Loan officer incentives and the limits of hard information

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Abstract

Poor loan quality is often attributed to loan officers exercising poor judgment. A potential solution is to base loans on hard information alone. However, we find other consequences of bypassing discretion stemming from loan officer incentives and limits of hard information verifiability. Using unique data where loans are based on hard information, and loan officers are volume-incentivized, we find loan officers increasingly use multiple trials to move loans over the cut-off, both in a regression-discontinuity design and when the cut-off changes. Additional trials positively predict default suggesting strategic manipulation of information even when loans are based on hard information alone.

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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 designed 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? While the common wisdom is that basing loans on hard information makes the loan making process "objective" and does away with cronyism and other dark aspects of discretion, are there unintended consequences of taking judgment out of loan-making?

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, where officers are incentivized by loan volume, by accessing a unique data set from a major European bank. This bank uses only hard information. This information is collected and inputted into the system by loan officers. With this data we are able to address the following research questions. Do loan officers strategically manipulate hard information? Does this change the kind of loans that are made? If so, does this result in better or lower quality loans; in particular, what are the implications for 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 data is unique with some distinct features particularly suited to address the questions at hand. An important feature is that, here, 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. If the decision comes up as reject, the loan officer cannot override the decision or add soft information. However the loan officer can alter or update the information and do another scoring trial which will bring up a new decision. We are able to see how many times the loan officer does a scoring trial and also what kind of information is added 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 conduct two kinds of analysis. First, we take advantage of an exogenous change in the cut-off to see if loan officer behavior (number of scoring trials) around the cut-off changes when the cut-off is changed. Second, we run a regression discontinuity analysis in both regimes with different cut-offs to see if loan officer behavior of attempting more scoring trials changes at the cut-off.

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, then 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.

This evidence raises the important question of why additional scoring trials are conducted. Three hypotheses come to mind. First, the loan officer could manipulate the input data to get the loan over the cut-off with the purpose of receiving a higher bonus and a better recognition within the bank (information manipulation hypothesis). A second and more benign hypothesis is that the loan officer is aware of soft information on the loan applicant that cannot be recorded directly in the system, but which the loan officer incorporates by changing the recorded hard information (soft information hypothesis). Third, loan officers might not input data into the system in the initial scoring trial that would be too time-consuming to correctly collect. In this case, loans with just one scoring trial might underestimate the true creditworthiness while loans with several scoring trials correctly reflect the additional hard-to-collect information (closer examination hypothesis).

To assess these three hypotheses, we examine default rates. Our results support the information manipulation hypothesis. In particular, we find that the number of scoring trials positively predicts default rates. A one standard deviation increase 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 conduct three more tests to provide further evidence.

First, we regress default rates on the time a loan officer uses for each scoring trial. We find that default rates are negatively related to the time a loan officer uses for each scoring trial, and higher default rates are in particular driven by very short scoring trials that take less than half a minute to complete. These results are consistent with the information manipulation hypotheses rather than the other hypotheses.

Second, we find that default rates are positively related to a reduction in costs and liabilities. If the reduction in costs and liabilities was coming from more accurate new information default rates should not be higher with these changes. This finding is also in line with the information manipulation hypothesis. Note that manipulation of costs and liabilities implies leaving away information, which is much harder to detect than manipulation of existing information.

Finally, we analyze loan interest rates. Loan pricing is primarily a function of the credit rating. We compute the net margins for loans with multiple scoring trials given that they have higher default rates. We find that that interest margins for such loans are barely sufficient to cover the realized loan losses. Once operational and other costs are taken into account, these loans are likely negative net present value for the bank.

Our results suggest that when loan decisions are made based on hard information and credit scoring alone, loan officers' incentives can cause strategic manipulation of information. These changes in hard information are often very subtle, making it almost impossible to verify or detect manipulation. In principle, numbers like costs and liabilities are hard information because they are not judgement driven, and – in contrast to soft information – the bank can review the loan application data and penalize any wrong inputs. However, we show that loan officers can get away with manipulation of such hard information. Loan officers can strategically manipulate information such as costs and liabilities by omitting certain documents instead of manipulating existing documents. The cost of verifying such omissions is large.

