The Hidden Costs of Control

– Evidence from Small Business Lending

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

This Draft: February 2013

Abstract

Using proprietary data on 3,360 credit assessments by 340 loan-officers at six banks, we analyze how internal control affects the credit rating process. We document a positivity bias of control: Loan officers propose better ratings for their clients when they know that the rating is subject to internal approval. Our evidence suggests that this positivity bias is driven by strategic behavior: Loan officers inflate proposed ratings in reaction to past downward corrections by their current approver. Moreover, experienced loan officers inflate those parameters of a credit rating which are least likely to be corrected by approvers. Overall, we find that internal control does not improve the informational efficiency of the credit assessment process.

Keywords: Internal Control, Four-Eyes Principle, Credit Assessment.

JEL classification numbers: G21, L14, D82.

---

* University of St. Gallen, Switzerland (e-mail: martin.brown@unisg.ch), ** University of St. Gallen, Switzerland (e-mail: matthias.schaller@unisg.ch), *** University of Applied Sciences Northern Switzerland (simone.westerfeld@fhnw.ch), **** Risk Solution Network AG (e-mail: markus.heusler@rsnag.ch)

Acknowledgements: We thank Matthias Hoffmann, Lars Norden, as well as seminar participants at the University of St. Gallen for their valuable input and feedback. We thank Jochen Maurer and Marcus Kahler for their assistance in preparing the data.

1. Introduction

The "four-eyes" principle is a cornerstone of corporate governance and risk management in financial institutions.[1] The Basle Committee on Banking Supervision proposes that licensing procedures for banks should include checks on the banks' internal organization and control. These checks should be able to determine that "the four eyes principle (segregation of various functions, crosschecking, dual control of assets, double signatures, etc.)" will be followed.[2] Furthermore, in its guidelines for the management of credit risk[3] the Basle committee recommends that "banks should establish and enforce internal controls (…) to ensure that exceptions to policies, procedures and limits are reported in a timely manner to the appropriate level of management for action."

In contrast to ex-post audit or performance evaluation, the four-eyes principle is an instrument of preventive internal control: The approver/reviewer not only assesses the quality of a decision and its compliance with internal rules, but can also correct or adjust that decision before it is executed.[4] The intervention of the approver may enhance the quality of decision making by pooling knowledge (Blinder and Morgan, 2005) or providing salient feedback to the proposer (Christ et al., 2012). However, preventive control may also undermine the effort to gather and assess information

[1] In his final speech as the CEO of the U.K. Financial Services Authority in April 2012, Hector Sants emphasized that inadequate four-eye oversight of risk was one common feature of financial institutions that failed during the recent crisis (http://www.fsa.gov.uk/library/communication/speeches/2012/0424-hs.shtml).

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

[3] Basle Committee on Banking Supervision: Principles for the Management of Credit Risk, 2000.

[4] The accounting literature distinguishes between measures of preventive control (e.g. the four-eyes principle) and detective control (e.g. auditing and performance evaluation). See e.g. Romney and Steinbart (2009).

through the crowding-out of intrinsic motivation (Falk and Kosfeld, 2006; Christ et al. 2008), or free-riding (Holmström, 1992).

In this paper, we provide evidence for a further hidden cost of preventive control: The proposer may strategically misrepresent information in anticipation of a potential correction by the approver. Such opportunistic behavior is likely to arise when there is a conflict of interest regarding the outcome of the decision between the proposer and the approver. This is the case in the credit assessment process of banks that we study in this paper:[5] Loan officers have the responsibility for complementing the quantitative assessment of a client's financial statements with a subjective, qualitative assessment of creditworthiness. The remuneration or promotion chances of loan officers are typically linked to the volume of lending in their loan portfolio. As a consequence loan officers' have a vested interest that their clients meet the internal criteria for loan approval and low interest rates. The subjective assessment of the loan officer is often subject to approval by a line manager or back-office credit officer. The remuneration and promotion of credit officers is not linked to lending volumes, but may be linked to the performance of loans in their portfolio.

Our analysis suggests that the conflict of interest between loan officers and their approvers undermines the effectiveness of internal control in small-business lending. We exploit a dataset of 3'360 internal credit ratings by 340 loan officers at six

[5] Another example of conflicting interests between proposer and approver is corporate budgeting. Managers of business units have an interest to maximize their resources, while their superiors have an interest to make sure that resources are allocated efficiently across units. Unit managers may exaggerate their budgetary requirements in anticipation of subsequent cuts by their superior, especially if they experienced such cuts in the past (Jensen 2001).

different banks over the period 2006-2011. Due to bank-specific credit policies 73% of these credit ratings are subject to the internal control: The internal rating proposed by the loan officer must be approved by a second member of staff. For the remaining 27% of our observations the rating proposed by the loan officer is automatically approved.

We document that internal control is associated with a positivity bias: Loan officers propose better ratings for their clients when their assessment is subject to approval. We then provide evidence suggesting that this positivity bias is rooted in strategic behavior by loan officers: They assign better ratings to clients when their approver corrected ratings more often in the past. We find that the positivity bias of control is stronger for more experienced loan officers. Moreover, we find that experienced loan officers manipulate those parameters of a rating (qualitative assessments as opposed to overrides) which are least likely to be corrected by approvers. Overall, we find that the use of the four-eyes principle does not improve the informational efficiency of the small-business credit assessment process.

Our paper contributes to the growing literature on organizational design, incentives and the use of information in financial institutions. Stein (2002) models the use of information within organizations and conjectures that the production and use of non-verifiable (“soft”) information should be stronger in small, decentralized firms. In line with this prediction Berger et al. (2005) and Uchida et al. (2012) show that loan officers produce more soft information about their clients in small banks as compared to large banks. Liberti and Mian (2009) and Agarwal and Hauswald (2010) show that subjective information is less likely to be collected and also less frequently used in lending processes if the hierarchical or geographical distance between the loan officer and the approver is large. Berg et al. (2012) show that volume incentives for loan officers in combination with minimum rating thresholds for loan approval, leads to the strategic manipulation of credit ratings by loan officers in consumer lending.

Our findings also contribute to the recent literature on the discretion of loan officers and the use of soft versus hard information in bank lending. Degryse et al. (2012) show that the credit limits loan officers extend to their clients are highly sensitive to their qualitative assessments, while Cerquiero et al. (2011) and Qian et al. (2011) show that soft information has an important impact on the lending terms. In contrast to the above papers, Brown et al. (2013) show that the widespread use of discretion by loan officers in credit assessment may be driven by a central tendency bias rather than by soft information. Our findings complement this literature by showing that the use of soft information by loan officers may crucially depend on the internal control systems put in place by banks.

Closest to our paper is a study by Hertzberg et al. (2010) which shows that loan-officer rotation improves the informational efficiency of the credit assessment process. Their evidence suggests that, due to career concerns, loan officers are less likely to bias the ratings of their clients upwards when they expect that the client will be taken over by a another loan officer in the near future. The crucial 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 loan officer rotation) analyzed in their study. We thus contribute to the broader discussion of the impact of different types of internal control within organizations (Christ et al., 2012).

The remainder of this article proceeds as follows: The next section introduces the institutional setting of our study and describes our data. Section 3 documents that internal control leads to more positive credit assessments by loan officers. Section 4 documents that anticipated corrections by the approver are the driver behind the positivity bias of internal control. Section 5 examines how the control affects the informational efficiency of the credit rating process. Section 6 concludes.

2. Institutional Background and Data

In corporate and small-business lending the assessment of the creditworthiness of a client is typically based on a hybrid internal credit rating model: Banks conduct a quantitative assessment based on the firm's financial statement data and credit history.[6] This quantitative assessment is then complemented by a subjective assessment of the client by the loan officer. Our analysis is based on the internal credit rating data for six banks in Switzerland that all use the same hybrid credit rating tool for small-business loans.[7]. Our dataset includes the internal ratings of new loans as well as the periodical review of existing loans.

[6] See e.g. Berger & Udell (2003) for a discussion of the role of external credit bureau information in the assessment of small business loans.

[7] In our sample small-business loans are classified as loans to firms with less than 10 million Swiss Francs (CHF; 1CHF = 1.09 US Dollar) in annual turnover.

2.1 The Credit Rating Process

Figure 1 provides an overview of the internal credit rating process applied by the banks in our sample. At the beginning of each rating, the bank assigns a loan officer to the client. The loan officer is responsible for the collection of all required information during the application process. The 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 tool combines an array of quantitative indicators to a *Quantitative Score* which ranges from zero (highest probability of default) to one (lowest probability of default).

The qualitative assessment of the client by the loan officer is based on seven questions which elicit the current business conditions of the client and the client's industry. The categorical assessments of these seven indicators are aggregated to a *Qualitative Score* of the client which also ranges from zero (highest probability of default) to one (lowest probability of default).

[Figure 1 here]

The rating model combines the quantitative score and the qualitative score of a client to a discrete *Calculated Rating* class, 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 class depends on the quantitative score of a client: For quantitative scores lower than 0.75, the calculated rating results only from the quantitative score of a client ("*No Influence*"). For quantitative scores between 0.75 and 0.875, the influence of the qualitative score on the calculated rating increases with higher quantitative scores of a client ("*Increasing Influence*"). Finally, for quantitative scores above 0.875, changes in the resulting calculated ratings are only triggered by the qualitative information of a customer ("*High Influence*"). Appendix I presents a stylized user interface of the rating model to illustrate the process. Appendix II illustrates the relation between quantitative score, qualitative score and calculated rating in more detail.

Once the calculated rating is determined the loan officer has the option to *Override* the rating class. Overrides are possible in both directions, i.e. upgrades and downgrades, and are not restricted in the number of rating notches included. In case a loan officer decides to override a calculated rating, he/she has to file a report stating the reasons for the override.[8] We term 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 organizational design of the credit assessment process: In particular, the proposed rating may or may not be subject to approval by another member of the bank staff, i.e. another loan officer, a line manager, or a credit officer. We label those ratings which are subject to approval as *Control* cases, and those which are not subject to approval as *No-Control* cases. In no-control cases the rating proposed by the loan officer is identical to the *Approved Rating*. In control cases the approver reviews the entire

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

application file and then either accepts the rating proposed by the loan officer or makes a *Correction*. The correction is not restricted to a direction or the rating steps included. The rating assigned by the approver is final and is thus the *Approved Rating*.

Our raw data includes 31’260 credit assessments for 11’462 firms by 1’068 loan officers at 14 banks. We limit our analysis to a sample of 3,360 assessments by 340 loan officers at six banks. In order to examine the impact of exogenous and anticipated control we restrict our sample to those banks for which the assignment of control is a bank-policy which is clearly communicated and which is not influenced by the behavior of loan officers. We exclude eight banks at which the assignment of control may depend on the qualitative assessment or overrides by the loan officer. At the six banks which are included in the sample the assignment of control is either a bank-wide policy or depends primarily on the hierarchical rank of the loan officer. Loan officers know at the beginning of a credit application whether this application will be subject to control or not, i.e. they know if their competencies are sufficient to approve a rating or not.

