Loan officer incentives and the limits of hard information

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Preliminary

March 2012

Policymakers have argued that part of the reason for the current financial crisis is the poor quality of loans made when loan officers were allowed to exercise their discretion bypassing hard information. One potential solution to minimize risks in loan making is to automate the process, basing it solely on hard information, taking out ambiguous soft information. Yet this can potentially affect loan officer incentives and outcomes. In this paper, we access data from more than 240,000 loan applications at a major European bank, in a setting where loans are made based on hard information alone. We analyze loan officers' incentives as they input hard information into a scoring system and find that loan officers use more scoring trials for loan applications that do not pass the cut-off rating in the first trial. Furthermore, they use more scoring trials as they get closer to the cut-off rating, with a pronounced jump at the boundary. We exploit a change in the cut-off rating and show that this jump moves to the new cut-off boundary after the change. Finally, we show that the number of scoring trials positively predicts default rates, in particular at the cut-off. These results suggest that loan officers strategically manipulate information when loan decisions are based on hard information and credit scoring alone, and point to the limits of hard information.

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1. Introduction

Understanding how banks make loans is important. One of the questions at the forefront of the current financial crisis is how should the process of loan making by banks be regulated to minimize risks? Many have argued that part of the reason for the current financial crisis is the poor quality of loans made when loan officers were allowed to exercise their discretion or arbitrarily use their judgment. One potential solution is to automate the loan making process, basing it solely on hard information. By taking out discretion or ambiguous soft information, and relying solely on hard information, the argument is that better decisions and loans would be made.

However, it is unclear if a system where loans are made solely by hard information will yield better quality loans. There are other effects that need to be taken into account. In particular, what are the incentives of loan officers and how might this affect the kinds of loans being made? If all loans are made based on hard information, and an accept/reject decision is automatically generated, then loan officers no longer need to take responsibility for the loans that they make. On the other hand, if soft information or discretion is used, there is more of an onus on the loan officer to justify the loan and take responsibility for its performance.

In this paper we are able to empirically address the effect of loan officer incentives in a pure credit scoring model based on hard information alone by accessing a unique data set from a major European bank. This bank uses only hard information in making its loans to retail customers. The hard information is collected and inputted into the system by loan officers. These loan officers are incentivized with a fixed salary and a bonus which depends on the volume of loans they originate. With this data we are able to address the following research questions. Do loan officers strategically manipulate hard information? If yes, what loan, customer and loan officer characteristics drive this decision? Does this result in better or lower quality loans; how does this affect subsequent default rates?

We are able to access data on the universe of 242,011 consumer loan applications at a major European bank from May 2008 to June 2010. This dataset has a number of distinct features. First, loans are made solely based on hard information. The hard information is fed into the system and an accept/reject decision is made based on whether the loan is above the cut-off or not. The loan officer does not have the authority to override the decision made by the credit scoring system or to include "soft" or discretionary information. Second, there was an exogenous change in the cut-off. This exogenous shock of the change of cut-off allows us to parse out loan officer incentives to see how they process hard information around the cut-off. Third, we have detailed information on how loan officers enter hard information. Typically loan officers enter data into the system and request an internal rating. If the rating comes up with a decision to reject, the loan officer can then alter or update the information and request an updated internal rating. We are able to see how many times the loan officer does a scoring trial and also what kind of information is added prior to each scoring trial. In particular we are able to see whether the number of scoring trials for loans that are near the cut-off are different from other loans. We are also able to use the change in cut-off as a way to see if the number of scoring trials for the ratings that would have earlier made the cut-off but now do not, change.

We find there are more scoring trials for loan applications that do not pass in the initial trial. The number of scoring trials increases as one gets closer to the cut-off boundary, and jumps at the cut-off boundary. Interestingly, when the cut-off is changed, the jump in scoring trials moves to the new cut-off point. The number of scoring trials is also related to loan officer characteristics, e.g., more scoring trials for more experienced loan officers and when loan officers have been unsuccessful in making loans over the previous few months.

One question that arises is whether the additional information in successive scoring trials simply reflects more precision and accuracy in information, or whether it is manipulation to get the loan over the cut-off. To assess this we examine default rates. We find that the number of scoring trials positively predicts default rates. A one standard deviation in the number of scoring trials leads to a 10-15% increase in default rates after controlling for loan, customer and loan officer characteristics. This holds in particular around the cut-off where the manipulation of information by the loan officer can move loans from below to above the cut-off. We also find that default rates are negatively related to the time a loan officer uses for each scoring trial, suggesting that the loan officer does not carefully check or verify information in case of manipulation, but just plays around to reach the desired outcome. Finally, default rates are positively related to a reduction in costs and liabilities, which can be achieved much more easily and needs to be documented less than an increase in assets and income.

Our results suggest that when loan decisions are made on hard information and credit scoring alone, loan officers' incentives can cause strategic manipulation of information. These changes in hard information are often very small, making it almost impossible to verify or detect manipulation. Further, loan officers with more experience and who have not had good success in making loans over the last few months are more likely to engage in such manipulations. Finally, this manipulation leads to the making of loans with higher default rates.

Our paper relates to different strands of the literature. First, we contribute to the literature on agency problems within banks, e.g. Udell (1989) and Hertzberg, Liberti, and Paravisini (2010). Udell (1989) provides evidence that the purpose of the loan review function in a bank is to reduce agency problems between the bank and its loan officers. Hertzberg, Liberti, and Paravisini (2010) show that a rotation policy affects loan officers' reporting behavior. We document that agency problems do not necessarily disappear when credit decisions are based on hard information only. Second, our paper relates to the literature that differentiates between soft and hard information in the loan process, e.g. Stein (2002), Berger, Miller, Petersen, Rajan, and Stein (2005), Liberti and Mian (2009). We show that hard information is subject to manipulation by delegated monitors.

The rest of the paper is organized as follows. Section 2 describes our dataset and provides descriptive statistics. Section 3 explains our empirical strategy. Section 4 presents the empirical results and section 5 provides robustness tests. Section 6 concludes.

2. Data and descriptive statistics

A. Data and loan process

We obtain data on consumer loan applications and subsequent default rates from a major European bank. These data comprise detailed information on 242,011 loan applications at more than 1,000 branches of the bank between May 2008 and June 2010. From these 242,011 loan applications, 116,969 materialize and data on the performance and defaults of these 116,969 loans are available until May 2011. Loans are granted to both existing and new customers. During the loan application process, each customer is assigned an internal rating. The internal rating ranges from 1 (best rating) to 24 (worst rating) and is solely based on hard information. It consists of five parts: first, an external score, which is similar to a FICO score; second, a socio-demographic score, which is based on parameters such as age and sex; third, an account score if the customer has a savings account with the bank; fourth, a loan score if the customer already has a loan relationship with the bank; fifth an income score which aggregates income data, expenses, assets, and liabilities. Finally, these five parts are aggregated into an overall internal rating.

The loan application proceeds in the following way: First, the loan officer enters all the necessary data into the system. If the loan is given, the written documentation, such as a copy of the identification card and a salary certificate, has to be archived together with the loan agreement. The bank's risk management function periodically checks the validity of this documentation based on a random sample selection. If loan officers manipulate customer data, they thus face a risk of being caught later on. However, no loan-by-loan checks are conducted when the loans are granted.

Second, the loan officer requests a score from the internal rating system. This score determines whether a loan shall be given and the interest rate charged for this loan. Loan applications with an internal rating worse than the cut-off rating are automatically rejected by the system and receive the status 'automatically rejected'. Loan applications with an internal rating better or equal to the cut-off rating receive the status 'open', and the risk-based pricing scheme applies. The cut-off criterion is equal to a rating of 14 until 31 December 2008. This means that all loan applications with a rating of 14 or better can be accepted. This cut-off criterion is changed to 11 on 1 January 2009. To put these ratings into perspective, a rating of 14 is comparable to a B rating based on the Standard & Poor's rating scale; a rating of 11 is comparable to a BB rating. The cut-off criterion is changed as a result of growing concern about the status of the European economy in the wake of the financial crisis. The management of the bank decides to follow a prudent strategy and tighten lending standards in order to preserve the risk profile of the loan portfolio.

Third, the loan officer decides on how to proceed. She can either proceed with the application as entered into the system if the status is not 'automatically rejected', abort the loan application, or change any of the input parameters and request a new internal rating, i.e initiate a new scoring trial. There are 442,255 unique scoring trials for the 242,011 loan applications – an average of 1.83 scoring trials per loan application. Only the results of the last scoring trial are recorded in the official systems of the bank, while all former trials are deleted. The only exception is one specific risk management system used in this paper that archives each scoring trial separately. Loan officers are in general not aware that all scoring trials are recorded in this system, and also the bank's risk management function has rarely used it so far.

There are five major advantages of our setup: First, each separate scoring trial is recorded in the database. Second, loan officers are subject to a random review process. Therefore, they have an incentive to report truthfully as long as truthful reporting is not incompatible with their personal incentives. Third, we have information on individual loan officers which gives us the possibility to analyze incentives across individual loan officers. Fourth, the cut-off rating was changed during our sample period without any other change in the rating or incentive system. This gives us the unique opportunity to analyze the effect of tighter lending standards on loan officers' behavior. Fifth and finally, our dataset contains default information which enables us to link loan officer incentives and lending standards to actual defaults.