Our paper relates to different strands of the literature. First, we contribute to the literature on agency problems within banks. 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. Agarwal and Ben-David (2012) analyze incentive schemes within a bank. Cole, Kanz and Klapper (2012) use a laboratory experiment with loan officers in India to analyze the effects of different incentive schemes on loan officer effort. We show that – in the presence of internal agency problems – loan officers manipulate hard information whenever truthful reporting is incompatible with their personal incentives. Second, our paper relates to the literature that identifies hard information as a potential solution for internal agency problems. Stein (2002) argues that the potential for agency conflict between the bank and its loan officers is a function of how much soft information the agent has or can produce hence this could lead to large, centralized banks relying on hard information to reduce loan officer agency problems.[1] Consistently, Berger, Miller, Petersen, Rajan, and Stein (2005) find that large banks are less willing to engage in informationally difficult loans for which soft information is more important. Similarly, Liberti and Mian (2009) and Agarwal and Hauswald (2010) find borrower proximity is related to the use of soft information.

We provide evidence that simply codifying the lending process to remove soft information from the lending equation does not resolve agency problems.. Rather, contrary to conventional wisdom, agency conflicts between a bank and its employees can arise even in a lending process that does not rely on soft information. Our evidence suggests the limits of hard information in resolving agency problems – even hard information is subject to manipulation by delegated monitors at the margin.

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.

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[1] This is also the approach taken in Heider and Inderst (2012) who develop an optimal contracting model in a setting where loan officers are incentivized on loan screening and prospecting. Paravisini and Schoar (2013) present a countervailing view where summaries of complex hard information can enhance loan officer monitoring.

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 a financial 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 pressure to perform well. Each week, or even during each week, 'run lists' are compiled to rank each individual loan officer. We collectively refer to both monetary and non-monetary incentives as loan officer incentives and analyze how these incentives affect loan officer behavior in a hard information environment.

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. So while loan officer compensation and bonus criteria do not vary over time, the change of the cut-off provides different incentives to manipulate client data. It is this variation that we aim to analyze in this paper.

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

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.

An analysis which would have been natural in the absence of the change in the cut-off is regression discontinuity. We therefore also estimate the following regression discontinuity regression for each time period (before cut-off change, after cut-off change) separately:

$$NumberOfTrials_{i,j,t} = \beta_1\ CutOffDummy_{i,t} + f(DifferenceToCutOff) + g(DifferencToCutOff)^*\ CutOffDummy + \delta\ X_{i,j,t} + A_j + B_t + \varepsilon_{i,j,t} \quad , \qquad (2)$$

where *DifferenceToCutOff* is the re-centered running variable, i.e. the internal rating less the cut-off rating, and the function f and g are higher-order polynomials of this re-centered running variable. Effectively, the regression above fits higher-order polynomials on the left- and right-hand side of the cut-off, with the coefficient β_1 denoting the jump in the number of scoring trials at the cut-off.

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 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:

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

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 that 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 that 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 manipulating information they have about the customer in order to increase their income (information manipulation hypothesis), loan officers inputting wrong hard information for customers where they have positive soft information (soft information hypothesis), or loan officers honestly correcting a false entry from a former trial (closer examination hypothesis). To distinguish between these three hypotheses, we estimate the effect of multiple scoring trials on the default rate. If the information manipulation hypotheses is true we should not see a positive systematic effect of the number of scoring trials on default rates. If the other two hypotheses are true there should be no effect or even a negative effect. We therefore estimate the following regression:

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

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 are 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**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** 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**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.

Consistent with the descriptive difference-in-difference results, we 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.

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.[2] 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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[2] 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 5 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 48 percent more scoring trials, which is statistically significant at the 1 percent level. 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 (i.e. an increase of 27.5-31.3 percent). 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)·0.164=11.9 percent. 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.

Regression discontinuity

In the analysis above we took advantage of an exogenous change in the cut-off rating to identify the causal effect of loan officer incentives on the number of scoring trials. An analysis that would have been natural in the absence of such a change is regression discontinuity. The basic idea of regression discontinuity is to fit a regression function on both the left-hand side and the right-hand side of the cut-off and compare the predicted values of these two regression functions at the cut-off point (Thistlewaite and Campbell (1960), Imbens and Lemieux (2008), Keys, Mukherjee, Seru, and Vig (2010), and Roberts and Whited (2011)). If the predicted value at the cut-off using data from the right-hand side differs significantly from the predicted value at the cut-off using data from the left-hand side, this can be attributed to the different incentives prevalent on either side of the cut-off. An underlying assumption is that ratings just below and just above the cut-off are comparable. We therefore plot our set of covariates as a function of the initial rating (Figure 3). We observe that none of the control variables shows any discontinuity at the cut-off, supporting our argument that the increase in the number of scoring trials is driven by the cut-off boundary. Formal techniques used in the literature differ in the regression function (polynomial model or local linear regression), assumptions about the distribution of error terms (negative binomial or permutation tests). Furthermore, covariates can be used to control for possible discontinuities in any of the explanatory variables. We use all these models (polynomial and local linear regression, distribution of error terms based on the negative binomial model and based on permutation tests, with and without covariates) both before and after the change in the cut-off rating. In all cases, we find a significant jump in the number of scoring trials at the cut-off rating. The estimate of the jump at the cut-off rating ranges from 0.251 to 0.357 (see Panel I of Table 6) which is very close to the estimate of 0.288 from the standard negative binomial model presented in Table 5.