Within the selected six banks, we limit our analysis to the first observation for each firm. This choice is motivated by the conjecture that information asymmetries between banks and borrowers are most severe at the early stages of a credit relationship (Sharpe 1990, Petersen and Rajan 1994). Moreover, in a recent paper based on the same dataset Brown et al. (2013) show that in follow-up interactions with a given client, loan officers tend to use their discretion for smoothing shocks to a client’s quantitative information. In order to disentangle the impact of control on information use from the smoothing of credit ratings we exclude all follow-up interactions with a given client.

For each of the 3’086 credit assessments in our cross-sectional data set, we have access to all relevant information from the internal rating database: We observe the *Quantitative Score*, each of the components of the qualitative assessment as well as the resulting *Qualitative Score*. We further observe the *Calculated Rating*, the *Override* by the loan officer, the *Correction* by the approver (under control) and the resulting *Approved Rating*. As control variables we observe information on firm *Size* (total assets ln CHF), *Industry* and the *Year* of a credit assessment.

Table 1 presents details and definitions on all variables employed in our empirical analyses. Table 2 provides corresponding summary statistics. Table 3 provides an overview of the number of ratings per bank in our sample and the share which is subject to control. The banks in the sample introduced the credit rating model at different points in time with the first bank starting in 2006; two banks starting in 2007, two banks starting in 2008, and one bank starting in 2009. As shown by Table 3, 73% of all credit assessments in our final sample occur under control. At one banks in our sample (Bank E), the credit policy implies that almost all ratings proposed by loan officers are subject to approval. At two other banks (Bank D, F), the credit policy implies that almost none of the ratings proposed by loan officers are subject to approval. Finally at three banks (Bank A, B, and C) both control and no-control are common. Throughout our analysis we will provide subsample analysis for banks A, B and C controlling for bank fixed effects to rule out the possibility that our findings are driven by other unobserved differences in bank policies.

[Table 1]

[Table 2]

[Table 3]

A key concern with respect to our data is that the firms for which credit assessments are subject to control differ strongly from those which are not subject to control. In particular, the objective creditworthiness of firms under control and no-control may differ. Fortunately this is not the case. Figure 2 displays the distribution of quantitative scores for observations under control and those under no control. While observations under control seem have slightly lower quantitative scores a two-sided Kolmogorov-Smirnov test cannot reject the hypothesis that the two distributions are identical (p-value: 0.271).

[Figure 2 here]

3. The Positivity Bias of Control

In this section of results we document a positivity bias of control in credit assessment: Loan officers propose, ceteris paribus, better rating classes when their assessment is subject to internal approval. We then examine whether the positivity bias is driven by better qualitative assessments of the client or by a higher frequency of positive overrides. We find that both types of "manipulation" play an important role.

3.1. Proposed Ratings

Figure 3 displays the mean proposed rating under control and no-control, conditional on the quantitative score of the firm. If anticipated control affects loan officers' assessments of their clients, we expect to find different *Proposed Rating classes* for clients with similar quantitative scores. Figure 3 shows that this is the case: The mean *Proposed Rating* is consistently higher under control as compared to under no-control. The figure further shows that the positivity bias under control is larger for firms with higher quantitative scores.

[Figure 3]

Table 4 presents a multivariate regression analysis which confirms the picture displayed in Figure 3. In this analysis, we relate the *Proposed Rating* (1-8) to the dummy variable *Control*. We include fixed effects to control for the quantitative score of each firm[9] as well as the year in which the assessment took place. We further control for the *Size* of a client and include industry fixed effects as expert interviews suggest that the rating tool's accuracy might vary along both dimensions. We cluster all standard errors on the loan officer level.

[9] We include fixed effects on the quantitative scores as the quantitative information non-linearly influences the calculated rating class. Fixed effects correspond to the clusters presented in Figure 2.

[Table 4]

The Table 4 results confirm that loan officers propose significantly higher ratings for their customers when they know that their proposed rating is subject to approval. The full sample estimates in column (1) report a statistically significant impact of *Control* (0.216***). This estimate suggests that one in five clients, whose rating is subject to approval, receives a proposed rating that is one notch higher than it would be without control.

Since our sample is dominated by banks that either use control or no control on a more or less exclusive basis, our findings might be the result of unobservable differences across the banks rather than the policy of controlling a rating application. In column (2), we therefore provide estimates for observations from Banks A, B and C including bank fixed effects. The resulting point estimate for *Control* at these banks is even higher than in our full sample (0.229***) indicating that it is in fact *Control* that drives our full-sample results.

In columns (3) to (5), we repeat our analysis for customers with different levels of quantitative scores. For the subsample of clients with quantitative scores below 0.75 (where there is no influence of qualitative scores on calculated ratings), we find the smallest impact (0.111*). 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 is roughly twice as large (0.231**). This estimate gains again in economic magnitude and statistical significance (0.297***) 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.[10]

As discussed in Section 2, the loan officer can influence the proposed rating of a client both, through the qualitative score and an override of the calculated rating. The differences in estimates in columns (3-5) suggest that the ability of the loan officer to influence ratings through the qualitative score may be crucial to the positivity bias under control. In the following we disentangle the impact of control on the qualitative score and overrides.

3.2. Qualitative Scores and Overrides

Figure 4, Panel A presents the mean *Qualitative Score* under control and no-control, again conditional on the quantitative score of the client. On average qualitative scores are 0.064 or 12.6% higher under control than under no control. Panel B presents the resulting differences in calculated ratings: By design of the rating model we find no impact of control on the calculated rating when the qualitative score has no influence (quantitative score below 0.75). For clients where the qualitative score has an impact on the calculated score the higher qualitative assessments of customers under control do carry over to higher calculated ratings. However, due to limited weight of the qualitative score and the discreteness of the rating scale, the impact of

[10] In unreported analyses, we test the statistical significance for the different point estimates of the three subsamples using interactions terms of (*Control * Increasing Influence*) and (*Control * High Influence*). The estimated coefficient [standard error] for the *Increasing Influence* subsample is 0.0918 [0.105] and 0.314*** [0.103] for *High Influence*.

control on the calculated rating is smaller than its impact on the qualitative score. For example, for clients with a quantitative score exceeding 0.9375 the average qualitative score is 10.9% higher under control (0.61 vs. 0.55), whereas the calculated rating is only 5.6% higher under control (6.59 vs. 6.24).

[Figure 4]

Table 5 confirms that loan officers assign higher qualitative scores under control and that these higher scores translate into higher calculated ratings. In column (1), we regress our dummy variable *Control* on the *Qualitative Score* of a customer, employing the same covariates as in Table 4. We find that the *Qualitative Score* is, on average 0.0489*** units higher if a rating is subject to internal control.

In columns (2-3), we split the qualitative score into two subcomponents - the *Industry Score* and the *Firm Score* - by dividing the seven questions that make up the qualitative score into three questions that aim to assess the current and prospective state of the customer's industry and four questions on the subjective creditworthiness of the firm itself. Our conjecture is that if loan officers intentionally manipulate the rating of a client in anticipation of being controlled, they are more likely to manipulate the firm score as the validity of this score is more difficult to verify. Industry scores, by contrast, could be verified using cross-comparisons with clients of the same industry. In line with this conjecture, the estimates in column (2-3) show a stronger impact of *Control* on the *Firm Score* (0.0654***) than on the *Industry Score* (0.0376***).

In columns (4) we confirm that the higher qualitative assessment of customers under control also results in higher calculated ratings. We regress the *Calculated Rating* on the *Control* dummy and our standard set of covariates. The estimate reported for *Control* suggests that calculated ratings are 0.110*** notches higher if a rating is subject to approval.

[Table 5]

Our findings so far show that control is associated with an average increase in proposed ratings by 0.216 notches (Table 4, column 1) of which 0.110 rating steps are due to higher calculated ratings induced by higher qualitative scores (Table 5, column 4). We thus expect that control should also be associated with a higher frequency of positive overrides by loan officers. Figure 5 and Table 5, column (5) confirm that this is the case. Figure 6 shows that overrides are on average 0.143 rating steps higher under control than under no-control. The multivariate regression analysis reported in column (5) of Table 5 confirms that the positive impact of control on overrides is statistically significant (0.106*).

[Figure 5]

Overall, the findings in this section show that when credit assessments are subject to internal approval loan officers propose better credit ratings for their clients. This positivity bias of internal control is driven both by an increase in the qualitative assessment of the firm as well as by a higher frequency of positive overrides.

4. Anticipated Corrections and the Positivity Bias

If loan officers use their discretion to assign better ratings to customers, we would expect their approvers to realize this bias and correct proposed ratings accordingly. We would further expect that loan officers are more likely to bias their credit assessment upwards when they interact with an approver who is more likely to revise their assessment downwards. In this section we focus on those credit assessments which are subject to control and examine the interplay between approvers and loan officers.

4.1. Corrections

In Figure 6, we plot - for the subsample of observations under control - the mean of *Correction* conditional on the *Qualitative Score* (Panel A) and the *Override* (Panel B) assigned by the loan officer. Figure 6 suggests that approvers only correct the proposed ratings of loan officers if the manipulation of the rating is obvious: Panel A shows that there is no correlation between the approver's correction and the qualitative assessment of a client by the loan officer. By contrast, Panel B shows that corrections are strongly related to override by loan officers. In particular, large positive overrides by a loan officer trigger corrections.

[Figure 6]

The multivariate regression results presented in Table 6 confirm that approvers correct overrides while they hardly react to high qualitative scores of clients. We regress *Correction* on *Qualitative Score* (columns 1-3) and on *Override* (columns 4-6) while controlling for firm size and industry, the quantitative score of the firm and the year of the credit assessment. All standard errors are clustered at the approver-level. The specifications presented in columns (2, 5) and (3, 6) examine whether our baseline estimated (columns 1, 4) are robust to controls for heterogeneity across banks and approvers by including corresponding fixed effects.

The results in columns (1) to (3) show no statistically significant impact of the qualitative score on the approvers' corrections. The estimated coefficient of *Qualitative Score* is small and lacks statistical significance in all three specifications. By contrast, the results in columns (4-6), confirm that approvers are prone to reverse overrides by loan officers. The point estimate in our baseline regression suggests that approvers reverse roughly one out of five overrides by the loan officer (-0.173***). The column (5-6) results show that the economic magnitude and statistical significance of this estimate is robust to controlling for heterogeneity across banks as well as heterogeneity within banks across approvers.

[Table 6]

4.2. The Anticipation of Corrections

Do loan officers anticipate the corrections by approvers and strategically inflate the ratings of their clients? In this section we examine how loan officers react to previous corrections by their current approver. In the subsample of observations with control we have 294 different loan officers and 41 different approvers. Each loan officer interacts with 1 to 7 different approvers during our observation period. Our analysis focuses on 128 loan officer – approver relationships which involve at least 10 interactions. For each loan officer-approver pair we identify the first five interactions between the pair and compare them to the 6^{th} and later interactions. We compare the qualitative assessments and overrides by the loan officer in the later compared to the earlier interactions and examine whether any change in these assessments is related to the corrections by the loan officer in the first five interactions.

[Figure 7]

Figure 7 plots the mean *Qualitative Score* (Panel A) and *Overrides* (Panel B) by loan officers in early (1-5) and late interactions (6 and later) with a given approver conditional on whether the approver corrected a proposed rating of the loan officer downward during the early interactions. The figure shows that loan officers do adapt their assessments depending on their experience with their current approver. Loan officers assign higher qualitative scores (Panel A) and more positive overrides (Panel B) in response to negative corrections by the approver in early transactions.