B. Loan officer incentives

Loan officers receive a fixed salary and a bonus. The bonus is performance-based and can make up to 25 percent of the fixed salary. It depends on the volume of the loans that a loan officer generates in a given year and the conditions at which these loans are granted, but not on the default rates of these loans. In particular, loan officers receive a fee for each successful loan application. This fee increases in the interest rate charged for the loan and the creditworthiness of the customer, which is determined by the internal rating. Thus, a loan officer benefits from a better rating for a loan applicant for two reasons: First, a higher rating increases the likelihood of a loan application being successful. Second, a better rating results in a higher fee for a successful loan application. The average fee for a successful loan application is approximately 20 times larger than the fee increase for a one-notch higher rating. Thus, the first-order incentive effect comes from ensuring that the rating meets the minimum-creditworthiness condition, while further rating improvements have a second-order effect. At the same time, there is a significant psychological pressure to perform well. Each week, or even during each week, 'run lists' are compiled to rank each individual loan officer.

While lending standards are tightened in January 2009, the performance targets that are given to individual loan officers remain unchanged. This means that loan officers are faced with the same targets but a much smaller customer base that can make the cut-off rating after the change. This provides an incentive to loan officers to manipulate customer information to achieve their targets.

After origination, the loan is transferred to an internal portfolio management unit, and the loan officer is no longer responsible for the performance of the loan. The compensation of the loan officer does therefore not depend on whether the loan defaults.

C. Descriptive statistics

Table 2 presents descriptive statistics on loan application level (Panel A), scoring trial level (Panel B) and loan officer level (Panel C). All variables are explained in table 1. The information on the loan application level in Panel A is based on the last scoring trial per loan application. This is the only information that is available in the systems of the bank, apart from the single risk management system used for the analysis in this paper that tracks every trial. 13 percent of the loan applications have a rating below the cut-off and are therefore automatically rejected. On average, loan officers use the scoring system 1.83 times per loan application. The average acceptance rate is 48 percent, i.e. 48 percent of the loan applications are accepted by both bank and customer. The average loan amount is EUR 13,700, the average number of borrowers per loan application is 1.34, the average age of a borrower is 45.24 years, and his average net income per month is EUR 2,665. If a loan application has several borrowers, e.g., husband and wife, then parameters such as net income per month are aggregates over both borrowers with the only exception being the age, where the average age is reported. 63 percent of the customers are relationship customers who have either an existing account or another loan with the bank. The information about the internal rating, which ranges from 1 (best) to 24 (worst), shows that the average rating amounts to 8.40. The cut-off rating was set at 14 between May 2008 and December 2008 and at 11 between January 2009 and June 2010. 28 percent of our observations come from the earlier period, while 72 percent come from the latter period. Panel B shows that 20 percent of the scoring trials result in a rating below the cut-off. This is significantly higher than the 13 percent from the last trial, as shown in Panel A, and indicates that internal ratings are on average moved upwards with further trials. There is an unconditional likelihood of 45 percent of observing another subsequent scoring trial for the same loan application. Panel C shows that the 242,011 loan applications in our sample are arranged by 5,634 loan officers. During our sample period, an average loan officer uses the scoring system 78.50 times for 42.96 different loan applications of which 20.78 loans materialize, i.e. are finally accepted by both bank and customer.

Table 3 provides a concrete example on the workings of the different scoring trials. In this example, on 4 May 2009, a loan officer enters an application for a consumer loan of EUR 4,000 and records, among other parameters, existing liabilities of the customer of EUR 23,000 and a monthly net income of EUR 1,900. The resulting internal rating of 12 is worse than the cut-off rating of 11, therefore the loan application is automatically rejected by the system. The loan officer subsequently increases the income to EUR 1,950 and decreases the liabilities to EUR

10,000. These two changes result in a new rating of 11 so that the loan application can be accepted. However, the loan officer then decides to manually reject the loan application and corrects the liability amount to EUR 19,000. As this change results again in a rating below the cut-off, the loan officer reverses the liabilities back to EUR 10,000 and books the loan into the system. This loan application provides a particular striking example of a manipulation around the cut-off as the final amount for the liabilities of EUR 10,000 is clearly not a correction of a previously misspecified value. This is the type of behavior that we would like to analyze more thoroughly in this paper.

3. Empirical strategy

A. Loan officer incentives and the number of scoring trials

A1. Analysis on loan application level

The cut-off rating substantially affects loan officer incentives, as only loan applications with ratings better than or equal to the cut-off rating can generate fee income. The change of the cut-off rating during our sample period provides us with a clear identification strategy. We estimate the following regression:

$$NumberOfTrials_{i,j,t} = \beta_1\ CutOffDummy_{i,t} + \delta\ X_{i,j,t} + A_j + B_t + \varepsilon_{i,j,t} \qquad (1)$$

where $NumberOfTrials_{i,j,t}$ is the number of scoring trials for the loan application from customer i at time t arranged by loan officer j and $CutOffDummy_{i,t}$ is a dummy variable equal to 1 if the rating from the first scoring trial of the loan application from customer i at time t is worse than the cut-off rating, i.e. worse than rating 14 between May 2009 and December 2009 and worse than rating 11 between January 2009 and June 2010. $X_{i,j,t}$ is a set of control variables taken from the first scoring trial including loan, customer and loan officer characteristics and A_j and B_t are loan officer and time-fixed effects. Finally, $\varepsilon_{i,j,t}$ is an error term. The estimation method will be discussed in more detail in the results section.

A2. Analysis on scoring trial level

Regression (1) operates on the loan application level. It relates the cut-off status ($CutOffDummy_{i,t}$) and characteristics ($X_{i,j,t}$) of the first scoring trial to the number of scoring trials for a loan application. To make use of the full information at hand, we also estimate a hazard rate model which takes into account data from every single loan trial. In particular, we estimate:

$$AddTry_{i,j,t,n} = f(\beta_1, CutOffDummy_{i,t,n}, \delta\, X_{i,j,t,n}, A_j, B_t, epsilon_{i,j,t,n}) \qquad (2)$$

where $AddTry_{i,j,t,n}$ is a dummy variable equal to 1 if there exists another scoring trial after the nth-trial for the loan application from customer i at time t arranged by loan officer j. The dummy variable is therefore equal to zero for the last trial for each loan application and equal to one for all other trials. The variables $CutOffDummy_{i,t,n}$, $X_{i,j,t,n}$, A_j, B_t have the same meaning as in (1) but are now measured for each scoring trial separately. The function f is a link function such as the logistic function. Estimation method and link function will be discussed in more detail in the results section.

B. A closer review of multiple scoring trials

In regressions (1) and (2) the number of scoring trials acts as a proxy for changes in customer information during the loan application process. Here, we take a closer look at which parameters loan officers do actually change during the loan application process. We do so by using a difference-in-difference approach. First, we determine the difference between a certain parameter in the first scoring trial and the last scoring trial for the same loan application:

$$Delta^k_{i,j,t} := X^k_{i,j,t,N} - X^k_{i,j,t,1} \tag{3}$$

where $X^k_{i,j,t,N}$ and $X^k_{i,j,t,1}$ are the parameter values for parameter k (such as income, age or assets of the loan applicant) for the loan application from customer i at time t arranged by loan officer j in the last and first scoring trial, respectively. Second, we group the loan applications into two categories: First, all loan applications which pass the cut-off rating with the first scoring trial, i.e. where no information manipulation is necessary to generate a fee. Second, all loan applications which do not pass the cut-off rating with the first scoring trial, i.e. where a fee can only be generated if any of the input parameters is changed. We apply a difference-in-difference approach to analyze differences in changes to customer information between these two groups.

C. Loan officer incentives and default rates

Multiple scoring trials for a single loan application can be due to loan officers honestly correcting a false entry from a former trial (information correction hypothesis) or loan officers manipulating information they have about the customer in order to increase their fee income (information manipulation hypothesis). To distinguish between these two interpretations we estimate the effect of multiple scoring trials on the default rate. If the information correction hypothesis is correct, we would not expect a systematic effect of the number of scoring trials on default rates. The opposite applies for the information manipulation hypothesis. We therefore estimate the following regression:

$$DefaultDummy_{i,j,t,T} = f(\beta_1, NumberOfTrials_{i,j,t}, \delta X_{i,j,t}, A_j, B_t, \varepsilon_{i,j,t,T}) \quad (4)$$

where $DefaultDummy_{i,j,t,T}$ is a dummy variable equal to one if the loan to customer i originated by loan officer j at time t defaults within the first T months after origination, $NumberOfTrials_{i,j,t}$ is the number of scoring trials for this loan, $X_{i,j,t}$ is a set of control variables taken from the last scoring trial of the loan (i.e. the 'official' scoring trial which enters the bank's systems) and A_j and B_t are loan officer and time fixed effects. The function f is a link function such as the logistic function. Again, details on the estimation method will be discussed in section 4.

4. Empirical results

A. Loan officer incentives and the number of scoring trials

A1. Univariate results

We compare the average number of scoring trials before and after the change in the cut-off rating. Figure 1 shows the results for the comparison of the accepted loans, while figure 2 shows the respective results for all loan applications. In figure 1, we conduct the comparison based on the rating class in which a loan is finally accepted. The figure shows that the number of scoring trials is quite similar before and after the change in the cut-off rating for rating classes 1 to 10. Also, as the cut-off rating is decreased to 11 in January 2009, there are no more loans in rating classes 12 to 14 after this change. The most striking result is the significant increase in the number of scoring trials after January 2009 for the loans that are finally accepted in rating class 11. This evidence suggests that loan officers try much harder, by using more scoring trials, to move loans above the cut-off rating after the change. A similar pattern can be found in figure 2. Here we conduct the comparison based on the initial rating that a loan application receives. Here, loan applications with an initial rating between 1 and 11 do not exhibit different patterns before and after the change in the cut-off rating. In strict contrast, there are significantly more scoring trials for loan applications with an initial rating between 12 and 14 after the change, i.e. for those loan applications that fall just below the cut-off rating, but which the loan officer can potentially move above the cut-off rating with additional scoring trials. For the remaining rating classes 15 to 24, the number of scoring trials decreases after the change. These rating classes are now more remote from the cut-off rating so that the incentives for the loan officer to use more scoring trials are reduced.

