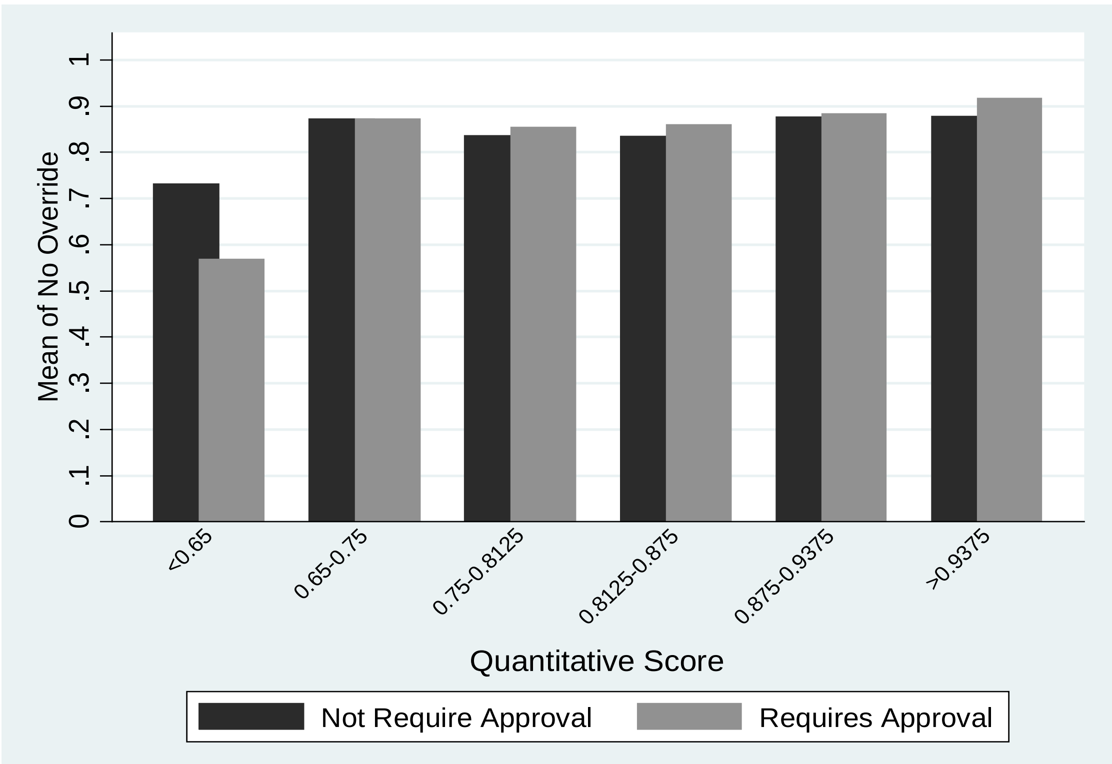
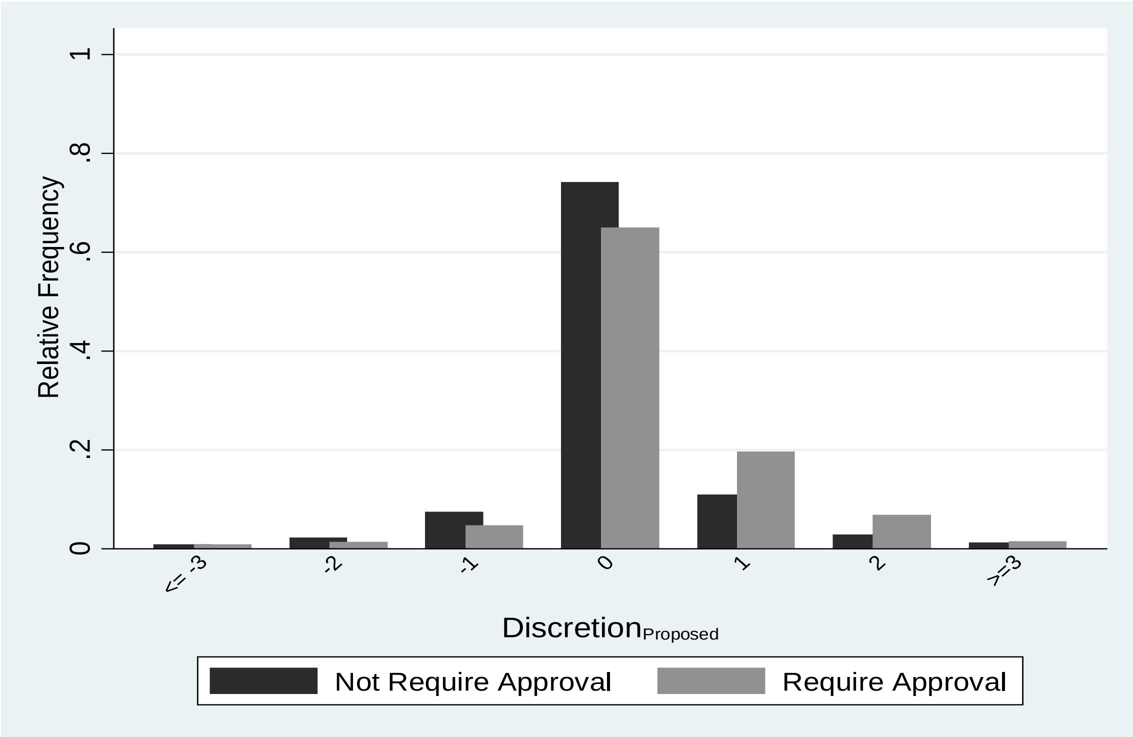