Table 8 reports a univariate difference-in-difference analysis which confirms that loan officers adjust their subjective assessments on the basis of their previous experience with an approver. Our unit of observation is a loan officer-approver relationship. The table reports the mean of *Qualitative Score* (Panel A) and *Override* (Panel B) across relationships for early interactions (1-5) and later interactions (6&up). As in Figure 7 we present separate means for relations with and without negative corrections in the first five interactions. The difference-in-difference estimates suggest that in relationships where approvers correct the loan officers' assessment in early interactions, loan officers increase their qualitative scores (0.02) and overrides (0.30**) in later transactions.[11]

[Table 7 here]

4.3 Loan Officer Experience

[11] In an unreported multivariate analysis with credit assessments as the unit of observation (but clustering standard errors at the relationship level) we yield the same qualitative results controlling for firm size, industry, the quantitative score and the year of the credit assessment.

The results displayed so far in this section suggest that approvers are more likely to correct overrides than high qualitative scores (Table 6) and that loan officers adapt their behavior to their experience with an approver (Table 7). Building on these observations, we expect that more experienced loan officers may use their discretion in the credit assessment process in a more subtle manner than inexperienced loan officers. In particular, we would expect them to make more use of qualitative scores rather than overrides to inflate their clients' ratings.

To examine how experience affects the credit assessments of loan officers, in Table 8 we repeat our previous analyses splitting our sample into *High Experience* and *Low Experience* loan officers. We define a *High Experience* (*Low Experience*) loan officer as one who completed more (less) rating applications than the median in our total sample (13) prior to the current credit assessment. Column (1) and (2) present the estimation results for the *Proposed Rating* as dependent variable, columns (3) and (4) for the *Qualitative Score*, columns (5) to (6) for the *Calculated Rating* and columns (7-8) for the *Override* by loan officers.

[Table 8]

The column (1-2) results shows that the impact of control on the proposed rating of a client increases with loan officer experience. For *Low Experience* loan officers, we find a point estimate for *Control* of 0.153*. For *High Experience* loan officers, this value increases to 0.228***.[12] Experienced loan officers not only show a stronger positivity-bias under control, but are also more likely to inflate qualitative scores as opposed to use overrides. The column (3-4) estimates show that impact of control on the *Qualitative Score* is four times stronger for experienced loan officers (*Low Experience*: 0.0174; *High Experience*: 0.0611***). Accordingly, the column (5-6) estimates show that the impact of control on the *Calculated Rating* is much stronger for experienced loan officers (*Low Experience*: 0.0130; *High Experience*: 0.164***). By contrast, the column (7-8) estimates show that experienced loan officers are less likely to use positive overrides. The point estimate for *Control* is 0.140* for loan officers with *Low Experience* and to 0.0635 for loan officers with *High Experience*.

Overall, the findings in this section suggest that under control loan officers strategically inflate internal credit ratings: They are more likely to assign positive ratings when they anticipate a downward correction by their current approver. Moreover, as approvers are more likely to correct overrides than inflated qualitative scores experienced loan officers make more use of the latter to inflate ratings.

5. The Impact of Control on the Efficiency of the Rating Process

In this section, we examine the impact of control on the informational efficiency of the rating process: We analyze whether approved ratings lead to a better or worse prediction of default under control than under no control.

[12] Using an interaction term on *Control * High Experience* to test the differences between column (1) and column (2) yields a qualitatively similar, yet statistically insignificant coefficient [standard error] of -0.0804 (0.0823).

For two banks in our sample (Bank A and Bank B) we can match our main dataset, which includes information on credit assessments to ex-post information on actual loan defaults. We define *Default* in accordance with the Basel II framework as an incidence of 90 days past due on an installment or a value-adjustment or definitive loss on a loan within 24 months after the credit assessment. As we have information on defaults at Banks A and B from 2006 to 2011, we restrict our analysis to the credit assessments made between 2006 and 2009. For these 1'015 credit assessments we observe a total of 82 defaults implying a default rate of 8.1%. The default rate is higher at Bank A (238 observations, 33 defaults, and 13.9% default rate) than at Bank B (777 observations, 49 defaults, and 6.3% default rate).

5.1. Informational Efficiency

In Figure 8A, we present the distribution of the default frequencies by *Approved Rating* class, comparing those observations that were subject to control and those that were not. The figure shows that default frequencies decrease exponentially for better rating classes. Standard measures on the efficiency of rating models, e.g. the accuracy ratio, measure to what extent the model assigns lower ratings to clients that eventually default.[13] Thus if control leads to a more efficient credit assessment process we would expect to see a stronger negative relationship between rating class and the frequency of default under control than under no-control. Figure 8A shows, by contrast, a distinctively flatter slope under control than under no-control. In particular, we find that default frequencies under control are lower for the worst two rating classes and

[13] For an introduction and definition on the accuracy ratio, see Sobehart and Keenen (2001).

higher for rating classes three to six. For rating classes seven and eight, we do not observe any defaults in either subsample. The accuracy ratio for observations under control (32%) is substantially lower than the accuracy ratio for observations under no-control (47%).

[Figure 8]

One reason for the lower accuracy of approved ratings under control may be that the quantitative part of the rating model could be less precise in forecasting defaults for this subsample of observations. In Figure 8B, we therefore display the relation between default frequencies and a hypothetical rating for each client that assumes a neutral qualitative score for each client (0.5) and no overrides. The picture shows similar distributions of defaults as in Figure 8A. The accuracy ratios based on the *Quantitative Score* alone is almost identical to those based on the approved ratings for ratings under control (34%) and for ratings under no-control (47%). Figure 8 thus suggests that, while under control the informational efficiency of the rating model is lower, this may be due to inaccuracy in the quantitative part of the model rather than in the loan-officer's assessment.

[Table 10]

Table 10 presents a multivariate analysis of the relation between default and approved ratings based on our dataset from Bank A and B. We report marginal effects of probit estimations with *Default* as the dependent variable. We include the *Approved Rating* and an interaction term of the *Approved Rating * Control* as relevant independent variables. As in all previous analyses, we control for firm size, industry, quantitative score and year of the credit assessment. We also include bank fixed effects to account for unobserved heterogeneity in client composition between the two banks. Importantly, we also include interaction terms of *Control* and the fixed effects for quantitative scores in order to account for the differences in the relation between quantitative scores and defaults across our subsamples as shown in Figure 9B. In column (1) we report estimates for our full sample. In column (2), we exclude any observations from our analyses that have a Quantitative Score higher than 0.75, as we observe very little defaults for these customers.

The point estimates reported in Table 10 confirms previous evidence that the subjective assessment by loan officers is valuable in predicting default (see e.g. Grunert et al. 2005) In both specifications we yield a negative and significant coefficient for *Approved Rating* suggesting that that, conditional on the quantitative score, clients which receive a higher qualitative score or positive override from their loan officer are less likely to default. The economic magnitude of this effect is substantial: The point estimate reported in columns (1) and (2) suggests that clients which the loan officer upgrades by one notch on the rating scale are 2 to 8 percentage points less likely to default.

[Figure 9]

The reported estimate for the interaction term *Approved Rating * Control* is positive in both specifications in Table 9, suggesting that default prediction of approved ratings is less precise under. While the point estimate lacks statistical significance, the interpretation of this interaction term should be taken with care due to the non-linear estimation model applied. As pointed out by Ai and Norton (2003), inference about the marginal effect of interaction terms in non-linear models should rely on an assessment of the distribution of its predicted value across all observations rather than on the reported point estimate at the mean. Figure 9 presents an analysis of the estimated interaction term based on the procedure suggested by Ai and Norton (2003) for our specification in column (1) of Table 10. We find that for most observations in our sample, the estimated marginal effect of *Approved Rating * Control* is not statistically significant. Indeed, only 7.2% of our observations display a significant positive estimate at the 10% level, while no observation displays a significant negative estimate and 92.8% display an insignificant estimate.

Overall, our results suggest that while internal control does induce strategic behavior by loan officers it does not lead to a reduced informational efficiency of the rating model. That said, given the considerable additional resources allocated to the credit assessment process one would expect internal control to improve the informational efficiency of the rating model. Our findings suggest that strategic behavior by loan officers undermines this objective.

6. Conclusions

In this paper, we examine how preventive internal control, affects loan officers' assessment of their small business clients. We find that ratings proposed by loan officers are more positive when these ratings are subject to internal approval. Our results strongly suggest that the positivity bias is driven by a hidden cost of control: In anticipation of potential downgrades by the approver, loan officers inflate proposed credit ratings. Additionally, we find that experienced loan officers skillfully hide their activities from the approvers by manipulating those parameters of a rating which are least verifiable and thus least likely to be corrected.

Our results have important practical implications for the role of internal control systems in the management of financial institutions. In particular, the conjecture of bank regulators that the "four-eyes" principle may improve governance and risk management may not be warranted, especially when there are conflicting interests within banks regarding decision outcomes. More generally, our findings confirm the limits of the four-eyes principle as an instrument of governance management in financial and non-financial corporations. Anticipated control may not only undermine the effort provision of staff due to a crowding-out of intrinsic motivation (Falk and Kosfeld, 2006). Worse still, anticipated control may trigger active opportunistic behavior within organizations

References

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

Ai, C. and Norton, E. (2003): “Interaction Terms in Logit and Probit Models”, Economic Letters, 80, 123 – 129.

Basle Committee on Banking Supervision (1997): “Core Principles for Effective Banking Supervision”, Basle, 1997.

Basle Committee on Banking Supervision (2000): “Principles for the Management of Credit Risk”, Basle, 2000.

Berg, T., Puri, M. and Rocholl, J. (2012): “Loan Officer Incentives and the Limits of Hard Information”, Working paper.

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

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

Blinder, A. and J. Morgan (2005): “Are Two heads Better than One? An Experimental Analysis of Group vs. Individual Decision Making”, Journal of Money, Credit and Banking, 37, 789-812.

Brown, M., Schaller, M., Westerfeld, S. and Heusler, M. (2013): “Information or Insurance? On the Role of Loan Officer Discretion in Credit Assessment”, University of St. Gallen , School of Finance Working Paper 2012/3.

Cerquiero, G., Degryse, H., and Ongena, S. (2011): “Rules versus Discretion in Loan Rate Setting”, Journal of Financial Intermediation, 20 (4), 503 – 529.

Christ, M., Sedatole, K., Towry, K., and Thomas, M. (2008): “When Formal Controls Undermine Trust and Cooperation”, Strategic Finance, January, 38 - 44.

Christ, M., Emett, S., Summers, S., and Wood, D. (2012): “The Effects of Preventive and Detective Controls on Employee Performance and Motivation”, Contemporary Accounting Research, 29 (2), 432 – 452.

Degryse, H., Liberti, J., Mosk, T., and Ongena, S. (2012): “Is Loan Officer Discretion Advised When Viewing Soft Information?”, Working Paper, 2012.

Kosfeld, M. and Falk, A. (2006): “The Hidden Cost of Control”, American Economic Review, 96(5), 1611-1630.

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

Hertzberg, A., Liberti, J., and Paravasini, D. (2010): “Information and Incentives inside the Firm: Evidence form Loan Officer Rotation”, Journal of Finance, LXV (3), 795 – 828.