We test the results in figure 2 more formally by running a t-test for the difference, and the results are reported in table 4. Consistent with the results from the figure, there are barely any differences in rating classes 1 to 11, in particular from an economic standpoint. The differences are positive and highly statistically and economically significant for rating classes 12 to 14, while they are negative and mostly significant for rating classes 15 to 24. In particular, a loan application with an initial rating of 12 has on average 0.83 more scoring trials after than before the change. We also observe a significant increase in the number of scoring trials at the cut-off boundary both before and after the change in the cut-off rating. Before the change, the number of scoring trials is 2.09 for the cut-off rating of 14 and it jumps to 3.23 for a rating of 15. After the change, the number of scoring trials increases from 1.93 at the cut-off rating of 11 to 2.76 for a rating of 12.

We repeat the previous analysis by considering for each rating class the likelihood of another scoring trial, instead of comparing the number of scoring trials as before. The results are reported in table 5, and they are consistent with those reported in table 4. The likelihood of another scoring trial jumps by more than 20 percentage points at the cut-off boundary, from 0.51 at the cut-off rating of 14 to 0.74 at a rating of 15 before the change and from 0.48 at the cut-off rating of 11 to 0.70 at a rating of 12 after the change. Also, the difference between the two periods is again positive and highly economically and statistically significant for the rating categories 12 to 14. We also observe again that the likelihood for another scoring trial for rating classes worse than 14 is significantly lower after the change. Again, these rating categories are now more remote from the cut-off rating which reduces the chances for the loan officer to push these loan applications above the cut-off rating.

A2. Multivariate results

We now estimate a multivariate model (Regression (1)) to control for other factors that may drive our results. These control factors comprise loan, customer and loan officer characteristics. In particular, we use a dummy to control for the effect of being a relationship customer, the logarithm of the customer's age, the logarithm of his income, and rating fixed effects to control for the creditworthiness of the customer. On the loan side, we control for the size of the loan, which can be regarded as a proxy for the fee potential, and for the number of borrowers. On the loan officer level, we control for the past average number of trials per loan application and the past absolute number of trials. Both measures are averaged over the previous three months and transformed on a log-scale. As a third control variable on the loan officer level, we use the prior 3-months success rate of the loan officer, measured as the ratio of successful loan applications, i.e. loan applications that are accepted by bank and customer, and total loan applications. All variables are explained in table 1. Finally, we add fixed effects for year, month-of-the-year, branch, and loan officer. Loan officers are assigned to exactly one branch so that loan officer fixed effects implicitly capture branch fixed effects as well. Using both branch and loan officer fixed effects thus results in perfect collinearity and we therefore either use branch fixed effects or loan officer fixed effects but not both at the same time. To account for possible autocorrelation at the branch level, we cluster standard errors accordingly.

We use a count variable (Number of scoring trials) as dependent variable. Both a Poisson regression and a negative binomial regression are well suited to cope with count data. The Poisson regression forces the conditional variance to be equal to the mean. A test for overdispersion yields a statistically significant positive overdispersion of 0.05, i.e. conditional variances are larger than means. We therefore use a negative binomial model which is well suited to cope with overdispersion. Finally, we control for a large number of fixed effects which may give rise to an incidental parameter problem (Neyman and Scott (1948)). Allison and Waterman (2002) argue based on simulations that there does not appear to be any incidental parameter bias in the negative binomial model.[1] We therefore present the results for a negative binomial model in the first place and provide estimates from a Poisson model and a linear model as robustness checks in section 5. We estimate the negative binomial model in the form of the more common NB2 model, i.e. the mean μ and the variance σ^2 are related by the overdispersion parameter *k* via $\sigma^2 = \mu + k\,\mu^2$ (Cameron and Trivedi (1998)).

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[1] Hausmann, Hall, and Griliches (1984) have proposed to use a conditional maximum likelihood estimate to circumvent the incidental parameter problem for a negative binomial model. However, Allison and Waterman (2002) have criticized this approach for not providing additional leverage compared to the Poisson model for dealing with overdispersion.

Table 6 shows a correlation analysis of the dependent variable (number of scoring trials) and the independent variables. The number of scoring trials is highly correlated with the cut-off-dummy (0.224), the internal rating (0.202) and the loan amount (0.163). These are also the three main variables which determine loan officer incentives. The number of trials is significantly negatively correlated with the relationship dummy, the age of the borrower, and the success rate of the loan officer, i.e. more scoring trials are used for new customers, for old customers, and by loan officers who have been less successful over the last three months. The variables log(3M average number of trials per loan application) and log(3M absolute number of trials) have the largest correlation (0.514) between all independent variables, i.e. loan officers who have used the scoring system frequently over the previous three months (in absolute numbers) also use the highest number of scoring trials per loan application.

Table 7 shows the results for regression (1). We start in column (1) by regressing the number of scoring trials on a dummy variable that takes a value of 1 if the initial rating is worse than the cut-off rating and a value of 0 if the initial rating is better or equal to the cut-off rating. A rating worse than the cut-off rating in the first scoring trial is associated with 0.480 more scoring trials, which is statistically significant at the 1 percent level. This coefficient is also economically highly significant given the unconditional number of trials of 1.83. Columns (2) and (3) add customer, loan and loan officer characteristics. The results for the cut-off-dummy remain economically and statistically highly significant in all specifications, ranging from 0.275 to

0.313. The loan amount is highly statistically and economically significant with a coefficient estimate between 0.157 and 0.164. An increase in the loan amount from the median loan amount of EUR 10,000 by one standard deviation (EUR 10,665) to EUR 20,665 therefore leads to an increase in the number of scoring trials by $\ln(20{,}665/10{,}000)\cdot 0.164=0.119$. The results here are consistent with the notion that loan officers move the ratings in particular for larger loans, as they receive a fee that is proportional to the loan amount. Finally, less scoring trials are used for relationship customers. For relationship customers, a much larger proportion of the internal rating is determined by parameters that the loan officer cannot manipulate such as the account activity. For these customers, the chances for a loan officer to push these loan applications above the cut-off rating by changing parameters that the loan officer can manipulate, such as income or assets, is much lower.

To make use of the full information; we further estimate regression (2) on the scoring trial level. We use the same control variables as in table 7. In addition, we control for duration dependence by introducing a control variable which captures the log of the current trial number of this particular loan application.

Our setup is similar to a survival analysis: We use set-up with a dummy-variable (*AddTry*) as dependent variable which is equal to 1 as long as we observe a subsequent scoring trial for the same loan application and 0 for the last scoring trial in each loan application. We therefore use a discrete hazard rate model to estimate regression (2). A natural candidate for the survival function is a logistic function which is bounded between 0 and 1 and therefore adequate for discrete data. However, standard logistic models suffer from the incidental parameter problem (Neyman and Scott (1984)), i.e. the structural parameters cannot be estimated consistently in large but narrow panels. There are two possible ways to circumvent the incidental parameter problem: First, a conditional logistic regression can be estimated (Chamberlain (1980), Wooldridge (2002)). This approach has the drawback that the estimator is no longer efficient (Andersen (1970)) but it yields consistent estimates of the structural parameters. Second, we can use a linear probability model which leads to both efficient and consistent estimates of the structural parameters. We follow Puri, Steffen, and Rocholl (2011) and use the latter approach to estimate regression (2). Results for the conditional logit model will be presented as a robustness check in in section 5.[2]

The results are reported in table 8 and they support the findings from table 7. The coefficient for the cut-off dummy in columns (2) to (6) ranges between 0.137 and 0.154, i.e. a scoring trial with a rating worse than the cut-off rating increases the likelihood of another scoring trial by 13.7-15.4 percentage points. This is statistically significant at the 1 percent level in all specifications and also economically highly significant, as it compares to the unconditional mean of 45% (cf. table 2). As in the negative binomial regression, the loan amount is also highly statistically and

[2] Computationally, the discrete hazard rate model we use is equivalent to a multi-period panel model with an adjusted standard-error structure (cf. Shumway (2001) and Duffie, Saita, and Wang (2007)) and it can therefore be easily estimated with standard panel methods.

economically significant, and the other coefficients have the same sign as in table 7. Also, being a relationship customer is still significantly negatively related to the likelihood of another scoring trial. We also observe a positive duration effect: The more trials have already been used for a loan application, the larger is the likelihood that another scoring trial is observed. This evidence suggests that the n-th information manipulation for a loan application does not seem to hurt as much as the 1st manipulation.

B. A closer review of multiple scoring trials

The analysis so far has centered on the number of scoring trials as an aggregate statistic for changes to customer information. Now we analyze in more detail the changes to customer information. In particular, we look at which parameters are actually changed during the loan application process.