The regression discontinuity approach relies on a no-manipulation assumption of the running variable, i.e. the initial rating. Economically, this is not an issue here, as the loan officers do not know that individual scoring trials are recorded. Hence, there is no reason to manipulate the initial scoring trial.

Nonetheless, we conduct a formal statistical test developed by McCrary (2008) which tests for a discontinuity in the density of the running variable at the cut-off point. Indeed, we do not find any evidence for a discontinuity in the density of the internal rating at the cut-off point (Figure 4 and Panel II of Table 6).

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 7 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 financial 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 financial 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 trial 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 financial score implies a better internal rating, thus the financial score systematically improves between the initial and the last scoring trial and this improvement is significantly higher for loan applications that do 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 financial 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 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

C1.1 Univariate results

The evidence from the previous analyses is consistent with three hypotheses: First, loan officers strategically manipulate customer information in order to get loans through (information manipulation hypothesis). Second, loan officers enter wrong hard information for customers to reflect positive soft information that they have (soft information hypothesis). Third, loan officers use several scoring trials as they correct misspecified data from a previous trial (closer

[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.

examination hypothesis). In this section, we make use of the default data to provide more direct evidence and to distinguish between these hypotheses. While the first hypothesis predicts higher default rates for loans with many scoring trials, the latter two hypotheses predict similar or even lower default rates for loans with few and loans with many scoring trials.

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 8. 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. We further explore these results using a difference-in-difference setting by comparing the difference in default rates for the rating class just below the cut-off rating to the difference in default rates for the rating class one and two notches above the cut-off rating. This estimate is highly significant both before and after January 2009.[4] For example, before January 2009, the default rate for loans with a rating of 14 with more than two scoring trials is 5.06% higher than the default rate for loans with two and less trials (12.15% versus 7.09%). This difference is only 0.486% for a rating of 12 and the difference-in-difference estimate of 4.57% is significant at the 1% level. Similar, after January 2009, the difference between loans with more than two scoring trials and loans with two and less scoring trials is 2.29% for a rating of 11. It is -0.17% for a rating of 9, with the difference-in-difference estimate of 2.45% again being significant at the 1% level.[5] 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.

C1.2 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 5. We estimate regression (4) using a linear probability model to address the incidental parameter problem.[6]

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[4] These results are available upon request.

[5] The detailed results for the difference-in-difference estimates are available upon request.

[6] 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

Columns (1)-(3) in Table 9 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%.[7] 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.

We also regress the default rate on both the initial rating and the change in the rating between the initial and the final scoring trial. If the additional information that is added between the initial and the final scoring trial was informative, we would expect the change in the rating to predict default rates,

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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 (4). Results for the conditional logit model are presented as a robustness check in in section 5.

[7] 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.

beyond the information in the initial ratings. However, consistent with the manipulation hypothesis, we find it is the initial rating, rather than the change in rating that is informative.[8]

We analyze further determinants for default rates in Table 10. 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. If, however, multiple scoring trials are due to the closer examination of information or information verification from the first trial, we would expect the opposite result. 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. Combining 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-

[8] These results are available upon request.

month default rate, even after controlling for loan, customer and loan officer characteristics.

D. Loan officer incentives and net present values of loans

A question that arises from the previous analysis is whether the bank willingly allows multiple scoring trials because they might result in positive NPV loans. We do some analysis to assess this. Loan pricing is primarily a function of the credit rating. Table 11 depicts the median gross margins – the loan interest rate less the refinancing costs (5-year risk-free rate plus 5-year CDS spread) of the bank – per rating grade before and after the cut-off change for loans with one or two scoring trials and for loans with more than two scoring trials (columns A1 and B1). In columns A2 and A3 (before the cut-off change) as well as B2 and B3 (after the cut-off change), we show the net margin, i.e. the margin adjusted for loan losses but before operational costs and cost of capital.[9] Before the cut-off change, net margins for loans with more than two scoring trials directly above the cut-off are not sufficient to cover the realized loan losses (net margin = -1.12%). After the change in the cut-off, net margins for loans with more than two scoring trials directly above the cut-off have a slightly positive net margin (0.49%). This implies for the median loan amount of EUR 10,000 a net margin of EUR 50 per annum. It is very hard to see how a bank could cover its operational and other costs for a loan with this amount.