Figure 4. Rating Inflation

Panel A of this figure displays the distribution of $Discretion_{proposed}$ for ratings which require approval and ratings which do not require approval. Panel B of the figure displays the mean of $Discretion_{proposed}$ conditioned on the quantitative score of the client.

Panel A. Distribution of $Discretion_{proposed}$



Panel B. Mean of $Discretion_{proposed}$ by Quantitative Score

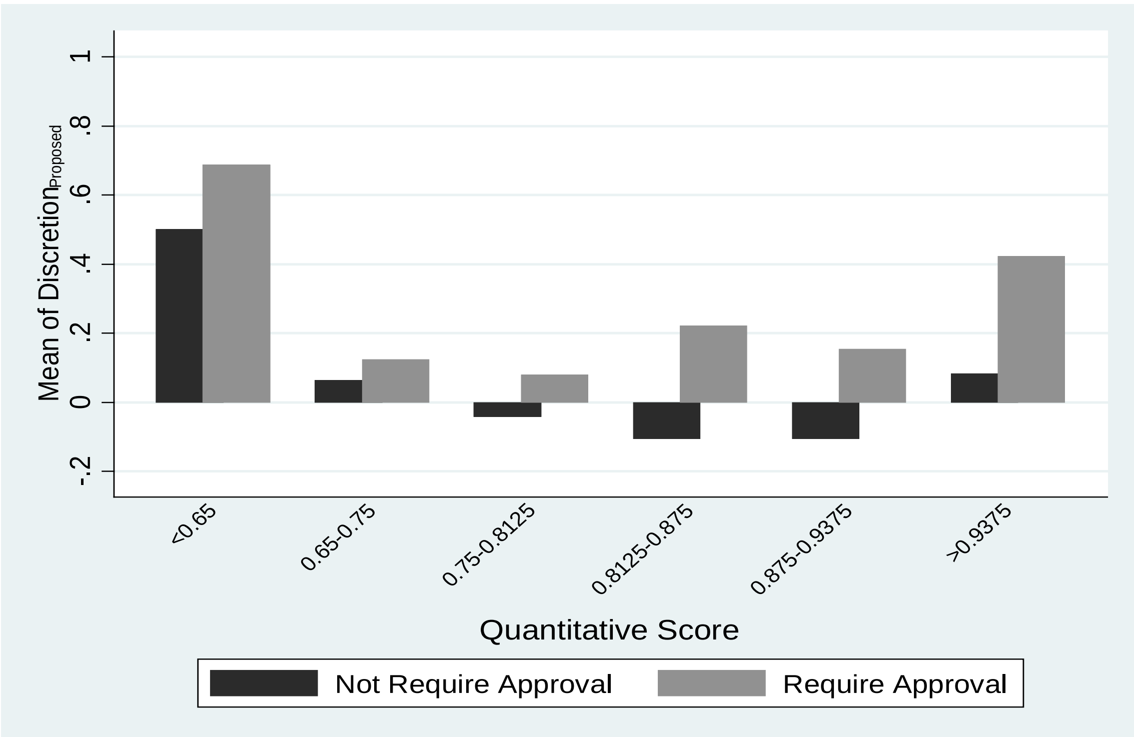


Figure 5: Rating Corrections

This figure displays the frequency of the credit officer *Correction* depending on $Discretion_{proposed}$. Sizes of the bubbles indicate relative frequencies and sum to 100% by value of $Discretion_{proposed}$.