Table 9 provides a difference-in-difference analysis for the internal rating and the main parameters which enter the calculation of the internal rating. We observe that the internal rating only slightly improves by 0.023 notches between the initial scoring trial and the last scoring trial for the subset of loan applications where the initial scoring trial already results in a rating better or equal to the cut-off rating. This increase is also only marginally significant. On the contrary, the internal rating improves by 0.608 notches for the subset of loans where the initial scoring trial results in a rating worse than the cut-off rating. This increase is significant at the 1 percent level. Looking at individual parameters which enter the calculation of the internal rating, we observe that changes are significant for the income score, which is rather easy to manipulate, but not for the socio-demographic score, the Schufa score, the account or loan score, all of which are less susceptible to manipulation. The income score changes on average by a marginal 0.0029 for the subset of loans where the first scoring trial results in a rating better or equal to the cut-off and by 0.188 for the subset of loans where the first scoring trials results in a rating worse than the cut-off rating. The Diff-in-Diff estimate is highly significant at the 1 percent level. A higher income score implies a better internal rating, thus the income score systematically improves between the initial and the last scoring trial and this improvement is significantly higher for loan applications that to not pass the cut-off rating in the initial scoring trial compared to loan applications that pass the cut-off rating in the initial scoring trial.[3] We further observe that the ratio "Assets/Liabilities", one of the key ratios that enters the calculation of the income score, is increased by 7.8% for loan applications where the initial rating is better or equal to the cut-off rating and by 16.9% for loan applications where the initial rating is worse than the cut-off rating. Again, the Diff-in-Diff estimate is statistically significant at the 1 percent level. The second key ratio, "(Income - Costs)/Liabilities", increases by 0.3% from the initial to the last scoring trial for loan applications where the initial rating is better or equal than the cut-off rating. The increase

[3] The probability of default is determined as $PD = 1 / (1+exp(\alpha + \Sigma s_i))$ where s_i denotes the individual scores. The constant term α cannot be split to the five scores, therefore the scores cannot be directly converted into a probability of default.

for the loan applications where the initial rating is worse than the cut-off rating is 2.0%, again with a highly significant Diff-in-Diff estimate.

C. Loan officer incentives and default rates

C1. Univariate results

The evidence from the previous analyses is consistent with two hypotheses: First, loan officers use several scoring trials as they correct misspecified data from a previous trial (information correction hypothesis). Second, loan officers strategically manipulate customer information in order to generate fee income (information manipulation hypothesis). The fact that scoring trials happen most frequently at the cut-off boundary can be seen as a first indication for the latter explanation. In this section, we make use of the default data to provide more direct evidence and to distinguish between these two hypotheses.

We compare the default rates for loans with more than two scoring trials to those for loans with two or less scoring trials, where the default rate of a loan is measured by using a time horizon of 12 months after the origination of the loan. The results are presented in table 10. They show that the default rate for loans with more than two trials is significantly higher than the default rate for loans with one or two trials. This pattern holds before and after the change in the cut-off rating. Before the change in the cut-off rating, the default rate for loans with more than two trials amounts to 3.33%, while the default rate for loans with two or less trials amounts to 2.16%. After the change in cut-off rating, the respective values are 3.67% and 2.28%. These differences are statistically significant at the 1 percent level.

We explore this pattern more by analyzing the respective differences in default rates for each of the rating classes before and after January 2009. If loan officers indeed manipulate information and use multiple scoring trials to generate more loans, then the difference in default rates between loans with more than two trials and loans with two or less trials should only exist just above the cut-off, where the loan officer can use multiple scoring trials to move a loan from below to above the cut-off. The results show that the difference in default rates is indeed statistically and economically significant only at the cut-off of 14 before January 2009 and 11 after January 2009, respectively. For the rating class 14 before January 2009, the default rate is 7.09% for loans with one or two trials, while it is 12.15% for loans with more than two trials. Similarly, for the rating class 11 after January 2009, the default rate is 7.83% for loans with one or two trials, and it is 10.11% for loans with more than two trials. These results provide further evidence that the use of several scoring trials is driven by loan officers' manipulation of information with the goal to generate more loans.

C2. Multivariate results

In the multivariate tests, we control again for customer, loan and loan officer characteristics, and the control variables are thus identical to the ones used in table 7. We estimate regression (4) using a linear probability model to address the incidental parameter problem.

Columns (1)-(3) in table 11 report a step-by-step development of our regression without control variables in column (1), with customer and loan characteristics in column (2) and with all control variables in column (3). Columns (4) to (6) add fixed effects for branch and loan officer and cluster standard errors by branch. The results show that the number of scoring trials predicts the default rate in all specifications with a coefficient between 0.3% and 0.4%. These coefficients are statistically significant throughout at the 1 percent level. The effect is also economically highly significant. Increasing the number of scoring trials from the median of 1 scoring trial by one standard deviation (1.63 scoring trials) to 2.63 scoring trial leads to an increase in the default rate of approximately 0.3-0.4%.[4] Compared to the unconditional default rate of 2.49% this is a relative increase in the default probability of 12-16%. We also observe that the experience of the loan officer (3-months absolute number of scoring trials) positively predicts the default rate. This suggests that experienced loan officers are more efficient at manipulating the internal rating in the desired direction and magnitude and therefore need fewer trials to achieve the desired result.

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[4] Increasing the number of scoring trials from 1.00 to 2.63 increases the log by *ln(2.63)=0.97*. Multiplying the coefficient of 0.3-0.4% by 0.97 yields the stated result.

We analyze further determinants for default rates in table 12. If a loan officer uses multiple scoring trials to manipulate information, then the time between the scoring trials should be negatively related to the default rates. In this case, the loan officer does not carefully check or verify the existing information, but simply plays with the input parameters to change the rating outcome. The results in column (1) show that shorter trials lead indeed to higher default rates and thus suggest that the loan officer does not give much care when revising the information. Furthermore, it should be much easier for the loan officer to change information on liabilities and costs rather than on assets and income to achieve the desired outcome. While adding assets and income would have to be proven by respective documents, reducing liabilities and costs could be achieved by simply ignoring certain positions. This link is tested in columns (2) to (4). The results in column (2) show that it is indeed the change in liabilities and costs that increases default rates, while the results in column (3) show that it is a reduction in both positions that increases default rates. Combing the results from column (1) and column (3), the results in column (4) show that a shorter time per trial as well as a reduction in costs and liabilities lead to higher default rates.

In sum, the results from the default regression provide evidence that loan officers systematically manipulate customer information for their own advantage. This results in a statistically and economically significant increase in the 12-month default rate, even after controlling for loan, customer and loan officer characteristics.

5. Robustness

In this section we provide robustness tests for the main results from section 4. In particular, we explore alternative models for estimating the number of scoring trials, the likelihood of another scoring trial, and the default rate.

A. Robustness: Number of scoring trials

In the previous section, we have estimated the regression for the number of scoring trials (regression (1)) with a negative binomial model. One remaining concern with the negative binomial model is its susceptibility to the incidental parameter problem. Previous researchers have argued based on simulation studies that the negative binomial model does not suffer from an incidental parameter problem. For the case of the Poisson model, consistency of the parameter estimates in the presence of a large number of fixed effects is analytically proven (Cameron and Trivedi (1998)). The Poisson model is not able to cope with overdispersion, however, the overdisperion of 0.05 in our case is economically small (although statistically significant). A linear model is able to cope with both overdispersion and does not suffer from an incidental parameter problem. In addition to the negative binomial model from section 4, we therefore provide robustness tests based on both a Poisson regression and a linear model.

The results are shown in Panel A of table 13. For brevity, we only report the coefficient and standard error of the cut-off dummy for the full specification which includes customer, loan and loan officer characteristics as well as time and loan officer fixed effects (i.e. specification as in column (6) of table 7). The coefficient of 0.288 in the first row of Panel A therefore corresponds to the first coefficient in column (6) in table 7. The use of different models results in very similar and highly statistically significant coefficients of 0.290 (Poisson model) and 0.226 (Linear model), respectively.

B. Robustness: Likelihood of another scoring trial

In the previous section, we have estimated the likelihood of another scoring trial (regression (2)) with a linear probability model. One concern with the linear model is that it does not suit the dummy-type nature of our dependent variable. We therefore estimate a conditional logit model as a robustness test. The conditional logit model is suited for a dependent dummy variable and yields consistent estimates even for a large number of fixed effects. The drawback of the conditional model is that it does not yield efficient estimates.

Panel B of table 13 presents the results of this robustness test. Again, the coefficient for the linear model repeats the results from specification (6) in table 8. Using a conditional logit model results in a highly stastically and economically significant coefficient as well. The magnitude of the marginal effect at the mean of 0.166 is similar to the results from the linear regression (0.151).

C. Robustness: Default rate

Based on the same arguments as in the previous subsection, we use a conditional logit regression as a robustness test for the default rate regression (4). Panel C of table 13 presents the results. Using a linear model results in a coefficient of 0.4% for the logarithm of the number of scoring trials (see also specification (6) in table 11). The conditional logit regression yields similar, but slightly smaller, marginal effects at the mean. In sum, the robustness tests confirm both the statistical and economic magnitude of the effect of scoring trials on the default rate.

6. Conclusion

The current financial crisis has raised an important question of how the loan making process shall be regulated to minimize risks and reduce default rates. In this context, it has often been suggested that excessive discretion and arbitrary judgment by the loan officer have resulted in poor loan performance. As a consequence, it has been advocated that the loan making process shall be automated and rely more or even exclusively on hard information.

This paper analyzes the loan making process in a system where loan decisions are based purely on hard information. In this system, there is a predefined cut-off rating which determines whether a loan application can be accepted or not. Based on a sample of more than 240,000 loan applications at a major European bank, we analyze how loan officer incentives are affected by the exclusive use of hard information. We show that loan officers use more scoring trials if the initial scoring trial is not successful. They increase the number of scoring trials in particular when the initial scoring trial is close to the predefined cut-off rating and even more at the boundary. We use a change in the cut-off rating during our sample period and find that this change moves the significant increase in scoring trials to the new cut-off ratings. This pattern is most pronounced for more experienced loan officers and for those loan officers who have been unsuccessful in attracting new loans in the months before. We find that the number of scoring trials is positively related to default rates, suggesting that loan officers strategically manipulate information in a system that is based on hard information and credit scoring alone.

Our results suggest that a pure reliance on hard information in the loan making process can lead to adverse outcomes and in particular a worse loan performance. These results have important implications for the current academic and regulatory debate on how to reform the loan making process to minimize risks.

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Figure 1: Accepted Loans

This figure compares the number of scoring trials for each loan that is accepted in each rating class for the periods before and after January 2009.