[9] We use the bank's expected recovery rate of 40%. Loans are not collateralized and therefore, recovery rates are lower than in other segments, such as retail mortgages.

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 and the default rate.

A. Number of scoring trials

One remaining concern with the negative binomial model used in Table 5 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 12. 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 5). The coefficient of 0.288 in the first row of Panel A therefore corresponds to the first coefficient in column (6) in Table 5. The use of different models results in very similar and highly statistically significant coefficients of 0.290 (Poisson model) and 0.226 (Linear model[10]), respectively.

To make use of the full information at hand, we also estimate a discrete hazard rate model that takes into account data from every single loan trial. Consistent with the previous results, we find that a scoring trial worse than the cut-off rating significantly increases the likelihood of another scoring trial. The detailed results for this hazard rate regression are available on request.

We conduct two robustness tests for the regression discontinuity analysis. First, we estimate the model using 1st, 3rd, 5th, and 9th order polynomials instead of the 7th order polynomials. The results are very similar; with the estimate for the cut-off dummy being slightly smaller for lower order polynomials (Table 13). Second, we collapse the data into bins by the initial rating and run the same regression as before using average values per bin for the dependent variable (number of scoring trials) as well as for the control variable. We follow the procedure outlined in McCrary (2008) to determine the bin-size. The estimates for the cut-off dummy are slightly smaller but still highly significant and, as expected, R-squares of the regression increase significantly as taking averages per bin eliminates idiosyncratic dispersion.[11]

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[10] The Poisson model and the negative binomial model use the logarithm of the number of scoring trials as the dependent variable. To be consistent with these models, we also use the logarithm of the number of scoring trials, and not the number of scoring trials itself, as the dependent variable in the linear model.

[11] These collapsed regressions give the same weight to bins close to the cut-off as to bins far away from the cut-off. In our set-up, bins close to the cut-off have a lot more observations than bins far away from the cut-off. Furthermore, the number of scoring trials is largest directly below the cut-off, and subsequently decreases for worse rating grades. Therefore, the collapsed regressions yield somehow smaller coefficients than the non-collapsed version.

Finally, loan size can be changed from one scoring trial to another. Changes in loan size may not be manipulation, it could be an outcome of a prudent strategy to offer a smaller loan volume to the client if the originally requested loan volume results in a rating below the cut-off. Hence as a robustness test, we exclude scoring trials in which only the loan size changes. The results are qualitatively similar. Detailed results are available on request.

B. Default rate

We use a conditional logit regression as a robustness test for the default rate regression (4). Panel B of Table 12 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 9). 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.

As a further robustness test, we use the difference between the initial and the final internal rating instead of the number of scoring trials. We therefore regress the default rate on both the initial rating and the change in the rating between the initial and the final scoring trial. If the additional information that is added between the initial and the final scoring trial was informative, we would expect the change in the rating to predict default rates, beyond the information in the initial ratings. However, consistent with the manipulation hypothesis, we find it is the initial rating, rather than the change in rating that is informative. Detailed results are available on request.

Finally, we decompose the strategy of loan officers into three distinct buckets: First, loan applications in which only the loan volume is changed. Second, loan applications in which only parameters (e.g. costs, liabilities, etc.) but not the loan volume is changed. Third, loan applications in which both parameters and the loan volume is changed. We do not report the tables to conserve space but as expected, the effect of the number of scoring trials on loan default rates is most pronounced for the second strategy.

6. Conclusion

The current financial crisis has raised an important question of how the loan making process should be designed and 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 should 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 rating. 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 pure reliance on hard information in the loan making process does not necessarily lead to better outcomes. The underlying incentives are important, and in the setting at hand, where loan officers are incentivized based on loan volumes, reliance on hard information actually leads to outcomes with 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.

References

Agarwal, S. and I. Ben-David (2012): “Do Loan Officers’ Incentives Lead to Lax Lending Standards?,” Working Paper.

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

Allison, P. D., and R. Waterman (2002): “Fixed-effects negative binomial regression models," Sociological methodology, 32, 247-265.

Andersen, B. E. (1970): “Asymptotic Properties of Conditional Maximum-likelihood Estimators," Journal of the Royal Statistical Society, 32(2), 283-301.