Holmström, B. (1992): “Moral Hazard in Teams”, Bell Journal of Economics, 13, 324-340.

Jensen, M. (2001): “Corporate Budgeting is Broken – Let’s Fix it”, Harvard Business Review, November 2001, 94-101.

Liberti, J. and Mian, A. (2009): “Estimating the Effect of Hierarchies on Information Use”, Review of Financial Studies, 22 (10), 4057 – 4090.

Petersen, M. and Rajan, R. (1994) The Benefits of Lending Relationships: Evidence from Small Business Data, Journal of Finance 49, 3-37.

Qian, J., Strahan, P., and Yang, Z. (2011): “The Impact of Incentives and Communication Costs on Information Production: Evidence from Bank Lending”; Working Paper, 2011.

Romney, M. and Steinbart, P. (2009): “Accounting Information Systems”, Prentice Hall, 11th Edition, Upper Saddle River, NJ.

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

Sobehart, J. and Keenen, S. (2001): “Measuring Default Risk Accurately”, Risk, 31-33.

Stein, J. (2002): “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms”, Journal of Finance, LVII (5), 1891 – 1922.

Uchida, H., Udell, G., and Yamori, N. (2012): “Loan Officers and Relationship Lending to SMEs”, Journal of Financial Intermediation, 21 (1), 97 – 122.

Figure 1. The Credit Rating Process

This figure illustrates the credit rating process as used for the observations in our data. The hybrid credit rating model uses quantitative and qualitative information for generating a calculated rating. The loan officer responsible for the respective client is allowed to overwrite the calculated rating, resulting rating in the proposed rating. Depending on the organizational structure, the proposed rating either equals the approved rating ("No Control") or needs to be reviewed and finally approved by a second person ("Control").

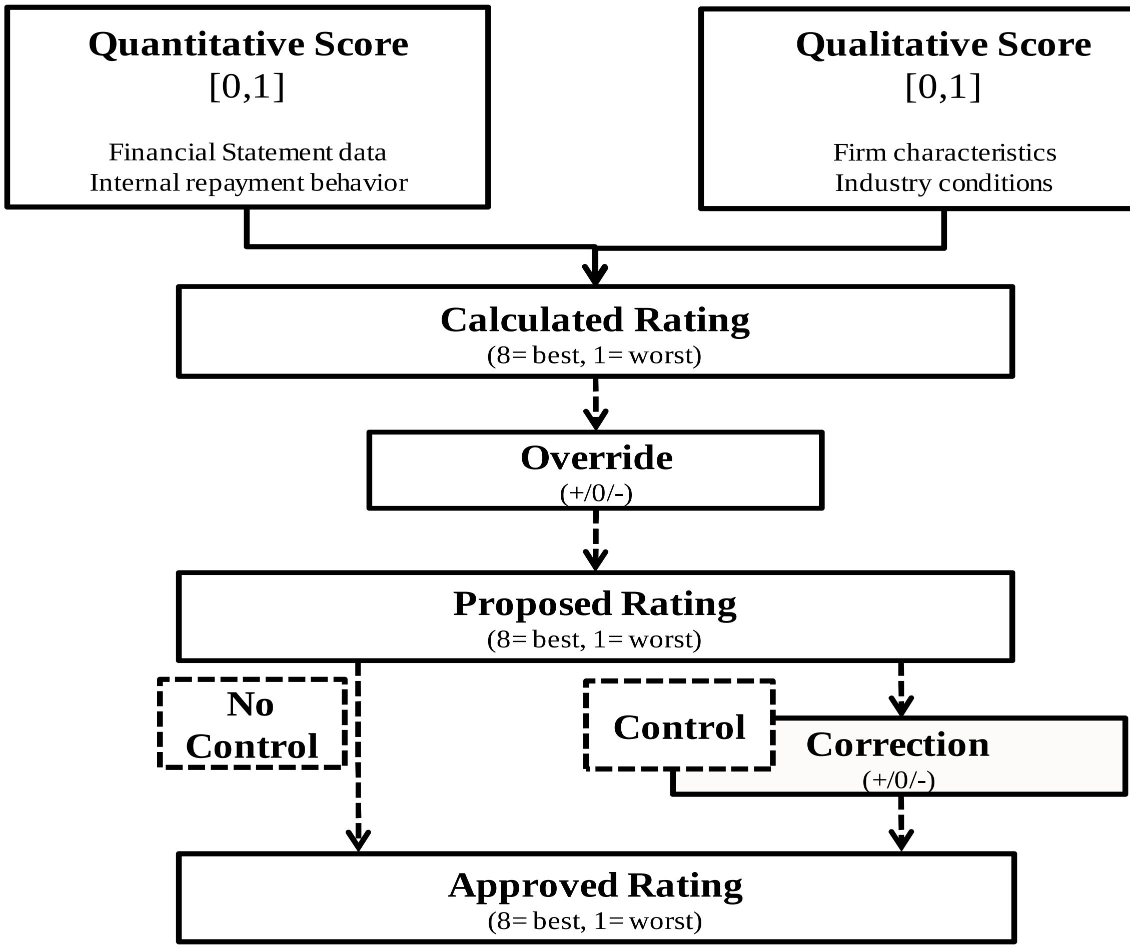


Figure 2. Distribution of Approved Credit Ratings

This figure presents the frequency distributions of observations across different quantitative scores. The graph presents separate distributions for observations under control and under no-control. A two-sample Kolmogorow-Smirnow test reports insignificant differences between the distributions (p-value = 0.288).

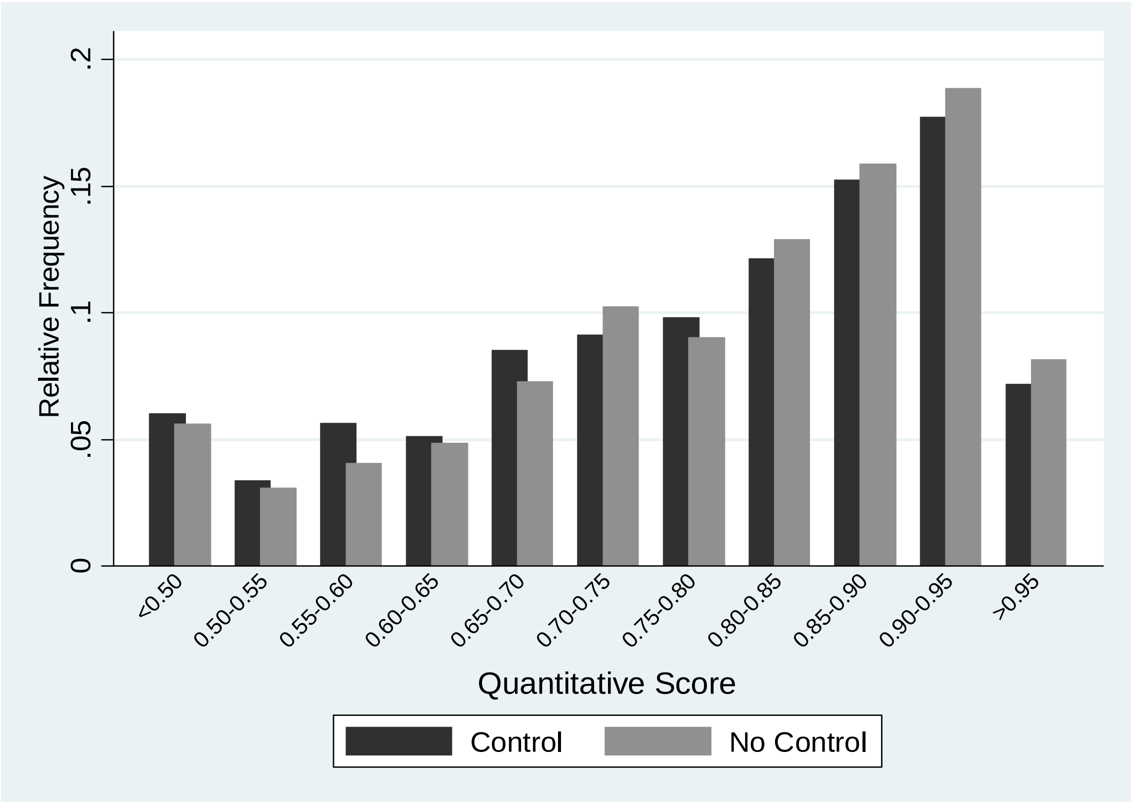


Figure 3. Impact of Control on Proposed Ratings

This figure shows differences in proposed ratings for applications under control and under no-control. Observations are clustered across quantitative scores. Vertical lines identify areas with differing influence of the qualitative score on the calculated rating.