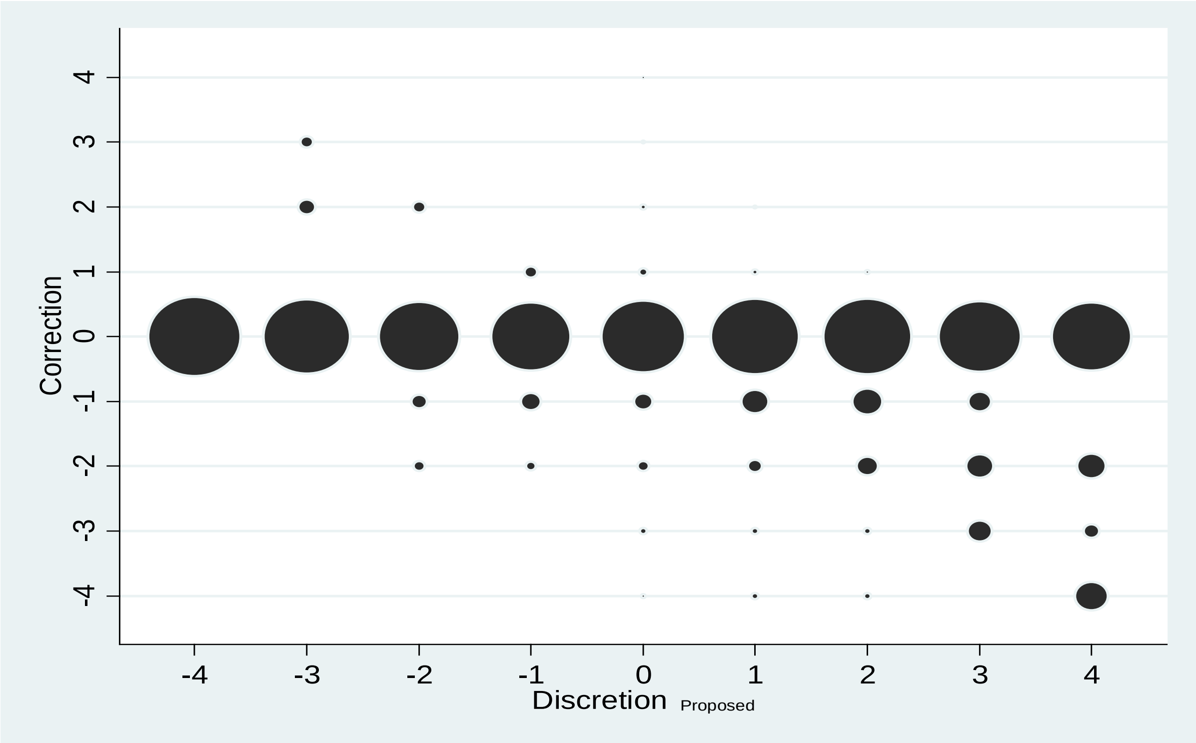


Table 1. Observations by Bank

The table shows the number of observations across banks and years.The year refers to the year of the latest financial statement data of the client used for the rating. Banks are coded using alphabetic characters from A to F. The table also shows the share of ratings which require approval by a credit officer as well as the number of clients, loan officers, and credit officers per bank.