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

Cameron, A. C., and P. K. Trivedi (1998): Regression analysis of count data. Cambridge University Press.

Chamberlain, G. A. (1980): “Analysis of Covariance with Qualitative Data," Review of Economic Studies, 47, 225-238.

Cole, S., M. Kanz and L. Klapper (2012): “Incentivizing Calculated Risk Taking: Evidence from a Series of Experiments with Commercial Bank Loan Officers,” Harvard Working Paper.

Hausmann, J. A., B. H. Hall, and Z. Griliches (1984): “Econometric Models for Count Data with an Application to the Patents-R&D Relationship," Econometrica, 52, 909-938.

Heider, F. and Inderst, R. (2012): "Loan Prospecting, Review of Financial Studies," 25(8), 2381-2415.

Hertzberg, A., J. M. Liberti, and D. Paravisini (2010): “Information and Incentives Inside a Firm: Evidence from Loan Officer Rotation," Journal of Finance, 65(3), 795-828.

Imbens, G.W. and T. Lemieux (2008): “Regression discontinuity designs,” Journal of Econometrics, 142, 615-635.

Keys, B. J., T. K. Mukherjee, A. Seru and V. Vig (2010): “Did Securitization Lead to Lax Screening? Evidence from Subprime Loans," Quarterly Journal of Economics, 125(1), 307-362.

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

McCrary, J. (2008): "Manipulation of the running variable in the regression discontinuity design: A density test," Journal of Econometrics, 142(2), 698-714.

Neyman, J., and E. Scott (1948): “Consistent Estimates Based on Partially Consistent Observations," Econometrica, 16, 1-32.

Paravisini, A., and A. Schoar (2013): "The incentive effect of IT: Randomized evidence from credit committees," NBER Working Paper, 2013.

Puri, M., J. Rocholl, and S. Steffen (2011): “Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects," Journal of Financial Economics, 100(3), 556-578.

Roberts, M.R. and T.M. Whited (2011): “Endogeneity in Empirical Corporate Finance,“ Working Paper.

Stein, J. C. (2002): “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms," Journal of Finance, 57(5), 1891-1922.

Udell, G. F. (1989): “Loan Quality, Commercial Loan Review and Loan Officer Contracting," Journal of Banking & Finance, 13, 367-382.

Wooldridge, J. M. (2002): "Econometric Analysis of Cross Section and Panel Data." The MIT Press, Cambridge, Massachusetts.

Thistlewaite, D., and D. Campbell, (1960): “Regression-discontinuity analysis: an alternative to the ex-post facto experiment,” Journal of Educational Psychology, 51, 309-31.

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.

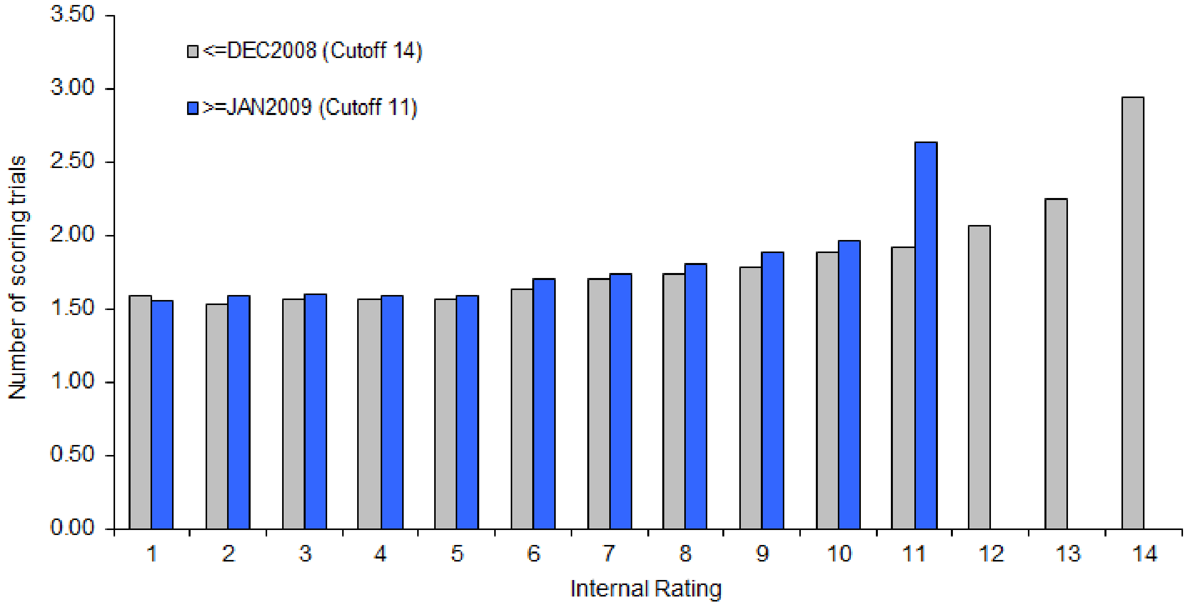

Figure 2: Loan applications

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.