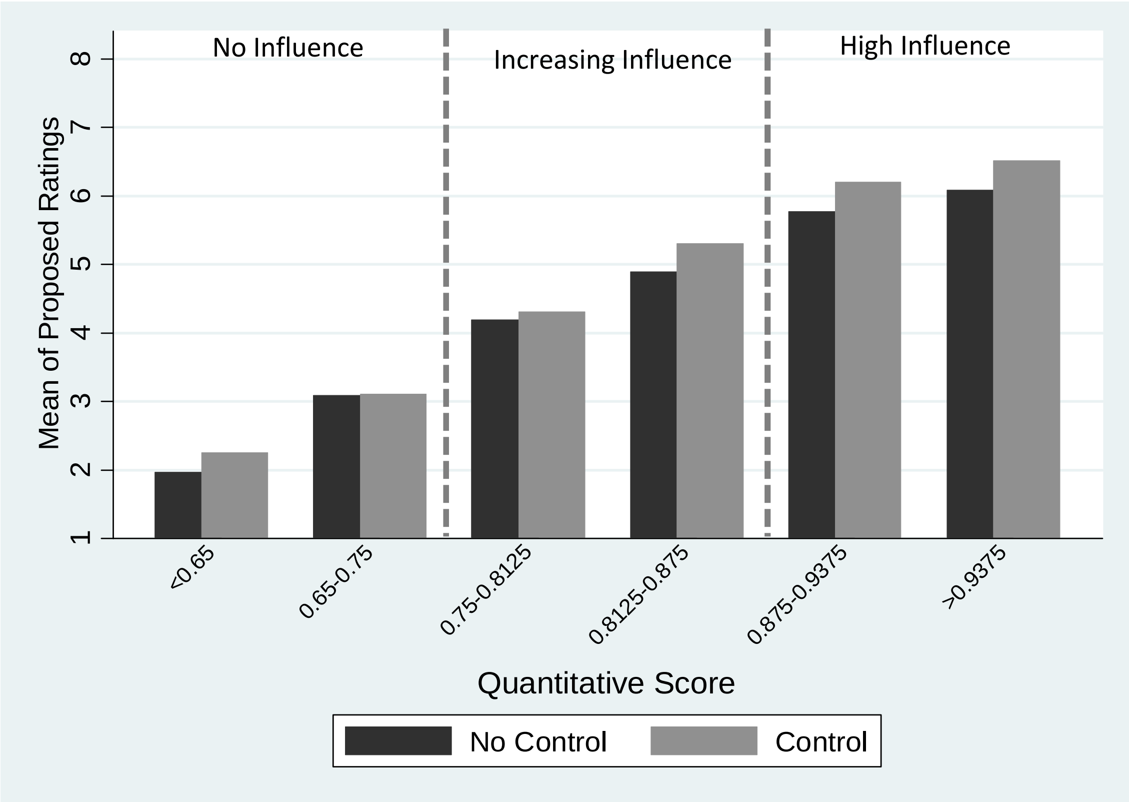
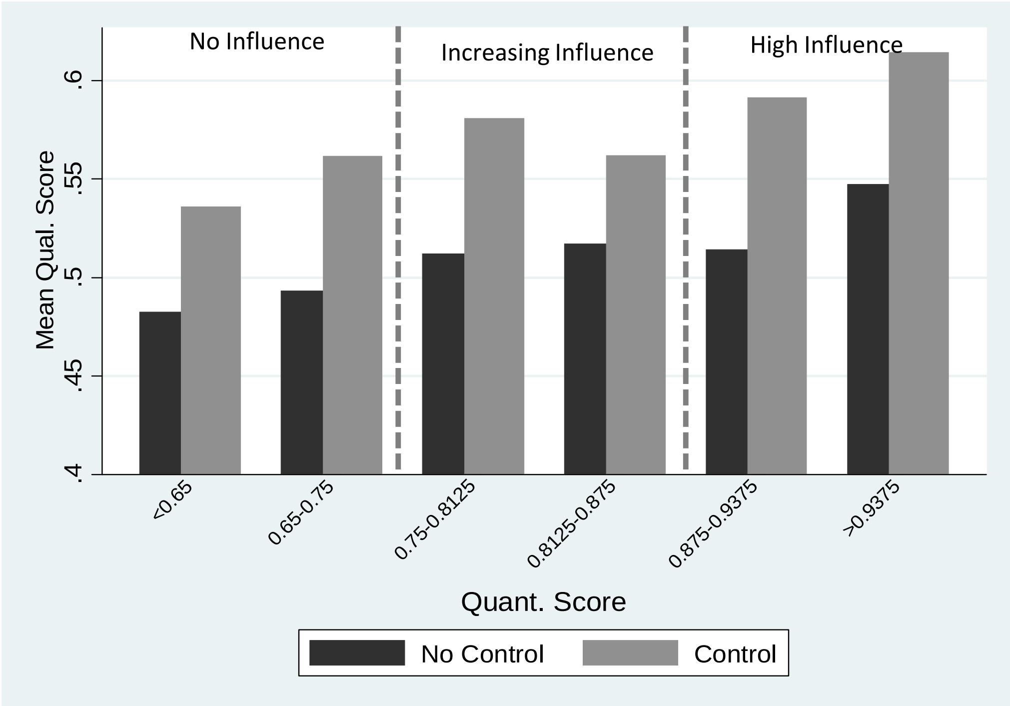


Figure 4. The Impact of Control on the Qualitative Assessment

Panel A. Differences in Qualitative Scores between Control and No-Control

This panel illustrates the differences in the qualitative assessment of clients depending on additional control of the proposed rating. The figure plots the mean of the qualitative scores across different classes of quantitative scores. Vertical lines identify areas with differing influence of the qualitative score on the calculated rating.



Panel B. Differences in Calculated Ratings between Control and No-Control

This panel presents the differences in calculated ratings resulting from different qualitative assessments of the clients. The figure plots the mean calculated ratings across different classes of quantitative scores. Observations are clustered based on whether or not an application is controlled by a second person.

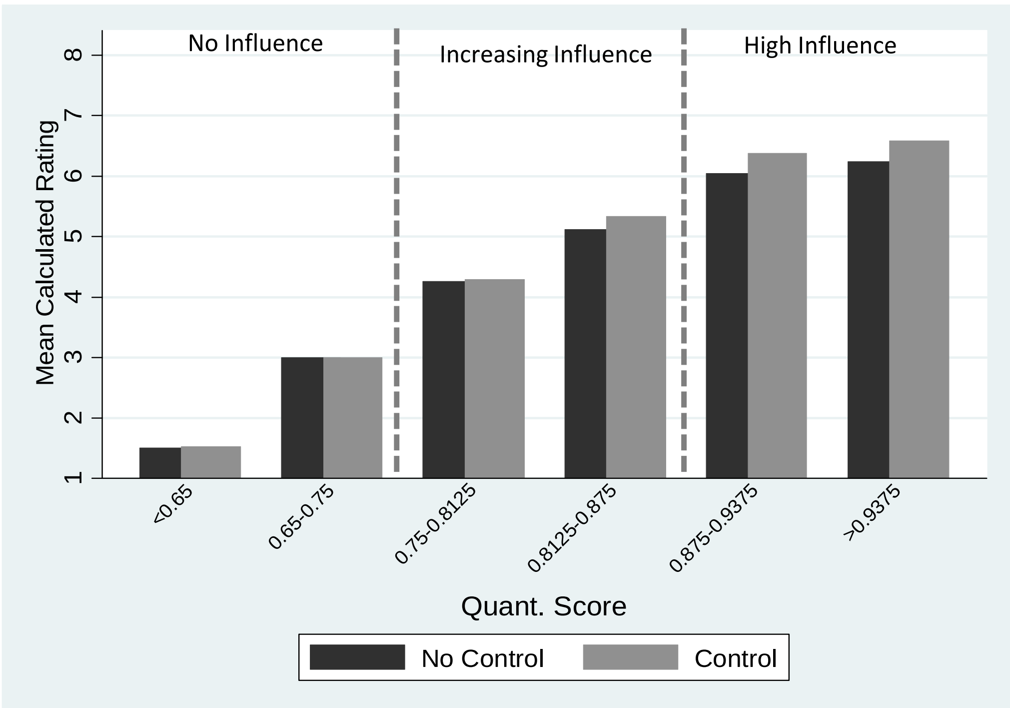


Figure 5. The Impact of Control on Overrides

This figure plots the average override depending on the calculated rating of a client. The lowest and highest two rating classes are aggregated to keep the number of observations within the different categories similar. On top of each bar, the number of observations is displayed.

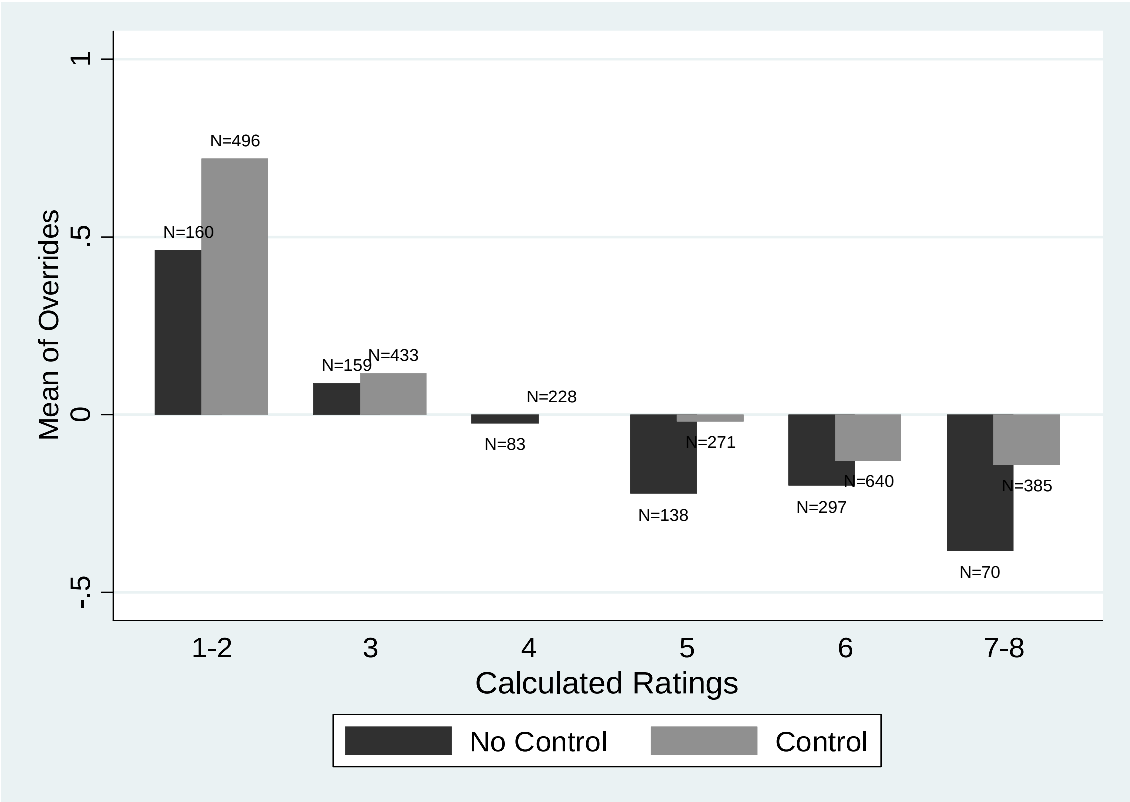
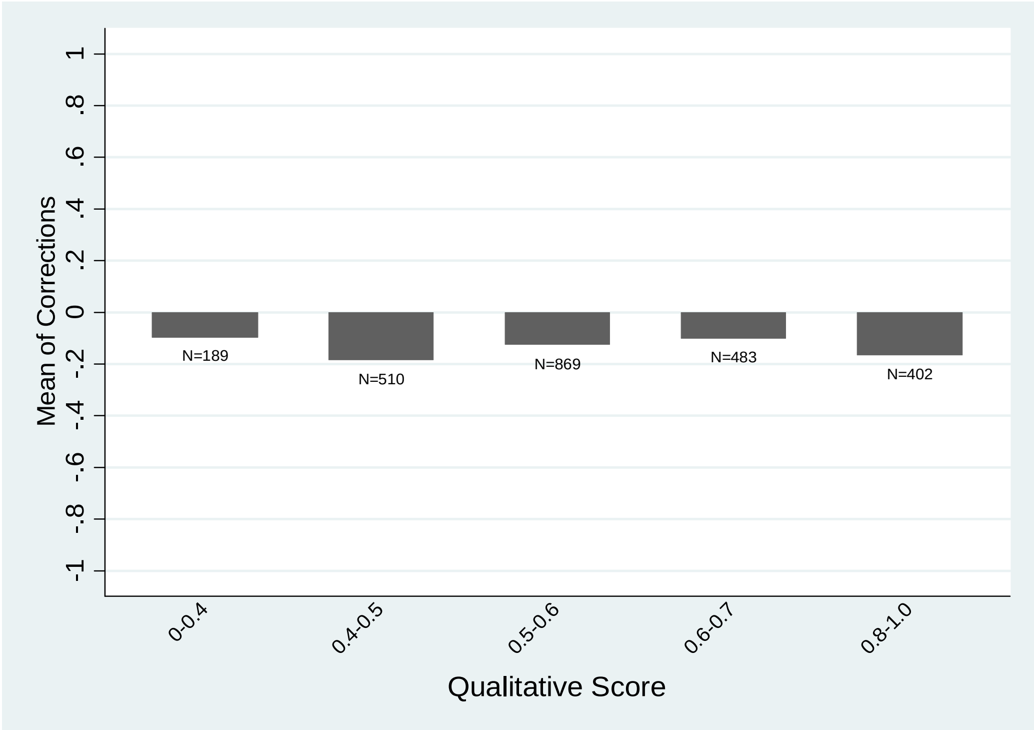


Figure 6: Corrections by Approvers

Panel A: Corrections and Qualitative Scores

This figure plots the mean of the corrections by the approver depending on the qualitative assessment of the loan officer. At the bottom of each bar, the number of available observations is displayed.