Bank	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**Total**	**Requires Approval**	**# Clients**	**# Loan officer**	**# Credit officer**
A	0	54	196	168	178	150	148	46	940	**0.90**	295	42	4
B	175	464	399	480	453	477	450	51	2'949	**0.74**	868	216	16
C	0	248	340	318	303	308	280	31	1'828	**0.93**	571	48	6
D	0	0	13	31	22	82	136	3	287	**0.02**	210	32	5
E	0	0	53	845	879	943	828	0	3'548	**0.97**	1'282	233	26
F	0	0	0	25	250	411	296	34	1'016	**0.00**	435	9	0
Total	**175**	**766**	**1'001**	**1'867**	**2'085**	**2'371**	**2'138**	**165**	**10'568**	**0.77**	**3'661**	**580**	**57**

Table 2. Client Characteristics and Required Approval

Mean values of client characteristics are presented for the full sample as well as separately for the subsamples of ratings which require credit officer approval and those which do not require approval. Results of a parametric test of equality of means (T-Test), as well as a non-parametric test of equality of distribution (Kolmogorov Smirnov Test), between the two subsamples are presented. Assets are measured in Swiss Francs, whereby 1.06 CHF = 1 Euro.

	Mean Values			**T test**	**Kolmogorov-Smirnov test**
	Full sample	**Requires Approval**			
		No	**Yes**	(p-value)	(p-value)
Quantitative Score	0.782	0.783	0.781	0.59	0.299
Service Industry (1=yes)	0.589	0.593	0.587	0.63	1.00
Assets (in CHF)	752'721	581'753	811'257	0.00	0.00
Observations	10'568	2'380	8'188	10'568	10'568

Table 3. Use of Discretion

This table presents results of regression analyses which examine the relation between loan officer use of discretion and whether a rating requires credit officer approval. The dependent variables are *Neutral Qualitative* (columns 1,3,5) and *No override* (columns 2,4,6). Columns (1-2) report full sample results. Columns (3-4) report results for observations form Banks D,E,F only. Columns (5-6) report results for observations form Bank B only. We report linear regresion estimates with standard errors clustered on the loan officer level. All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Score.* All regressions also include the client characteristics Size, *Industry* and *Rating number*, as well as the loan officer characteristics *Experience* and *Gender.* Statistical significance of coefficients at the 10% / 5% / 1%-level are indicated by * / ** / ***. See Appendix II and Appendix III for definitions and summary statistics of all variables.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent variable:	**Neutral Qualitative**	**No override**	**Neutral Qualitative**	**No override**	**Neutral Qualitative**	**No override**
Banks:	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**D,E,F**	**D,E,F**	**B**	**B**
Requires Approval	-0.108	0.0139	-0.230	-0.0605***	0.0741	-0.00473
	[0.192]	*[0.0313]*	*[0.321]*	*[0.0180]*	*[0.150]*	*[0.0462]*
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Client characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Mean of dependent variable	4.71	0.82	4.71	0.86	4.77	0.83
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.028	0.107	0.025	0.244	0.098	0.078
Clustered Standard Errors	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer
# Rating Applications	10,568	10,568	4,851	4,851	2,949	2,949
# Loan officers	580	580	274	274	216	216
# Banks	6	6	3	3	1	1

Table 4. Rating Inflation

This table presents results of regression analyses which examine the relation between the proposed rating by loan officers and whether a rating requires credit officer approval. The dependent variables are *Discretion* $_{proposed}$ (columns 1-4), *Discretion* $_{qualitative}$ (column 5) and *Override* (column 6). All columns present results based on the full sample of banks. Columns (2-6) display results for subsamples depending on the influence of the qualitative score on the calculated rating. For ratings with a quantitative score of less than 0.75 the qualitative score has no influence. For ratings with a quantitative score of 0.75-0.875 the qualitative score has increasing influence. For ratings with a quantitative score exceeding 0.875 the qualitative score has a strong influence.We report OLS estimates with standard errors clustered on the loan officer level. All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Score*. All regressions also include the client characteristics *Size*, *Industry* and *Rating number*, as well as the loan officer characteristics *Experience* and *Gender*. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / ***. See Appendix II and Appendix III for definitions and summary statistics of all variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Discretion$_{proposed}$**				**Discretion$_{qualitative}$**	**Override**
Banks:	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**
Observations:	**All**	**No Influence**	**Increasing Influence**	**Strong Influence**	**Strong Influence**	**Strong Influence**
Requires Approval	0.197***	0.0978*	0.220***	0.261***	0.208***	0.0536
	[0.0430]	*[0.0539]*	*[0.0612]*	*[0.0722]*	*[0.0538]*	*[0.0541]*
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**	**No**	**No**	**No**
Client characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Mean dependent variable	0.23	0.39	0.01	0.25	0.40	-0.15
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.125	0.174	0.099	0.118	0.121	0.037
Clustered Standard Errors	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer
# Rating Applications	10,568	3,792	3,159	3,617	3,617	3,617
# Loan officers	580	432	413	418	418	418
# Banks	6	6	6	6	6	6