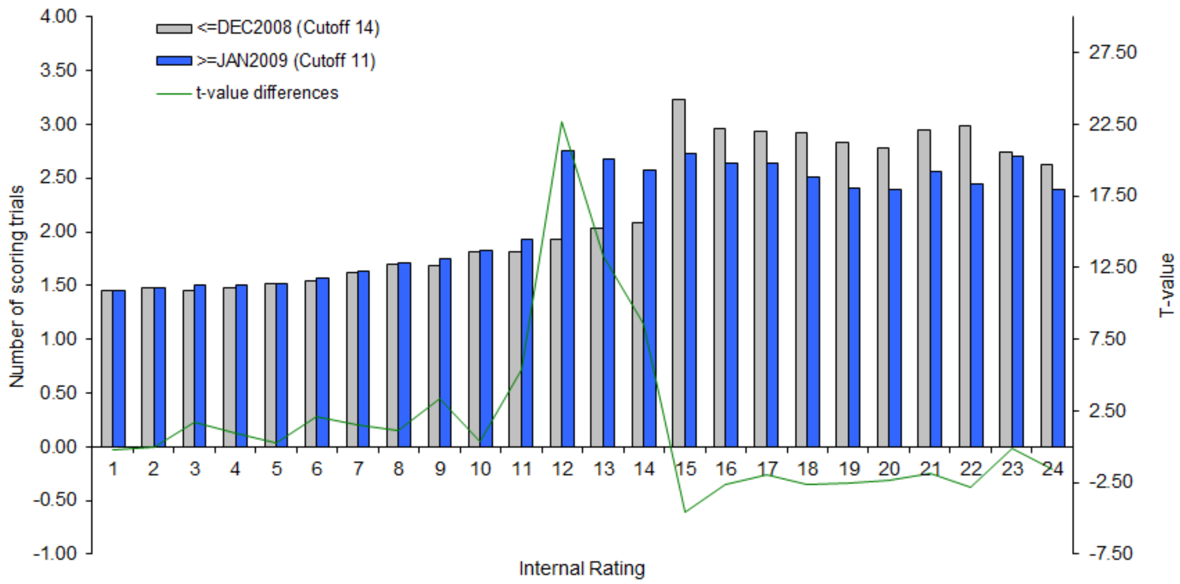

Figure 3: Covariates by rating grade before January 2009

This figure shows customer and loan characteristics by rating class for the period before January 2009. As reference the average number of scoring trials from Figure 2 is shown with grey bars.