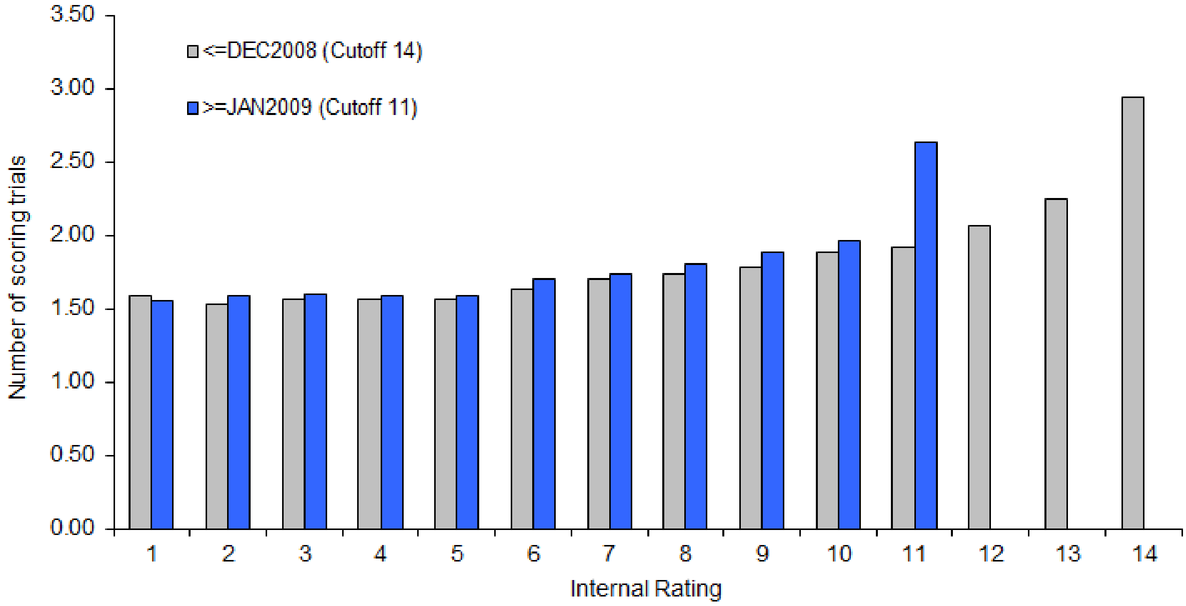

Figure 2: Loan applications

This figure compares the number of scoring trials for each loan application based on the initial rating class for the periods before and after January 2009.

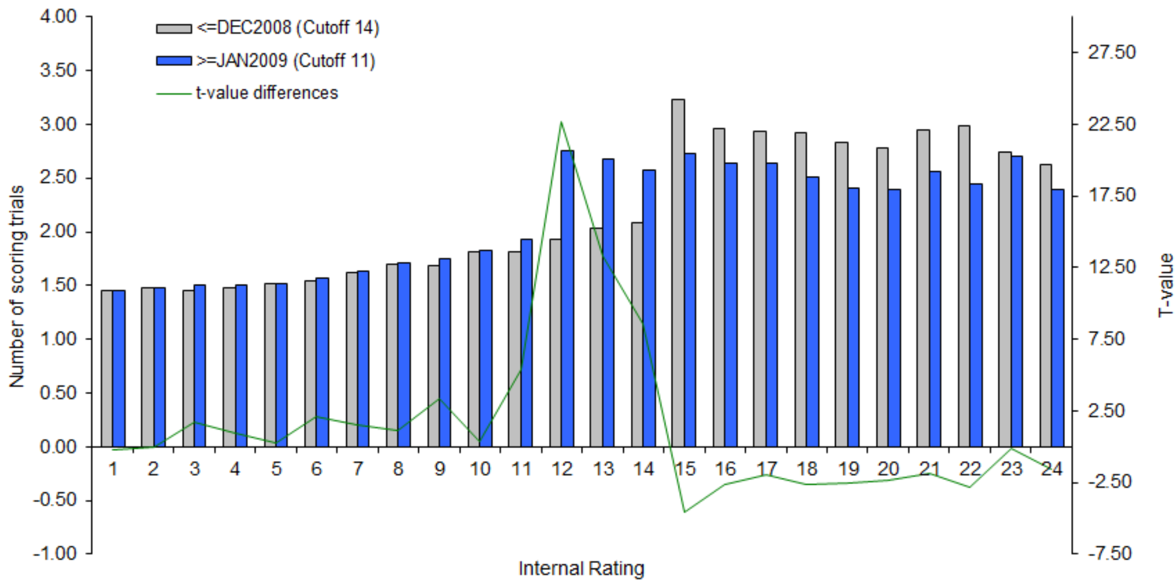

Table 1: Explanation of variables

Name	Description
Inference and dependent variables	
Cutoff	Dummy variable equal to one if the internal rating is worse than the cutoff rating and zero otherwise. Only loan applications with an internal rating equal or above the cutoff rating can be accepted, loan applications with ratings below the cutoff are rejected.
Number of scoring trials	Number of distinct scoring trials for a loan application.
Additional trial	Dummy variable equal to one if there exists another scoring trial for the same loan application, equal to zero for the last scoring trial for each loan application.
Default rate 12 months	Dummy variable equal to 1 if a loan has defaulted during the first 12 months after origination.
Customer characteristics	
Internal rating	Internal rating ranging from 1 (best) to 24 (worst). The internal rating is based on the income score, the socio-demographic score, the account score, the loan score and the SCHUFA score. These scores are consolidated into one overall score and calibrated to historical default experience. Each internal rating is associated with a default probability for the borrower.
Probability of default	Probability of default based on the internal rating system. The probability of default is calibrated to past default experience.
Income score	Internal score based on income, costs, assets, and liabilities of the borrower. A higher score implies a lower probability of default.
Socio-demographic score	Internal score based on socio-demographic data (e.g. age, sex, etc.). A higher score implies a lower probability of default.
Account score	Internal score based on the past account activity of the borrower. A higher score implies a lower probability of default.
Loan score	Internal score based on the history of past loans with the same borrower. A higher score implies a lower probability of default.
Schufa score	External score similar to the FICO score in the U.S. A higher score implies a lower probability of default.
Relationship customer	Dummy variable equal to 1 if the customer had a checking account or a current loan with the bank before the loan application.
Age	Age of borrower. If a loan application has several borrowers, the average age is used.
Assets	Total assets of the borrower in Euro. If a loan application has several borrowers, e.g., husband and wife, then the combined assets are used.
Liabilities	Total liabilities of the borrower in Euro. If a loan application has several borrowers, e.g., husband and wife, then the combined liabilities are used.
Income	Monthly net income of the borrower in Euro. If a loan application has several borrowers, e.g., husband and wife, then the combined income is used. The income includes wages as well as capital income and other income.
Costs	Monthly net costs of the borrower in Euro. If a loan application has several borrowers, e.g., husband and wife, then the combined costs are used. The costs include cost of living, rents and costs for existing loans.
Loan characteristics	
Loan amount	Loan amount in EUR.
Number of borrowers	Number of borrowers, usually equal to one.
Accepted by bank	Dummy variable equal to one if the loan application is accepted by the bank, i.e. an offer is made to the customer.
Accepted by bank and customer	Dummy variable equal to one if the loan application is accepted by the bank and the customer.
Loan officer characteristics	
3M average number of trials per loan application	The average number of trials per loan application over the previous three months, calculated on loan officer level.
3M absolute number of trials	The absolute number of scoring trials over the previous three months, calculated on loan officer level.
Success rate 3M	Success rate of the loan officer over the month preceding the current month. The success rate is measured as accepted loans divided by total loans. Accepted loans are loans which were accepted by the bank and the borrower, i.e. where a loan contract was signed. All loans is the number of distinct loan applications that a loan officer entered into the system.
Other variables	
Status	Status of a scoring trial. The status can be either 'automatically rejected' if the internal rating is worse than the cutoff rating, 'manually rejected' if the loan application is manually rejected by the loan officer and 'accepted' if the loan application is accepted by the bank and customer.
Trial number	The number of the current trial, e.g. '1' for the first scoring trial for each loan application, '2' for the second trial, etc.
Month-of-year	Month of year coded as 1 (January) through 12 (December)

Table 2: Descriptive statistics

This table presents summary statistics for the sample of loan applications between May 2008 and June 2010. Panel A presents summary statistics on the loan application level based on the last scoring trial for each loan application, Panel B on the scoring trial level and Panel C on the loan officer level. E.g. Panel A shows that 13% of the loan applications do not pass the cut-off rating based on the last scoring trial while Panel B shows that 20% do not pass the cut-off rating based on all scoring trials. For variable definitions see table 1.