Table 5. Rating Inflation - Robustness Checks

This table presents robustness checks on the relation between the proposed rating and whether a rating requires credit officer approval. The dependent variable is $Discretion_{proposed}$ in all columns. Column (1) reports results for observations from Banks D,E,F only. Columns (2-3) report estimates for Bank B only. Columns (4-5) display results for all banks in the sample, spllitting the sample into ratings conducted during/after the first year after the introduction of the rating tool at a bank. We report OLS estimates with standard errors clustered on the loan officer level. All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Score*. All regressions also include the client characteristics *Size, Industry* and *Rating number*, as well as the loan officer characteristics *Experience* and *Gender (except in column 3).* Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / ***. See Appendix II and Appendix III for definitions and summary statistics of all variables.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			**$Discretion_{proposed}$**		
Banks:	**D,E,F**	**B**	**B**	**A,B,C,D,E,F**	**A,B,C,D,E,F**
Observations:	**All**	**All**	**All**	**First Year**	**Later Years**
Requires Approval	0.237***	0.0926	0.164**	0.193**	0.183***
	[0.0478]	*[0.0825]*	*[0.0691]*	*[0.0795]*	*[0.0474]*
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Client characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**No**	**Yes**	**Yes**
Mean dependent variable	0.39	0.025	0.025	4.56	4.55
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.153	0.221	0.218	0.119	0.134
Clustered Standard Errors	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer
# Rating Applications	4'851	2,949	2,949	2,694	7,874
# Loan officers	274	216	216	255	472
# Banks	3	1	1	6	6

Table 6. Rating Corrections

The regression analyses in this table examine the corrections of proposed ratings by credit officers. All columns present linear estimation results with *Correction* as the dependent variable. Columns (1) presents estimates with *Discretion* $_{proposed}$ as the main explanatory variable. Column (2) presents estimates with *Discretion* $_{qualitative}$ as the main explanatory variable. Column (3) presents estimates with Override as the main explanatory variable. In columns (4-5) we replicate the column (1) specification for subsamples of observations where the rating was proposed by loan officers with low / high average discretion. Low Discretion loan officers are those for who the mean of proposed Discretion is less than 0.1 over all of their observations in the sample. High Discretion loan officers are those for who the mean of Discretionproposed is at least 0.28 over all of their observations in the sample. All columns present estimates for the five banks A, B, C, D, E. All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Score* as well as *Credit officer* fixed effects. All regressions also include the client characteristics *Size, Industry* and *Rating Number*, as well as the loan officer characteristics *Experience* and *Gender*. Standard errors are clustered at the credit officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Appendix II and Appendix III for definitions and summary statistics of all variables.

Panel A. Corrections in response to use of loan officer Discretion.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			**Correction**		
Banks:	**A, B, C, D, E**	**A, B, C, D, E**	**A, B, C, D, E**	**A, B, C, D, E**	**A, B, C, D, E**
Credit officers:	**All**	**All**	**All**	**All**	**All**
Loan officers:	**All**	**All**	**All**	**Low Discretion**	**High Discretion**
$Discretion_{proposed}$	-0.123***			-0.129***	-0.131***
	[0.0177]			[0.0294]	[0.0168]
$Discretion_{qualitative}$		-0.0144			
		[0.0147]			
Override			-0.172***		
			[0.0218]		
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Client characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Credit officer FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Mean dependent variable	-0.12	-0.12	-0.12	-0.10	-0.13
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.107	0.077	0.118	0.109	0.131
Clustered Standard Errors	Credit officer	Credit officer	Credit officer	Credit officer	Credit officer
# Rating Applications	8,188	8,189	8,188	4,082	4,106
# Credit officers	57	57	57	52	49
# Banks	5	5	5	5	5