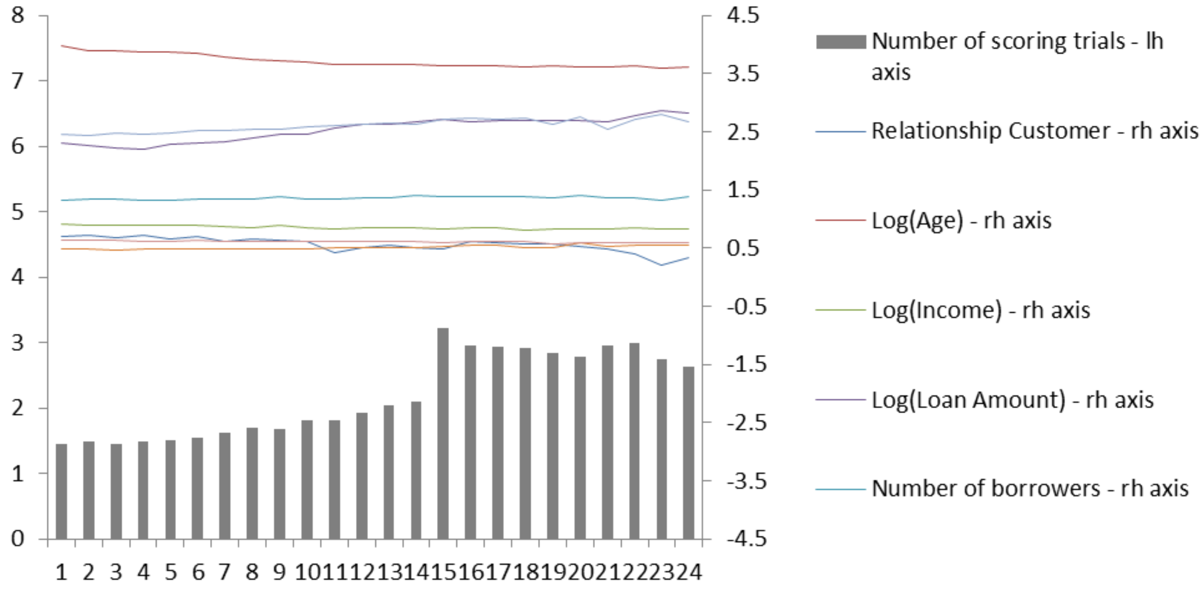

Figure 4: Distribution of the initial rating grade before January 2009

This figure shows the distribution of ratings based on the initical scoring trial for the period before January 2009. As reference the average number of scoring trials from Figure 2 is shown with grey bars.

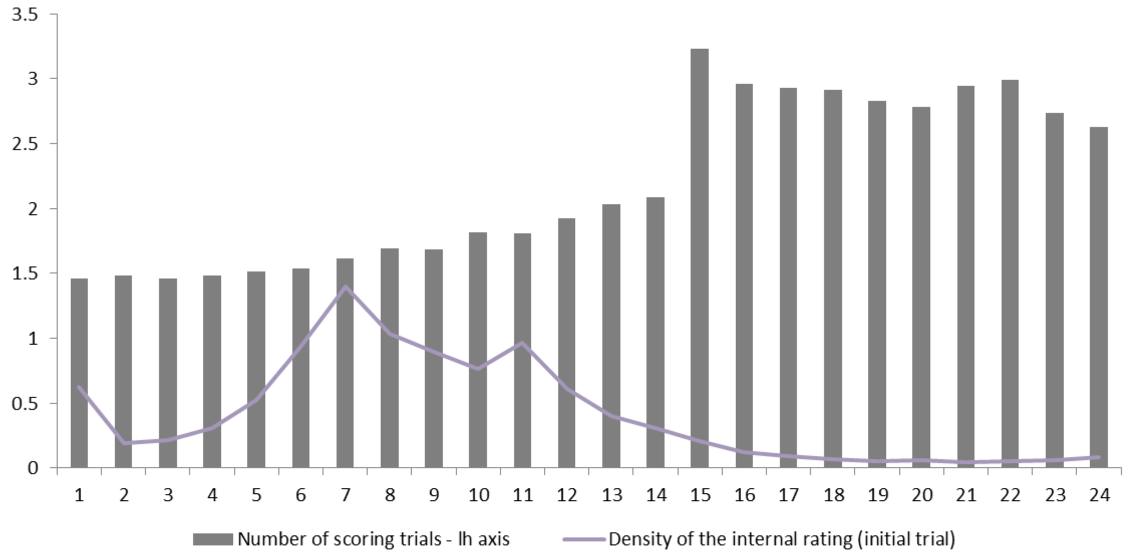

Table 1: Explanation of variables

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.
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 financial 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.
Financial 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, e.g., husband and wife, 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.
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: 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 6: Multivariate results for the number of scoring trials – Regression discontinuity