	Unit	N	Mean	Stddev	Median	Min	Max
Panel A: Loan applications							
Inference and dependent variables							
Number of scoring trials		242,011	1.83	1.63	1.00	1.00	69.00
Cutoff	Dummy (0/1)	242,011	0.13	0.33	0.00	0.00	1.00
Default rate 12 months	Dummy (0/1)	116,969	0.025	0.156	0.00	0.00	0.00
Customer characteristics							
Internal Rating	Number (1=Best, 24=Worst)	242,011	8.40	3.99	8.00	1.00	24.00
Relationship customer	Dummy (0/1)	242,011	0.63	0.48	1.00	0.00	1.00
Age	Years	242,011	45.24	13.32	44.00	18.00	109.00
Net income per month	EUR	242,011	2,665	5,208	2,321	300	2,300,000
Loan characteristics							
Loan amount	EUR	242,011	13,700	10,665	10,000	2,000	50,000
Number of borrowers		242,011	1.34	0.47	1.00	1.00	2.00
Accepted by bank	Dummy (0/1)	242,011	0.70	0.46	1.00	0.00	1.00
Accepted by bank and customer	Dummy (0/1)	242,011	0.48	0.50	0.00	0.00	1.00
Panel B: Scoring Trials							
Inference and dependent variables							
Cutoff	Dummy (0/1)	442,255	0.20	0.40	0.00	0.00	1.00
Additional trial	Dummy (0/1)	442,255	0.45	0.50	0.00	0.00	1.00
Panel C: Loan officers							
Aggregate statistics							
Number of scoring trials		442,255	78.50	95.79	43.00	1.00	974.00
Number of distinct loan applications		242,011	42.96	47.80	25.00	1.00	390.00
Number of accepted loans		116,969	20.78	23.93	12.00	0.00	207.00
Success Rate 3M	%	242,011	45.85	22.01	47.53	0.00	100.00

Table 3: Example

This table presents the scoring trials for one single consumer loan originated on May, 04th, 2009. Changes in input parameters are highlighted in bold. For variable definitions see table 1.

Trial No.	Date	Internal rating	Cutoff	Loan amount	Assets	Liabilities	Income	Costs	Status
1	4 May 2009 4:03:24 PM	12	1	4,000	1,800	23,000	1,900	1,080	Automatically rejected
2	4 May 2009 4:14:28 PM	12	1	4,000	1,800	23,000	**1,950**	1,080	Automatically rejected
3	4 May 2009 4:15:00 PM	11	0	4,000	1,800	**10,000**	1,950	1,080	Manually rejected
4	4 May 2009 4:15:31 PM	12	1	4,000	1,800	**19,000**	1,950	1,080	Automatically rejected
5	4 May 2009 4:16:23 PM	11	0	4,000	1,800	**10,000**	1,950	1,080	Accepted

Table 4: Univariate results for the number of scoring trials

This table presents for each rating class the number of scoring trials before and after the change in the cutoff rating in January 2009. The rating class is based on the initial rating for each loan application. An internal rating of '1' is the best rating and an internal rating of '24' is the worst rating. In January 2009 the cutoff rating was changed from 14 to 11. Column A shows the number of scoring trials before January 2009, Column B shows the number of scoring trials after January 2009 and Column C provides a t-test for the difference. Standard errors are shown in parentheses. ***, **, * denotes significance at the 1, 5 and 10 percent level, respectively.

	(A) Before January 2009			(B) After January 2009			(C) Difference	
Internal rating	N	Mean	SE	N	Mean	SE	Mean	SE
1	4,382	1.456	(0.0144)	9,674	1.453	(0.0097)	-0.004	(0.0174)
2	1,325	1.479	(0.0258)	3,128	1.480	(0.0162)	0.000	(0.0305)
3	1,515	1.459	(0.0232)	3,674	1.507	(0.0162)	0.048*	(0.0283)
4	2,150	1.480	(0.0219)	5,221	1.504	(0.0136)	0.024	(0.0258)
5	3,699	1.516	(0.0164)	9,516	1.520	(0.0106)	0.004	(0.0195)
6	6,569	1.540	(0.0134)	18,275	1.573	(0.0083)	0.033**	(0.0157)
7	9,828	1.615	(0.0122)	25,969	1.637	(0.0073)	0.022	(0.0143)
8	7,299	1.692	(0.0159)	19,951	1.713	(0.0093)	0.021	(0.0185)
9	6,269	1.686	(0.0157)	17,144	1.749	(0.0102)	0.062***	(0.0188)
10	5,356	1.816	(0.0202)	13,567	1.824	(0.0121)	0.008	(0.0235)
11	6,803	1.809	(0.0177)	16,101	1.928	(0.0135)	0.119***	(0.0223)
12	4,280	1.927	(0.0248)	9,334	2.759	(0.0270)	0.832***	(0.0367)
13	2,790	2.035	(0.0330)	5,808	2.680	(0.0352)	0.645***	(0.0483)
14	2,143	2.088	(0.0416)	4,085	2.578	(0.0394)	0.490***	(0.0573)
15	1,471	3.231	(0.0969)	2,755	2.730	(0.0524)	-0.501***	(0.1102)
16	872	2.956	(0.1035)	1,683	2.636	(0.0670)	-0.321***	(0.1233)
17	630	2.932	(0.1162)	1,190	2.638	(0.0926)	-0.294**	(0.1486)
18	486	2.916	(0.1343)	889	2.506	(0.0798)	-0.410***	(0.1563)
19	386	2.832	(0.1357)	718	2.405	(0.0989)	-0.426**	(0.1679)
20	399	2.779	(0.1306)	590	2.393	(0.0970)	-0.386**	(0.1626)
21	335	2.946	(0.1710)	481	2.557	(0.1296)	-0.389*	(0.2146)
22	356	2.989	(0.1574)	520	2.448	(0.1142)	-0.541***	(0.1945)
23	402	2.736	(0.1317)	578	2.709	(0.1154)	-0.027	(0.1751)
24	585	2.627	(0.1141)	830	2.396	(0.0967)	-0.231	(0.1496)

Table 5: Univariate results for the likelihood of another scoring trial

This table presents for each rating class the likelihood of another scoring trial before and after the change in the cutoff rating in January 2009. The rating class is based on the contemporaneous rating class for each scoring trial. An internal rating of '1' is the best rating and an internal rating of '24' is the worst rating. In January 2009 the cutoff rating was changed from 14 to 11. Column A shows the likelihood of another scoring trial before January 2009, Column B shows the likelihood of another scoring trial after January 2009 and Column C provides a t-test for the difference. Standard errors are shown in parentheses. ***, **, * denotes significance at the 1, 5 and 10 percent level, respectively.

	(A) Before January 2009			(B) After January 2009			(C) Difference	
Internal rating	N	Mean	SE	N	Mean	SE	Mean	SE
1	6,527	0.309	(0.0068)	14,201	0.305	(0.0046)	-0.004	(0.0082)
2	1,972	0.323	(0.0117)	4,678	0.329	(0.0076)	0.007	(0.0140)
3	2,275	0.322	(0.0110)	5,544	0.335	(0.0071)	0.013	(0.0130)
4	3,208	0.319	(0.0093)	7,894	0.336	(0.0060)	0.017	(0.0111)
5	5,542	0.337	(0.0073)	14,427	0.336	(0.0045)	-0.001	(0.0086)
6	10,255	0.347	(0.0056)	29,227	0.360	(0.0033)	0.013**	(0.0065)
7	15,953	0.385	(0.0047)	42,856	0.392	(0.0028)	0.007	(0.0055)
8	12,200	0.406	(0.0054)	34,330	0.416	(0.0032)	0.011*	(0.0063)
9	10,631	0.411	(0.0058)	30,315	0.429	(0.0035)	0.017**	(0.0068)
10	9,460	0.444	(0.0063)	25,165	0.453	(0.0039)	0.009	(0.0074)
11	12,340	0.448	(0.0057)	36,468	0.479	(0.0034)	0.031***	(0.0067)
12	8,333	0.481	(0.0074)	25,329	0.698	(0.0039)	0.217***	(0.0084)
13	5,743	0.502	(0.0084)	13,791	0.615	(0.0053)	0.113***	(0.0099)
14	5,188	0.511	(0.0089)	9,608	0.601	(0.0064)	0.091***	(0.0109)
15	4,624	0.740	(0.0087)	6,820	0.659	(0.0078)	-0.081***	(0.0117)
16	2,481	0.701	(0.0118)	3,779	0.616	(0.0102)	-0.085***	(0.0156)
17	1,686	0.680	(0.0143)	2,675	0.603	(0.0119)	-0.077***	(0.0186)
18	1,257	0.674	(0.0166)	2,023	0.617	(0.0136)	-0.057***	(0.0215)
19	983	0.624	(0.0189)	1,541	0.576	(0.0154)	-0.047*	(0.0244)
20	1,033	0.677	(0.0184)	1,223	0.582	(0.0178)	-0.094***	(0.0256)
21	799	0.641	(0.0207)	1,008	0.589	(0.0189)	-0.052*	(0.0280)
22	917	0.678	(0.0194)	1,006	0.559	(0.0196)	-0.120***	(0.0276)
23	921	0.637	(0.0204)	1,201	0.622	(0.0180)	-0.015	(0.0272)
24	1,278	0.601	(0.0185)	1,540	0.542	(0.0172)	-0.059**	(0.0253)

Table 6: Correlations

This table presents the Pearson correlation coefficient between the dependent and independent variables. For variable definitions see table 1. The number of observations is 242,011. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

No.	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Number of scoring trials	1.000***	0.224***	-0.059***	-0.066***	0.036***	0.163***	0.024***	0.124***	0.084***	-0.031***	0.202***
(2)	Cutoff		1.000***	-0.076***	-0.180***	-0.030***	0.114***	0.015***	0.053***	0.081***	-0.056***	0.676***
(3)	Relationship Customer			1.000***	-0.002	-0.208***	-0.142***	-0.596***	-0.018***	-0.013***	0.000	-0.139***
(4)	Log(Age)				1.000***	0.194***	0.056***	0.146***	-0.038***	-0.055***	0.009***	-0.316***
(5)	Log(Income)					1.000***	0.426***	0.429***	-0.020***	-0.110***	-0.021***	-0.042***
(6)	Log(Loan amount)						1.000***	0.161***	0.008***	-0.024***	-0.005**	0.176***
(7)	Number of borrowers							1.000***	-0.017***	-0.026***	-0.001	0.025***
(8)	Log(3M average number of trials per loan)								1.000***	0.514***	-0.037***	0.054***
(9)	Log(3M absolute number of trials)									1.000***	-0.055***	0.074***
(10)	Success rate 3M										1.000***	-0.023***
(11)	Internal rating											1.000***