Table 7. Rating Inflation and Loan Officer Experience

This table documents how experience of loan officers influences the relation between required approval and the discretionary input by loan officers. The dependent variables are *Discretion* $_{proposed}$ (columns 1-2), *Discretion* $_{qualitative}$ (columns 3-4) and *Override* (columns 5-6). Columns (1,3,5) present results for loan officers while they have low experience. Columns (2,4,6) present results for loan officers when they have high experience. The definition of low (high) experience is based on whether the loan officer has less (more) prior credit assessments than the median per loan officer in the sample. All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Scor* e. All regressions also include the client characteristics *Size, Industry* and *Rating number* , as well as the loan officer characteristics *Experience* and *Gender.* Standard errors are clustered on the loan officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Appendix II and Appendix III for definitions and summary statistics of all variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Discretion$_{proposed}$**		**Discretion$_{qualitative}$**		**Override**	
Banks:	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**	**A,B,C,D,E,F**
Observations:	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**
Requires Approval	0.205***	0.201***	0.0450**	0.129***	0.160***	0.0718**
	[0.0402]	*[0.0331]*	*[0.0220]*	*[0.0165]*	*[0.0349]*	*[0.0281]*
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Client characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Mean dependent variable	**0.29**	**0.17**	**0.19**	**0.15**	**0.10**	**0.02**
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.134	0.122	0.152	0.117	0.211	0.184
Clustered Standard Errors	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer	Loan officer
# Rating Applications	5,284	5,284	5,284	5,284	5,284	5,284
# Loan officers	580	126	580	126	580	126
# Banks	6	6	6	6	6	6

Table 8. Loan Officer Reaction to Corrections

The regression analyses in this table examine the reaction of loan officers to previous corrections of proposed ratings by credit officers. The dependent variables are *Discretion* $_{proposed}$ (column 1), *Discretion* $_{qualitative}$ (column 2) and Override (column 3). The explanatory variable in all specifications is a dummy variable which is 1 if the loan officer experienced a correction to the proposed rating for the most recent client rating. All columns present estimates for the five banks A, B, C, D, E. All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Score* as well as *Loan officer* fixed effects. All regressions also include the client characteristics *Size, Industry* and *Rating Number*, as well as the time-varying loan officer characteristic *Experience*. Standard errors are clustered at the credit officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Appendix II and Appendix III for definitions and summary statistics of all variables.

	(1)	**(2)**	**(3)**
Dependent variable:	Discretion$_{proposed}$	Discretion$_{qualitative}$	Override
Banks:	**A, B, C, D, E**	**A, B, C, D, E**	**A, B, C, D, E**
Credit officers:	**All**	**All**	**All**
Correction in Previous Rating	-0.00176	-0.00210	0.000339
	[0.0199]	[0.0109]	[0.0194]
Year FE	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**
Client characteristics	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**Yes**
Loan Officer FE	**Yes**	**Yes**	**Yes**
Mean dependent variable	0.30	0.19	0.10
Method	OLS	OLS	OLS
R-squared	0.269	0.291	0.344
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	4,759	4,759	4,759
# Credit officers	47	47	47
# Banks	5	5	5