Panel B: Corrections and Overrides

This figure plots the mean of the corrections by the approver depending on the override by the loan officer. Overrides exceeding three rating steps are clustered into one category each. Above/below of each bar, the number of available observations in this category is displayed.

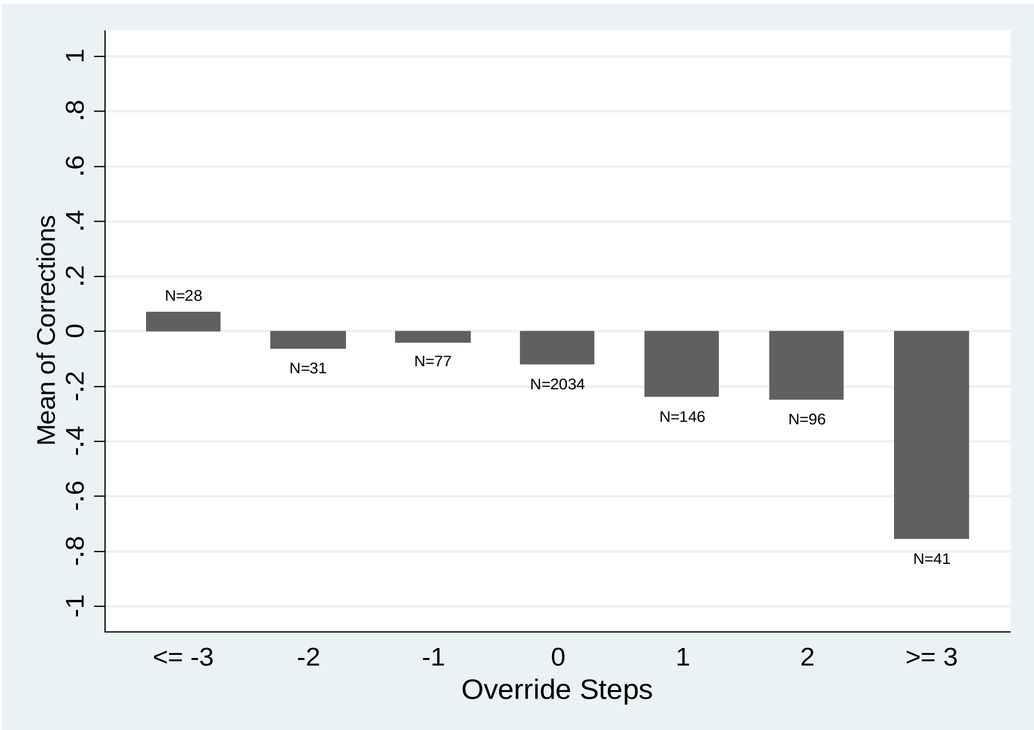
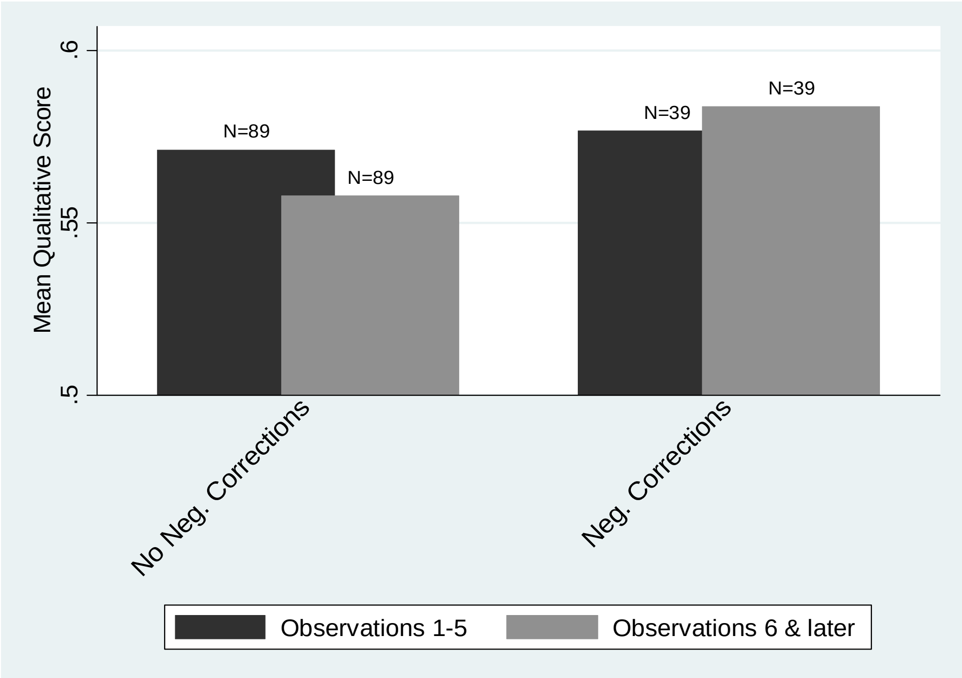


Figure 7: Loan Officers' Reaction to Corrections

This figure illustrates the impact of previous corrections by the approver on the behavior of the loan officer. The figure presents observations separately for loan officers that were corrected by the approver during the first five interactions (Neg. Corrections) and loan officers that were not corrected (No Neg. Correction). Additionally, separate bars are presented for the first five and all subsequent interactions between a loan officer and an approver. On top of each bar, the number of available observations (collapsed at the loan officer-approver level) is displayed.

Panel A: Corrections and the Qualitative Score

This figure depicts the mean qualitative scores depending on loan officers being corrected in previous assessments.



Panel B: Corrections and Overrides

This figure depicts the mean of overrides depending on loan officers being corrected in previous assessments.

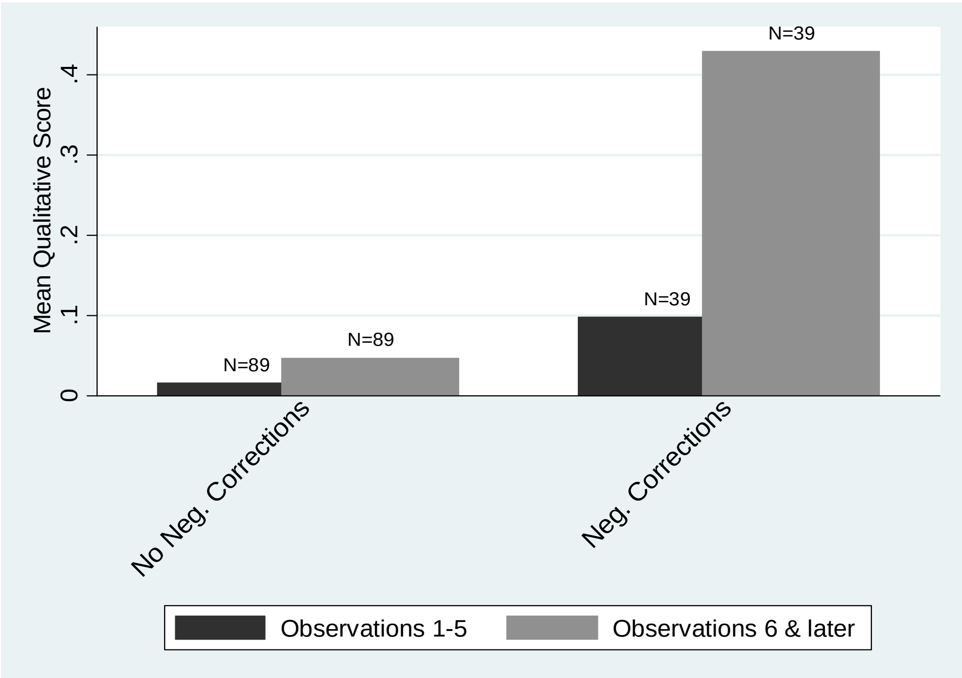
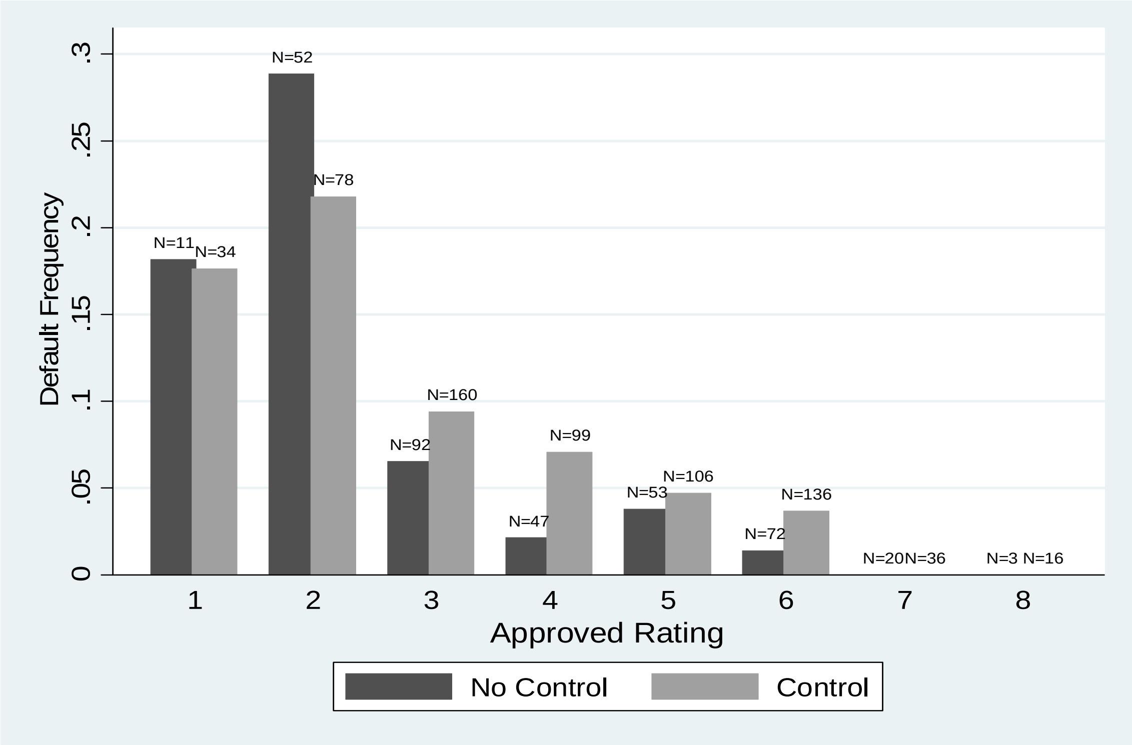


Figure 8. Control and Default Prediction

This figure shows default frequencies across ratings. We observe default information for two banks in our sample (A and B). The observations are divided into controlled and uncontrolled rating applications. On top of each bar, the number of available observations is displayed. Panel A presents the results for approved ratings, Panel B presents the results for quantitative ratings.