Table 7: Multivariate results for the number of scoring trials

We estimate the determinants for the number of scoring trials. The models are estimated using a negative binomial model. All incentive, customer, loan, and loan officer characteristics are based on the first scoring trial for each loan application. For variable definitions see table 1. Intercept, year, month-of-the-year, branch and loan officer fixed effects are not shown. Heteroscedasticity consistent standard errors are shown in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent	Number of Trials		Number of Trials		Number of Trials		Number of Trials		Number of Trials		Number of Trials	
Model	Negative Binomial		Negative Binomial		Negative Binomial		Negative Binomial		Negative Binomial		Negative Binomial	
INCENTIVE												
Cutoff	0.480***	(0.0040)	0.313***	(0.0093)	0.275***	(0.0099)	0.289***	(0.0104)	0.289***	(0.0142)	0.288***	(0.0104)
CUSTOMER												
Relationship Customer			-0.043***	(0.0041)	-0.040***	(0.0042)	-0.040***	(0.0043)	-0.040***	(0.0057)	-0.041***	(0.0043)
Log(Age)			-0.056***	(0.0058)	-0.051***	(0.0060)	-0.047***	(0.0061)	-0.047***	(0.0069)	-0.047***	(0.0061)
Log(Income)			-0.020***	(0.0045)	-0.014***	(0.0048)	-0.014***	(0.0049)	-0.014**	(0.0056)	-0.009*	(0.0051)
LOAN												
Log(Loan amount)			0.157***	(0.0024)	0.157***	(0.0024)	0.162***	(0.0025)	0.162***	(0.0031)	0.164***	(0.0025)
Number of borrowers			-0.016***	(0.0045)	-0.014***	(0.0046)	-0.009*	(0.0048)	-0.009	(0.0057)	-0.010**	(0.0048)
LOAN OFFICER												
Log (3M average number of trials per loan application)					0.271***	(0.0057)	0.158***	(0.0062)	0.158***	(0.0087)	-0.057***	(0.0073)
Log (3M absolute number of trials)					0.015***	(0.0021)	0.023***	(0.0025)	0.023***	(0.0033)	0.005*	(0.0033)
SuccessRate 3M					-0.066***	(0.0066)	-0.055***	(0.0073)	-0.055***	(0.0085)	-0.002	(0.0081)
Rating fixed effects	No		Yes		Yes		Yes		Yes		Yes	
Month-of-year fixed effects	No		Yes		Yes		Yes		Yes		Yes	
Year fixed effects	No		No		No		Yes		Yes		Yes	
Branch fixed effects	No		No		No		Yes		Yes		Implicit in loan officer FE	
Loan officer fixed effects	No		No		No		No		No		Yes	
SE clustered on branch level	No		No		No		No		Yes		Yes	
Diagnostics												
Adj. R^2	3.92%		6.27%		13.76%		15.13%		15.13%		17.40%	
N	242,011		242,011		226,757		226,757		226,757		226,757	

Table 8: Multivariate results for the likelihood of another scoring trial

We estimate the likelihood of another scoring trial. The models are estimated using a linear probability model. For variable definitions see table 1. Intercept, year, month-of-the-year, branch and loan officer fixed effects are not shown. Heteroscedasticity consistent standard errors are shown in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent	Prob (AddTry)		Prob (AddTry)		Prob (AddTry)		Prob (AddTry)		Prob (AddTry)		Prob (AddTry)	
Model	Linear		Linear		Linear		Linear		Linear		Linear	
INCENTIVE												
Cutoff	0.246***	(0.0024)	0.154***	(0.0057)	0.137***	(0.0061)	0.146***	(0.0064)	0.146***	(0.0073)	0.151***	(0.0073)
CUSTOMER												
Relationship Customer			-0.014***	(0.0025)	-0.012***	(0.0026)	-0.013***	(0.0026)	-0.013***	(0.0029)	-0.013***	(0.0029)
Log(Age)			-0.029***	(0.0035)	-0.027***	(0.0036)	-0.026***	(0.0037)	-0.026***	(0.0042)	-0.026***	(0.0042)
Log(Income)			-0.011***	(0.0027)	-0.008***	(0.0029)	-0.008**	(0.003)	-0.008**	(0.0033)	-0.004	(0.0033)
LOAN												
Log(Loan amount)			0.089***	(0.0014)	0.088***	(0.0014)	0.091***	(0.0014)	0.091***	(0.0017)	0.093***	(0.0017)
Number of borrowers			-0.004	(0.0027)	-0.003	(0.0028)	-0.001	(0.0029)	-0.001	(0.0031)	-0.003	(0.003)
Log(Trial number)			0.090***	(0.0015)	0.078***	(0.0016)	0.066***	(0.0016)	0.066***	(0.0021)	0.046***	(0.0022)
LOAN OFFICER												
Log (3M average number of trials per loan application)					0.121***	(0.0036)	0.072***	(0.0038)	0.072***	(0.0047)	-0.026***	(0.0048)
Log (3M absolute number of trials)					0.004***	(0.0013)	0.008***	(0.0015)	0.008***	(0.0019)	0.000	(0.0023)
SuccessRate 3M					-0.034***	(0.0040)	-0.027***	(0.0045)	-0.027***	(0.0052)	-0.001	(0.0053)
Rating fixed effects	No		Yes		Yes		Yes		Yes		Yes	
Month-of-year fixed effects	No		Yes		Yes		Yes		Yes		Yes	
Year fixed effects	No		No		No		Yes		Yes		Yes	
Branch fixed effects	No		No		No		Yes		Yes		Implicit in loan officer FE	
Loan officer fixed effects	No		No		No		No		No		Yes	
SE clustered on branch level	No		No		No		No		Yes		Yes	
Adjusted SE structure	Yes		Yes		Yes		Yes		Yes		Yes	
Diagnostics												
Adj. R^2	3.89%		49.72%		50.29%		50.88%		50.88%		51.92%	
N	442,255		442,255		416,942		416,942		416,942		416,942	

Table 9: Difference-in-difference analysis for the changes from the first scoring trial to the last scoring trial

We estimate the changes in parameters between the first and the last scoring trial. Column (A) shows the results for all loan applications in which the first scoring trial results in a rating better or equal than the cut-off rating. Column (B) shows the results for all loan applications in which the first scoring trial results in a rating worse than the cut-off rating. Column (C) shows the difference-in-difference estimate. The variables "Assets / Liabilities" and "(Income-Costs)/Liabilities" are the two main ratios which determine the income score. For variable definitions see table 1. We report p-values of the difference and difference-in-difference estimates in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

		(A) Cutoff = 0			(B) Cutoff = 1			(C) Diff-in-Diff
Parameter	Unit	First Trial	Last Trial	Difference (p-value)	First Trial	Last Trial	Difference (p-value)	Diff-in-Diff (p-value)
Probability of default	%	0.481	0.482	0.001	5.398	4.790	-0.608	-0.609
				(0.6161)			(0.0000)	(0.0000)
Internal rating	Number (1 to 24)	7.362	7.339	-0.023**	15.214	14.584	-0.630***	-0.607***
				(0.0119)			(0.0000)	(0.0000)
Cutoff	Dummy (0/1)	0.000	0.004	0.004***	1.000	0.842	-0.158***	-0.162***
				(0.0000)			(0.0000)	(0.0000)
Income score		4.334	4.363	0.029***	3.620	3.807	0.188***	0.158***
				(0.0000)			(0.0000)	(0.0000)
Socio-demographic score		4.797	4.798	0.001	4.277	4.284	0.007*	0.006
				(0.7518)			(0.0565)	(0.1379)
Schufa score		4.794	4.794	0.000	3.824	3.831	0.007	0.007
				(0.9558)			(0.3111)	(0.3259)
Account score		5.198	5.194	-0.005	3.507	3.513	0.006	0.011
				(0.3652)			(0.5086)	(0.3085)
Loan score		4.109	4.108	-0.001	3.503	3.508	0.005	0.005
				(0.757)			(0.7577)	(0.7252)
Assets / Liabilities	%	184.852	192.605	7.753***	41.473	58.378	16.905***	9.151***
				(0.0009)			(0.0000)	(0.0035)
(Income – Costs) / Liabilities	%	11.881	12.224	0.342*	7.950	9.914	1.964***	1.621***
				(0.0883)			(0.0000)	(0.0000)

Table 10: Default rates by rating class and number of scoring trials

This table presents default rates by rating class and by number of scoring trials before and after the change in the cutoff rating in January 2009. The rating class is based on the final rating for each loan. An internal rating of '1' is the best rating, an internal rating of '14' is the worst rating for which loans could be accepted before January 2009, an internal rating of '11' is the worst rating for which loans could be accepted after January 2009. Column A shows the default rates before January 2009, Column B shows the default rates after January 2009. Column (A1) and (B1) show the default rates for loans with one or two scoring trials, Column (A2) and (B2) show the default rates for loans with more than two scoring trials, columns (A3) and (B3) show the difference between the default rate of loans with one or two and more than two scoring trials and columns (A4) and (B4) provide the respective p-values based on an exact Fisher test. For brevity, the number of observations is not shown. ***, **, * denotes significance at the 1, 5 and 10 percent level, respectively.