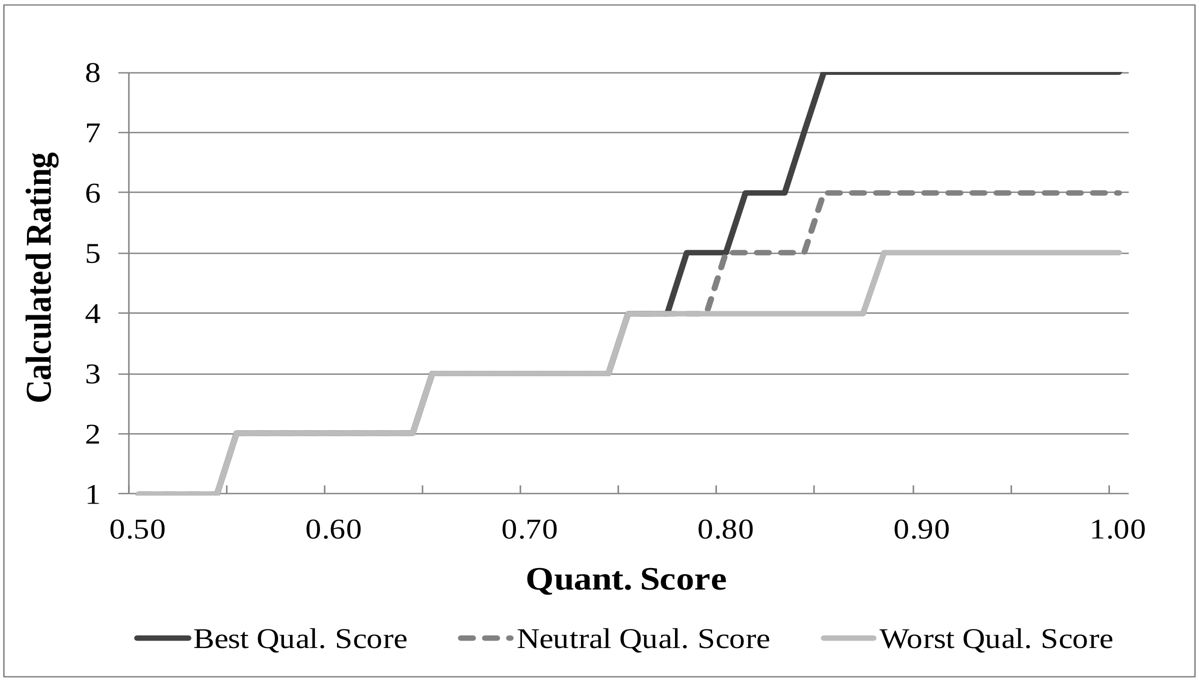
Table 9. Informational Efficiency

This table reports on the informational efficiency of the client rating process. The dependent variable is *Default* which takes on the value 1 if a client defaults (is 90 days past due on a loan or has earlier writedowns booked on the loan) within 24 months of a rating and 0 otherwise. The explanatory variables are $Discretion_{proposed}$ and *Correction* (column 3-4 only). All columns report marginal effects of probit estimates. Columns (1-2) present estimates for ratings which do not require credit officer approval. Columns (3-4) present estimates for ratings which require approval. Columns (1,3) present estimates for the full sample of clients, while columns (2,4) present estimtes for low-quality clients (i.e. quantitative score below 0.75). All regressions include fixed effects for *Year* as well as for 6 ranges of the *Quantitative Score*. All regressions also include the client characteristics *Size*, *Industry* and *Rating number*, as well as the loan officer characteristics *Experience* and *Gender*. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Appendix II and III for definitions and summary statistics of all variables.

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable:	**Default**		**Default**	
Banks:	**A & B**		**A & B**	
Observations:	**Do not require approval**		**Requires approval**	
Quantitative score:	**All**	**< 0.75**	**All**	**< 0.75**
$Discretion_{proposed}$	-0.0143***	-0.0396*	-0.0132***	-0.0550***
	[0.00356]	[0.0217]	[0.00268]	[0.0102]
Correction			3.06e-05	0.000180
			[0.00381]	*[0.0175]*
Year FE	**Yes**	**Yes**	**Yes**	**Yes**
Quantitative Score FE	**Yes**	**Yes**	**Yes**	**Yes**
Client characteristics	**Yes**	**Yes**	**Yes**	**Yes**
Loan officer characteristics	**Yes**	**Yes**	**Yes**	**Yes**
Mean dependent variable	0.056	0.125	0.037	0.078
Method	Probit	Probit	Probit	Probit
R-squared	0.260	0.156	0.162	0.0970
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	850	319	3,039	1,094

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

This appendix 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 Appendix II.