Panel A. Defaults and Approved Ratings



Panel B. Deafaults and Quantitative Rating

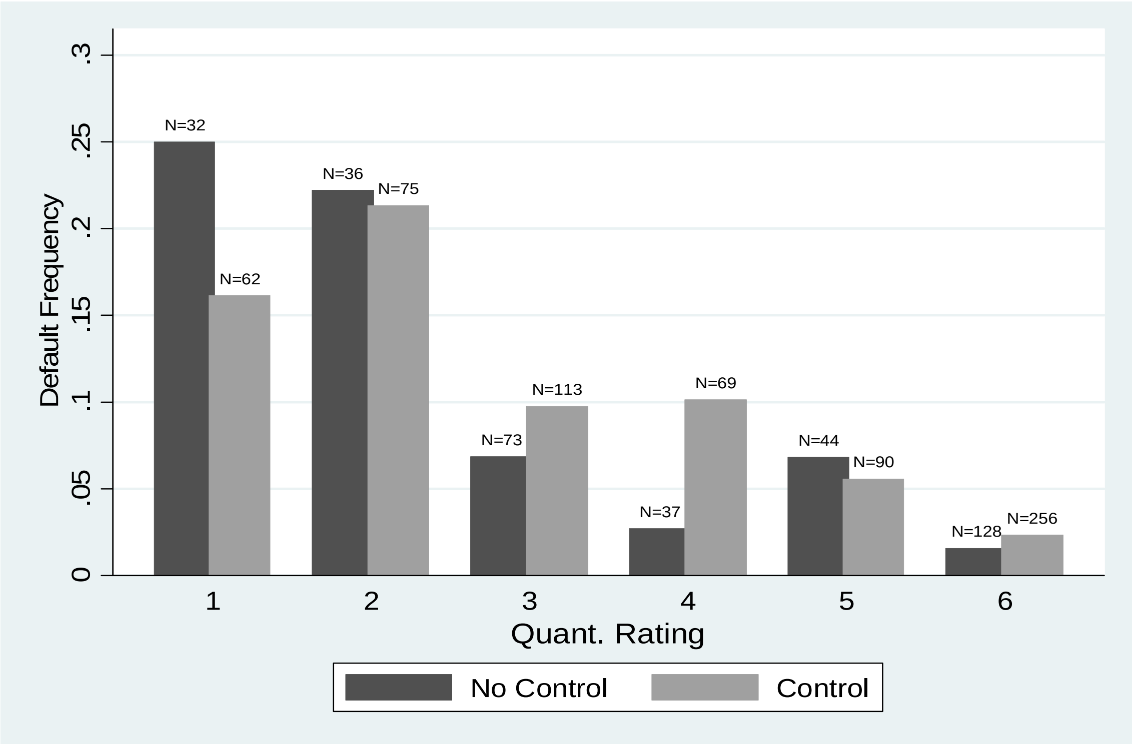
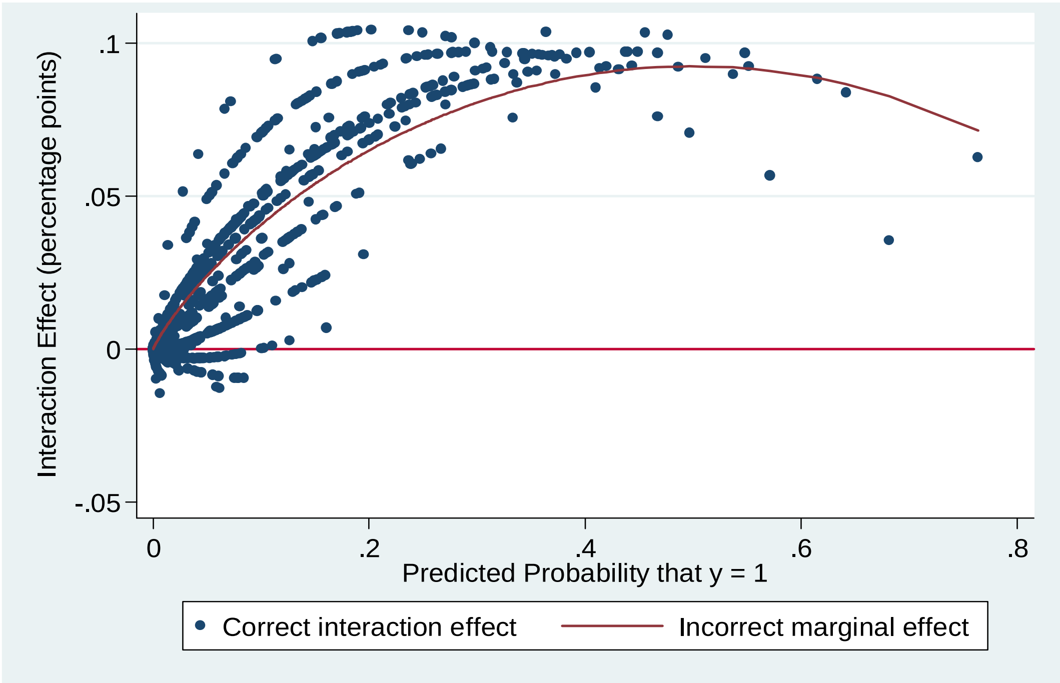


Figure 9. Interaction Terms in Default Prediction

These figures show the correct estimation results and z-statistics of the interaction term of control with approved rating. We use the procedure presented by Ai and Norton (2003) for this estimation.

Panel A. Interaction Effects after Probit

Panel A presents the estimations of the interaction effects depending on the predicted default probability of a client. Each dot represents one client in our regression model. The red curve illustrates the marginal effect calculated by a conventional standard linear estimation model.



Panel B. Z-Statistics of Interaction Effects after Probit

Panel B presents the corresponding z-statistics for each interaction term as estimated by the procedure of Ai and Norton (2003). Values are sorted on the x-axis based on predicted default probabilities. Values lying within the outer red horizontal lines are statistically indistinguishable from zero at the 5% confidence level.

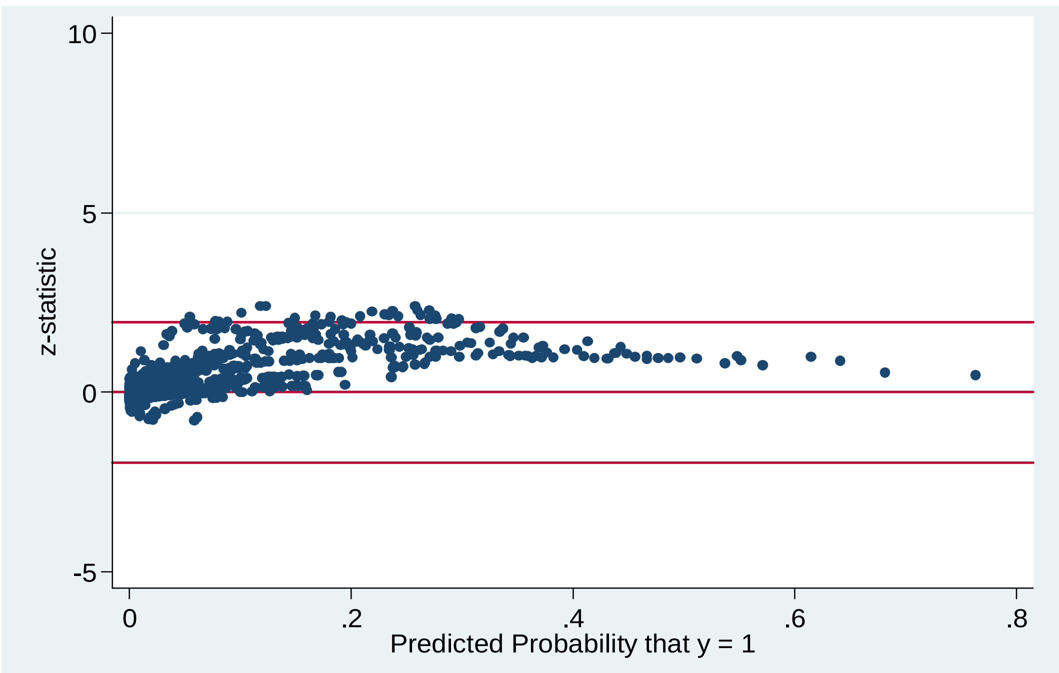


Table 1. Definition of Variables

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

Category	Variable	Definition
Rating Process	Control	Dummy variable (0; 1), indicating if the rating results need to be finally approved by a person other than the loan officer.
	Loan Officer	Person responsible for the loan process with a particular client. Each loan officer is identified using a unique dummy variable.
	Approver	Person responsible for the ultimate approval of the rating result for a particular client. Each approver is identified using a unique dummy variable. Not defined for rating application under no-control.
Rating Scores	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.
	Firm Score	Subset of the Qualitative Score consisting of the four items on the individual creditworthiness of the customer [0; 1].
	Industry Score	Subset of the Qualitative Score consisting of the three items on the industry outlook of the customer [0; 1].
Ratings	Calculated Rating	Rating result based on Quantitative and Qualitative Score alone.
	Proposed Rating	Rating result based on the Calculated Rating and any overrides by the Loan Officer.
	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.
	Quantitative Rating	Hypothetical rating based on the Quantitative Score of a client and a neutral (0.5) Qualitative Score.
Overrides	$\text{Override}_{\text{LoanOfficer}}$	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.
	$\text{Correction}_{\text{Approver}}$	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.
Influence & Experience	No Influence	Dummy variable (0; 1) that takes the value one if the loan applicants' Quantitative Score is below 0.75.
	Incresing Influence	Dummy variable (0; 1) that takes the value one if the loan applicants' Quantitative Score is above 0.75 and below 0.875.
	High Influence	Dummy variable (0; 1) that takes the value one if the loan applicants' Quantitative Score is higher than 0.875.
	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. Experience is measured as the number of applications completed by a loan officer.
	Default	Dummy variable (0;1) taking the value one if the customer defaults within two years following the loan application.
Control Variables	Size	Natural logarithm of the balance sheet total (in CHF).
	Industry	Dummy variable, coding the industry of a client into one of 21 categories.

Table 2. Summary Statistics

The table shows the summary statistics of the variables used throughout the analyses. The variables on proposed ratings and corrections are only applicable to controlled applications. Default information is only available for a subset of two banks in our sample (A & B).

							Percentiles		
Category	**Variable**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**75%**	**50%**	**25%**
Rating Design & Controls	Control	3'360	0.73	0.44	0	1	1	1	0
	Size	3'360	8.78	0.19	7.74	9.61	8.90	8.80	8.68
Rating Scores	Quantitative Score	3'360	0.78	0.15	0.21	0.97	0.90	0.81	0.68
	Qualitative Score	3'360	0.56	0.14	0.03	1	0.62	0.54	0.49
	Firm Score	3'360	0.54	0.15	0	1	0.55	0.55	0.55
	Industry Score	3'360	0.58	0.20	0	1	0.73	0.53	0.40
Ratings	Calculated Rating	3'360	4.45	1.96	1	8	6	5	3
	Proposed Rating	2'453	4.57	1.88	1	8	6	5	3
	Approved Rating	3'360	4.42	1.84	1	8	6	5	3
	Quantitative Rating	3'360	4.28	1.76	1	6	6	5	3
Over-rides	$\text{Override}_{\text{LoanOfficer}}$	3'360	0.07	0.81	-7	6	0	0	0
	$\text{Correction}_{\text{Approver}}$	2'453	-0.14	0.65	-6	4	0	0	0
Influence & Experience	No Influence	3'360	0.37	0.48	0	1	1	0	0
	Increasing Influence	3'360	0.29	0.46	0	1	1	0	0
	High Influence	3'360	0.34	0.47	0	1	1	0	0
	High Experience	3'360	0.49	0.50	0	1	1	0	0
	Default	961	0.08	0.27	0	1	0	0	0

Table 3. Observations by Bank and Year

The table shows the number of rating applications across banks and years. Banks are coded using alphabetic characters from A to F. In the last three columns, the table shows the share of controlled rating applications across banks, the number of different loan officers, and the number of different approvers.