	(A) Before January 2009				(B) After January 2009			
	(A1)	(A2)	(A3)	(A4)	(B1)	(B2)	(B3)	(B4)
Internal Rating (from last scoring trial)	Loans with ≤ 2 trials	Loans with > 2 scoring trial	Difference	p-value	Loans with ≤ 2 trials	Loans with > 2 scoring trial	Difference	p-value
1	0.088%	0.336%	0.248%	0.3083	0.195%	0.000%	-0.195%	0.6076
2	0.147%	0.000%	-0.147%	1.0000	0.144%	0.930%	0.786%*	0.0891
3	0.246%	0.000%	-0.246%	1.0000	0.509%	0.402%	-0.107%	1.0000
4	0.254%	0.575%	0.321%	0.4230	0.300%	0.542%	0.242%	0.3531
5	0.445%	0.365%	-0.080%	1.0000	0.813%	0.153%	-0.660%*	0.0798
6	0.742%	0.509%	-0.233%	0.7910	0.609%	0.680%	0.071%	0.7296
7	1.174%	0.530%	-0.645%*	0.0857	1.522%	1.185%	-0.337%	0.2510
8	1.297%	0.931%	-0.366%	0.4752	1.954%	1.729%	-0.225%	0.5830
9	1.961%	2.507%	0.546%	0.3836	2.769%	2.602%	-0.167%	0.7516
10	2.731%	2.370%	-0.360%	0.6879	3.910%	4.311%	0.401%	0.4735
11	4.745%	5.828%	1.083%	0.2166	7.829%	10.113%	2.285%***	0.0001
12	5.201%	5.687%	0.486%	0.6117				
13	7.759%	6.349%	-1.409%	0.3644				
14	7.091%	12.148%	5.057%***	0.0011				
All	2.159%	3.325%	1.166%***	0.0000	2.277%	3.672%	1.394%***	0.0000

Table 11: Multivariate results for the default rate

We estimate the probability of default over the first 12 months after origination. The models are estimated using a linear probability model. For variable definitions see table 1. Intercept, year, month-of-the-year, branch and loan officer fixed effects are not shown. Heteroscedasticity consistent standard errors are shown in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent	Default rate 12months		Default rate 12months		Default rate 12months		Default rate 12months		Default rate 12months		Default rate 12months	
Model	Linear		Linear		Linear		Linear		Linear		Linear	
INCENTIVE												
Log(Number of trials)	0.011***	(0.0010)	0.004***	(0.0010)	0.003***	(0.0010)	0.004***	(0.0010)	0.004***	(0.0011)	0.004***	(0.0012)
CUSTOMER												
Relationship Customer			-0.040***	(0.0017)	-0.040***	(0.0018)	-0.035***	(0.0017)	-0.035***	(0.0030)	-0.032***	(0.0027)
Log(Age)			-0.020***	(0.0018)	-0.019***	(0.0018)	-0.018***	(0.0019)	-0.018***	(0.0023)	-0.018***	(0.0023)
Log(Income)			-0.011***	(0.0014)	-0.009***	(0.0014)	-0.011***	(0.0015)	-0.011***	(0.0018)	-0.013***	(0.0019)
LOAN												
Log(Loan amount)			0.005***	(0.0008)	0.005***	(0.0008)	0.004***	(0.0008)	0.004***	(0.0012)	0.003***	(0.0011)
Number of borrowers			-0.040***	(0.0016)	-0.041***	(0.0017)	-0.035***	(0.0017)	-0.035***	(0.0028)	-0.032***	(0.0027)
LOAN OFFICER												
Log (3M average number of trials per loan application)					-0.001	(0.0017)	-0.001	(0.0017)	-0.001	(0.0021)	-0.004*	(0.0022)
Log (3M absolute number of trials)					0.007***	(0.0007)	0.004***	(0.0007)	0.004***	(0.0011)	0.006***	(0.0011)
SuccessRate 3M					0.001	(0.0019)	0.001	(0.0019)	0.001	(0.0023)	0.001	(0.0024)
Rating fixed effects	No		Yes		Yes		Yes		Yes		Yes	
Month-of-year fixed effects	No		Yes		Yes		Yes		Yes		Yes	
Year fixed effects	No		No		No		Yes		Yes		Yes	
Branch fixed effects	No		No		No		Yes		Yes		Implicit in loan officer FE	
Loan officer fixed effects	No		No		No		No		No		Yes	
SE clustered on branch level	No		No		No		No		Yes		Yes	
Diagnostics												
Adj. R^2	0.17%		4.06%		4.25%		6.95%		6.95%		11.46%	
N	116,969		116,969		109,787		109,787		109,787		109,787	

Table 12: Multivariate results for the default rate: Time per trial and changes to input parameters

We estimate the probability of default over the first 12 months after origination. The models are estimated using a linear probability model. *Log(Time per Trial)* denotes the time from the first to the last scoring trial (measured in hours) divided by the number of scoring trials minus 1. This item is therefore only available for loan applications with more than one scoring trial. *Δ(logAssets)* [*Δ(logLiabilities), Δ(logIncome), Δ(logCosts)*] denotes the logarithm of the assets [liabilities, income, costs] from the final scoring trial minus the logarithm of the assets [liabilities, income, costs] from the initial scoring trial. *Δ(logAssets)*>0 denotes max(*Δ(logAssets), 0), Δ(logAssets)*<0 denotes min(*Δ(logAssets), 0),* the same notation applies to liabilities, income and costs. For the remaining variable definitions see table 1. Intercept, year, month-of-the-year, branch and loan officer fixed effects are not shown. Heteroscedasticity consistent standard errors are shown in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default rate 12 months		Default rate 12 months		Default rate 12 months		Default rate 12 months	
Model	Linear		Linear		Linear		Linear	
INCENTIVE								
Log(Number of trials)	0.010***	(0.0027)	0.004***	(0.0012)	0.004***	(0.0013)	0.010***	(0.0027)
Log(Time per trial)	-0.0008***	(0.0003)					-0.0009***	(0.0002)
Δ(logAssets)			0.000	(0.0007)				
Δ(logAssets)<0					0.007	(0.0114)	0.003	(0.0119)
Δ(logAssets)>0					0.001	(0.0008)	0.000	(0.0008)
Δ(logLiabilities)			-0.002***	(0.0005)				
Δ(logLiabilities)<0					-0.002***	(0.0006)	-0.002***	(0.0006)
Δ(logLiabilities)>0					0.000	(0.0011)	0.000	(0.0012)
Δ(logIncome)			-0.027	(0.0205)				
Δ(logIncome)<0					-0.038	(0.0323)	-0.063*	(0.0351)
Δ(logIncome)>0					-0.017	(0.0279)	-0.006	(0.0291)
Δ(logCosts)			-0.015**	(0.0063)				
Δ(logCosts)<0					-0.023***	(0.0079)	-0.024***	(0.0084)
Δ(logCosts)>0					0.004	(0.0123)	0.004	(0.0131)
CUSTOMER								
Relationship Customer	-0.035***	(0.0037)	-0.032***	(0.0027)	-0.032***	(0.0027)	-0.035***	(0.0037)
Log(Age)	-0.023***	(0.0036)	-0.018***	(0.0023)	-0.018***	(0.0023)	-0.023***	(0.0036)
Log(Income)	-0.017***	(0.0029)	-0.013***	(0.0019)	-0.013***	(0.0019)	-0.017***	(0.0029)
LOAN								
Log(Loan amount)	0.003*	(0.0017)	0.003***	(0.0011)	0.003***	(0.0011)	0.003**	(0.0017)
Number of borrowers	-0.034***	(0.0037)	-0.032***	(0.0026)	-0.032***	(0.0026)	-0.034***	(0.0037)
LOAN OFFICER								
Log (3M average number of trials per loan application)	-0.006	(0.0037)	-0.004**	(0.0022)	-0.004**	(0.0022)	-0.006	(0.0037)
Log (3M absolute number of trials)	0.008***	(0.0018)	0.006***	(0.0011)	0.006***	(0.0011)	0.008***	(0.0018)
SuccessRate 3M	-0.006	(0.0040)	0.001	(0.0024)	0.001	(0.0024)	-0.005	(0.0040)
Rating fixed effects	Yes		Yes		Yes		Yes	
Month-of-year fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Branch fixed effects	Implicit in loan officer FE		Implicit in loan officer FE		Implicit in loan officer FE		Implicit in loan officer FE	
Loan officer fixed effects	Yes		Yes		Yes		Yes	
SE clustered on branch level	Yes		Yes		Yes		Yes	
Diagnostics								
Adj. R^2	16.55%		11.48%		11.49%		16.61%	
N	45,527		109,787		109,787		45,527	

Table 13: Robustness tests

This table presents robustness tests for the multivariate analyses from table 7, table 8, and table 11. Panel A shows a robustness test for the number of scoring trials using a Poisson and a linear model in addition to the negative binomial model presented in table 7. Panel B shows a robustness test for the likelihood of another scoring trial using a conditional logistic regression in addition to the linear probability model presented in table 8. Panel C shows a robustness test for the default rate using a conditional logistic regression in addition to the linear probability model presented in table 11. Only the coefficient for the cutoff dummy are shown in Panel A and B. Only the coefficient for the logarithm of the number of scoring trials is shown in Panel C. All coefficients are from a multivariate specification of the respective model including all customer, loan, and loan officer characteristics and year, month-of-the-year, and loan officer fixed effects. For the conditional logistic model in Panel B and C we report marginal effects to facilitate comparison of the coefficient to the linear model. Heteroscedasticity consistent standard errors are shown in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

Method	Parameter	Coefficient	SE
Panel A: Number of scoring trials			
Negative Binomial	Cutoff	0.288***	(0.0104)
Poisson	Cutoff	0.290***	(0.0100)
Linear	Cutoff	0.226***	(0.0105)
Panel B: Likelihood of another scoring trial			
Linear	Cutoff	0.151***	(0.0073)
Conditional Logistic	Cutoff	0.166***	(0.0084)
Panel C: Default rate			
Linear	Log(Number of trials)	0.004***	(0.0012)
Conditional Logistic	Log(Number of trials)	0.003***	(0.0008)