Appendix II. Definition of Variables

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

Category	Variable	Definition
Client Rating	Neutral Qualitative	Number of qualitative indicators are ticked as "average" [0,7].
	No Override	Dummy variable (0;1) taking the value one if the loan officer did not make an override.
	Quantitative Score	Rating score [0; 1] resulting from the balance sheet and income statement information as well as the company's age and its previous repayment behavior.
	Qualitative Score	Rating score [0; 1] resulting from seven dimensions on the subjective creditworthiness of the customer.
	Calculated Rating	Rating based on Quantitative and Qualitative Score.
	Proposed Rating	Rating result based on the Calculated Rating and the Override by the loan officer.
	Override	Difference between the Proposed Rating and the Calculated Rating. Negative values indicate a downgrade by the Loan officer, positive values indicate an upgrade by the Loan Officer. Values of zero indicate no override.
	Correction	Difference between the Approved Rating and the Proposed Rating. Negative values indicate a downgrade by the Approver, positive values indicate an upgrade by the Approver. Values of zero indicate no correction. Not defined for any applications under no-control.
	Approved Rating	Rating result based on the Proposed Rating and any corrections by the Approver. The Approved Rating equals the Proposed Rating for all applications under no-control.
	$\text{Discretion}_{\text{qualitative}}$	Rating change induced by the loan officers´qualitative assessment of a client. Calculated as the difference between Calculated Rating and a hypothetical rating based on the quantitative score and assuming an average qualitative score, no override and no correction.
	$\text{Discretion}_{\text{proposed}}$	Rating change induced by the loan officers´qualitative assessment and the override of a calculated rating. Calculated as the difference between Calculated Rating and a hypothetical rating based on the quantitative score and assuming an average qualitative score, no override and no correction.
	Year	Year of the latest available financial statement data for the client used for the client rating.
Rating process	Requires Approval	Dummy variable (0; 1), indicating if the client rating requires approval by a credit officer.
	No Influence	Dummy variable (0; 1) that takes the value one if the loan applicants' Quantitative Score is below 0.75.
	Increasing Influence	Dummy variable (0; 1) that takes the value one if the loan applicants' Quantitative Score is above 0.75 and below 0.875.
	Strong Influence	Dummy variable (0; 1) that takes the value one if the loan applicants' Quantitative Score is higher than 0.875.
Loan officer	Experience	The number of client ratings completed by a loan officer prior to the current one.
	High Experience	Dummy variable (0;1) taking the value one if the loan officer has, at the time of the loan application, above-median *Experience* with the rating tool.
	Gender	Dummy variable (1= Female; 0=Male) indicating the gender of the loan officer, derived from his / her given name.
Client	Size	Natural logarithm of the balance sheet total (in CHF).
	Industry	Dummy variable, coding the industry of a client into one of 21 categories.
	Rating Number	Number of the rating in the sequence of ratings conducted by the bank for this client.
	Default	Dummy variable (0;1) taking the value one if the customer defaults within two years following the client rating application.

Appendix III. Summary Statistics

This Appendix shows the summary statistics of the variables used throughout the analyses.

							Percentiles		
Category	**Variable**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**75%**	**50%**	**25%**
Client rating	Neutral Qualitative	10'568	4.71	1.53	0	7	6	5	4
	No Override	10'568	0.82	0.38	0.00	1	1.00	1.00	1.00
	Quantitative Score	10'568	0.78	0.15	0.21	1	0.90	0.82	0.69
	Qualitative Score	10'568	0.56	0.14	0.00	1	0.62	0.54	0.49
	Calculated Rating	10'568	4.49	1.94	1.00	8	6.00	5.00	3.00
	Override	10'568	0.06	0.78	-6	7	0	0	0
	Proposed Rating	10'568	4.56	1.82	1	8	6	5	3
	Correction	8'188	-0.12	0.56	-6	6	0	0	0
	Approved Rating	10'568	4.46	1.82	1	8	6	5	3
	$\text{Discretion}_{\text{qualitative}}$	10'568	0.17	0.49	-1	2	0	0	0
	$\text{Discretion}_{\text{proposed}}$	10'568	0.23	0.88	-5	7	1	0	0
Rating process	Requires Approval	10'568	0.77	0.42	0	1	1	1	1
	No Influence	10'568	0.36	0.48	0	1	1	0	0
	Increasing Influence	10'568	0.30	0.46	0	1	1	0	0
	Strong Influence	10'568	0.34	0.47	0	1	1	0	0
Loan officer	Experience (ln)	10'568	3.13	1.48	0	6.36	4.18	3.24	2.20
	High Experience	10'568	0.50	0.50	0	1	1	1	0
	Gender	10'568	0.23	0.42	0	1	0	0	0
Client	Size (in ln CHF)	10'568	13.53	1.18	7.60	21.82	14.26	13.60	12.81
	Service Industry	10'442	0.59	0.49	0	1	1	1	0
	Rating Number	10'568	2.52	1.49	1	8	3	2	1
	Default	3'889	0.04	0.20	0	1	0	0	0