Bank	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Total**	**Share Control**	**# Loan Officer**	**# Approver**
A		56	144	38	30	6	274	**83.9%**	28	3
B	203	378	97	99	83	32	892	**60.8%**	123	12
C		260	141	45	55	28	529	**90.9%**	47	8
D			13	24	6	40	83	**4.8%**	24	4
E			61	892	196	50	1'199	**99.1%**	110	11
F				26	243	114	383	**2.1%**	8	3
Total	**203**	**694**	**456**	**1'124**	**613**	**270**	**3'360**	**73.0%**	**340**	**41**

Table 4: Impact of Control on Proposed Rating

This table presents linear estimation results for the impact of control on proposed ratings. 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. Column (1) presents our baseline regression including all available observations. In column (2), we repeat the analysis for the banks that use both, control and no-control, to relevant degrees (Banks A-C). Columns (3) to (5) show the results for three subsamples depending on the impact of the qualitative score on the calculated rating. See Table 1 for detailed definitions on all variables.

Dependent:	**Proposed Rating**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Banks:	**All**	**A,B,C**	**No Influence**	**Increasing Influence**	**High Influence**
Control	0.216***	0.229***	0.111*	0.231**	0.297***
	[0.0566]	*[0.0781]*	*[0.0666]*	*[0.0894]*	*[0.0872]*
Controls for Size & Industry	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quant. Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Bank FE	No	**Yes**	No	No	No
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.789	0.792	0.291	0.445	0.173
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	3,360	1,695	1,248	983	1,129

Table 5. Impact of Control on Qualitative Assessment and Overrides

This table presents estimation results on the impact of control on qualitative scores and resulting calculated ratings. All estimations employ linear regression and cluster standard errors on the loan-officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 1 for definitions of all variables. Column (1) presents our baseline regression including all available observations. Column (2) shows the estimation result for the questions of the qualitative score that focus on the industry of the client. Column (3) presents the results for all questions of the qualitative assessment that target the client itself. Column (4) presenst regression estimates for the calculated rating, column (5) for the override by loan officers.

Dependent:	**Qualitative Score**	**Industry Score**	**Firm Score**	**Calculated Rating**	**Override$_{LoanOfficer}$**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Banks:	**All**	**All**	**All**	**All**	**All**
Control	0.0489***	0.0376***	0.0654***	0.110***	0.106*
	[0.0126]	*[0.0131]*	*[0.0156]*	*[0.0283]*	*[0.0607]*
Controls for Industry & Size	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quant. Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Bank FE	No	No	No	No	No
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.150	0.108	0.106	0.945	0.177
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	3,360	3,360	3,360	3,360	3,360

Table 6. Corrections by Approver

This table presents linear estimation results with the corrections by the approver as dependent variable. All standard errors are clustered on the approver level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. Columns (1) to (3) present estimation results with the qualitative score as independent variable. Columns (4) to (6) employ overrides as independent variables. See Table 1 for definitions of all variables.

Dependent: Correction$_{Approver}$

	(1)	(2)	(3)	(4)	(5)	(6)
Banks:	**All**	**All**	**All**	**All**	**All**	**All**
Qual. Score	0.00459	-0.0650	-0.0150			
	[0.102]	*[0.0945]*	*[0.0900]*			
Override$_{LoanOfficer}$				-0.173***	-0.175***	-0.188***
				[0.0291]	*[0.0292]*	*[0.0316]*
Controls for Industry & Size	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quant. Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Bank FE	No	**Yes**	No	No	**Yes**	No
Approver FE	No	No	**Yes**	No	No	**Yes**
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.033	0.046	0.076	0.072	0.086	0.118
Clustered Standard Errors	Approver	Approver	Approver	Approver	Approver	Approver
# Rating Applications	2,453	2,453	2,453	2,453	2,453	2,453

Table 7: Difference-in-Differences on Loan Officers' Anticipation of Corrections

These tables present difference-in-differences estimations for the qualitative scores (Panel A) and the overrides (Panel B) assigned by loan officers. The tables report mean values of qualitative scores and overrides for controlled rating applications only. Values are reported for loan officers that either were or were not negatively corrected by the approver in the first five interactions. Additionally, separate values are reported for the first five and all later interactions of a loan officer with an approver. Differences and statistical significance of the values are reported on the right and the bettom of the tables. The difference-in-differences is presented at the right bottom corner. Observations are collapsed on the loan officer - approver level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 1 for definitions on all variables.

Panel A: Qualitative Scores

	Interaction between Loan Officer and Approver		
	1-5 *(n = 128)*	*6 & later* *(n = 128)*	Diff / **Diff-in-Diff**
No Negative Corrections *(n = 178)*	0.571	0.558	-0.013
With Negative Corrections *(n = 78)*	0.577	0.584	0.007
Diff / **Diff-in-Diff**	0.006	0.026	**0.020**

Panel B: Overrides

	Interaction between Loan Officer and Approver		
	1-5 *(n = 128)*	*6 & later* *(n = 128)*	Diff / **Diff-in-Diff**
No Negative Corrections *(n = 178)*	0.016	0.047	0.031
With Negative Corrections *(n = 78)*	0.099	0.430	0.331***
Diff / **Diff-in-Diff**	0.083	0.383***	**0.300****

Table 8: Loan Officer Experience

This table shows how experience of loan officers influences their behavior in the credit assessment under control and no-control.Columns (1) and (2) use the proposed rating as dependent variable, columns (3) to (4), (5) to (6), and (7) to (8) use the qualitative score, the calculated rating, and the override, respectively. Additionally, odd columns present results for loan officers with low experience, while even columns show results for highly experienced loan officers. 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 Table 1 for detailed definitions on all variables.

Dependent:	**Proposed Rating**		**Qualitative Score**		**Calculated Rating**		**Override$_{LoanOfficer}$**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Sample:	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**
Control	0.153*	0.228***	0.0174	0.0611***	0.0130	0.164***	0.140*	0.0635
	[0.0858]	*[0.0699]*	*[0.0127]*	*[0.0160]*	*[0.0347]*	*[0.0335]*	*[0.0815]*	*[0.0652]*
Controls for Industry & Size	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Quant. Score FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.795	0.789	0.166	0.174	0.944	0.950	0.191	0.171
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	1,701	1,659	1,701	1,659	1,701	1,659	1,701	1,659

Table 9: Default

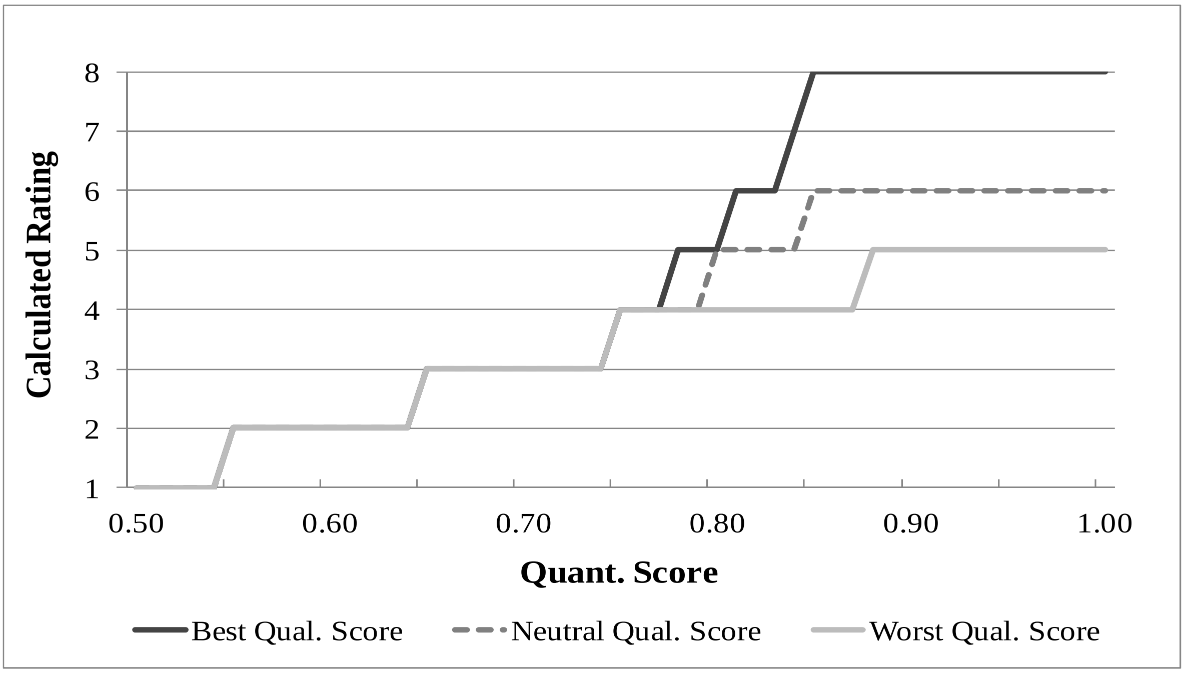
This table shows the results of a probit regression with the default of a client as dependent variable. The values reported are marginal effects with standard errors, clustered on the loan-officer level in brackets. Column (1) shows the results for our full sample of observations with default information. 54 observations are not used in this analyses due to lacking variance within fixed effects. Column (2) includes only observations with a quantitative scores lower than 0.75. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 1 for definitions on all variables.

Dependent: Default

	(1)	**(2)**
Banks:	**A & B**	**A & B**
Sample:	**All**	**Quant. Score < 0.75**
Control	-0.0622	-0.156
	[0.0563]	*[0.139]*
Approved Rating	-0.0223**	-0.0805
	[0.0103]	*[0.0548]*
Approved Rating * Control	0.0136	0.0400
	[0.0120]	*[0.0628]*
Controls for Industry & Size	**Yes**	**Yes**
Quant. Score FE	**Yes**	**Yes**
Quant. Score * Control FE	**Yes**	**Yes**
Year FE	**Yes**	**Yes**
Bank FE	**Yes**	**Yes**
Method	Probit	Probit
R-squared	0.219	0.151
Clustered Standard Errors	Loan Officer	Loan Officer
# Rating Applications	961	362

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. This section also reports the calculated rating score and the resulting calculated rating. The second section requires the loan officer to input the relevant quantitative information on the customer. For each of the seven different ratios, the quantile the current customer is in, is displayed. Besides the ratios, the rating model also includes additional quantitative information on two 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 to four categorical assessments. In the final section, the loan officer may calculate the rating and potentially redo his / her assessment before proceeding and saving the results.