This table reports estimates for regression that uses the number scoring trials for each initial rating class as the dependent variable. In order to estimate the discontinuity (Initial rating ≥ 14.5 for the period before January 2009, Initial rating ≥ 11.5 for the period after January 2009) we estimate seventh-order polynomials (Panel Ia) and local linear regressions (Panel Ib) on either side of the cutoff using a negative binomial model. Column (A) presents results for the period before January 2009, column (B) presents the results for the period after January 2009. Columns (A1) and (B1) report results for the estimate of the discontinuity, columns (A2) and (B2) report robust standard errors, columns (A3) and (B3) report the number of observations and columns (A4) and (B4) report the R-squared. We also report a permutation test p–value beneath each regression. "Without Covariates" denotes regressions without any covariates beyond the initial rating, "With Covariates" denotes regressions which include customer, client and loan officer characteristics (which are not shown for reasons of brevity). Panel II reports the results from the McCrary test for the manipulation of the running variable. Columns (C1) and (D1) report the estimate of the discontinuity in the density of the internal rating at the cutoff rating, columns (C2) and (D2) report the respective standard errors. ***, **, * 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)
Method	Initial rating > 14 (β)	(SE)	Observations	R^2	Initial rating > 11 (β)	t-stat	Observations	R^2
Panel I: Test for discontinuity at the cutoff rating								
Panel Ia: Polynomials								
without covariates	0.357***	(0.0735)	70,330	4.49%	0.281***	(0.0263)	171,681	4.82%
	Permutation test p-value: 0.0002				Permutation test p-value: 0.0021			
with covariates	0.331***	(0.0726)	61,065	19.76%	0.291***	(0.0259)	165,692	11.47%
	Permutation test p-value: 0.0006				Permutation test p-value: 0.0016			
Panel Ib: Local linear regression								
without covariates	0.346***	(0.0915)	1,920	1.36%	0.251***	(0.0285)	18,662	1.34%
	Permutation test p-value: <0.0001				Permutation test p-value: <0.0001			
with covariates	0.284***	(0.0877)	1,690	14.90%	0.252***	(0.0276)	18,043	5.70%
	Permutation test p-value: <0.0001				Permutation test p-value: <0.0001			

Panel II: Test for manipulation of the running variable at the cutoff rating

	(C1) Discontinuity at rating of 14.5	(C2) SE	(D1) Discontinuity at rating of 11.5	(D2) SE
McCrary test	0.078	(0.2479)	-0.031	(0.1106)

Table 7: 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 financial 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)
Financial 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 8: 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 9: 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 10: 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 11: Net margins by rating class and and number of scoring trials

This table presents gross and net margins by rating class before and after the change in the cutoff rating in January 2009. Gross margin is the interest rate on the loan less the refinancing costs (5-year risk-free rate plus 5-year CDS spread) of the bank. The net margin is defined as the gross margin less the realized loan losses, before consideration of operational costs and cost of capital. The realized loan losses are calculated using default rates from Table 8 and a recovery rate assumption of 40%. 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 gross and net margin before January 2009, Column B shows the gross and net margin after January 2009. Column (A1) and (B1) show the gross margin, , Column (A2) and (B2) show the net margins for loans with one or two scoring trials, columns (A3) and (B3) show the net margins for loans with more than two scoring trials.

	(A) Before January 2009			(B) After January 2009		
	(A1)	(A2)	(A3)	(B1)	(B2)	(B3)
		Net margin = Gross Margin less loan losses	Net margin = Gross Margin less loan losses		Net margin = Gross Margin less loan losses	Net margin = Gross Margin less loan losses
Internal Rating (from last scoring trial)	Gross Margin	Loans with ≤ 2 trials	Loans with > 2 scoring trial	Gross Margin	Loans with ≤ 2 trials	Loans with > 2 scoring trial
1	2.40%	2.35%	2.20%	4.08%	3.96%	4.08%
2	2.40%	2.31%	2.40%	4.08%	3.99%	3.52%
3	2.40%	2.25%	2.40%	4.08%	3.77%	3.84%
4	2.40%	2.25%	2.06%	4.08%	3.90%	3.75%
5	2.40%	2.13%	2.18%	4.08%	3.59%	3.99%
6	2.40%	1.95%	2.09%	4.08%	3.71%	3.67%
7	4.06%	3.36%	3.74%	5.66%	4.75%	4.95%
8	4.48%	3.70%	3.92%	6.08%	4.91%	5.04%
9	4.48%	3.30%	2.98%	6.08%	4.42%	4.52%
10	4.96%	3.32%	3.54%	6.56%	4.21%	3.97%
11	4.96%	2.11%	1.46%	6.56%	1.86%	0.49%
12	5.56%	2.44%	2.15%			
13	5.56%	0.90%	1.75%			
14	6.17%	1.92%	-1.12%			
All	4.06%	2.76%	2.07%	5.66%	4.29%	3.46%

Table 12: Robustness test / Model choice

This table presents robustness tests for the multivariate analyses from Table 5 and Table 8. 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 5. Panel B shows a robustness test for the default rate using a conditional logistic regression in addition to the linear probability model presented in Table 8. Only the coefficient for the cutoff dummy are shown in Panel A. Only the coefficient for the logarithm of the number of scoring trials is shown in Panel B. 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 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: Default rate			
Linear	Log(Number of trials)	0.004***	(0.0012)
Conditional Logistic	Log(Number of trials)	0.003***	(0.0008)

Table 13: Robustness test / Regression discontinuity

This table reports robustness tests for the regression discontinuity analysis. Panel I reports results for different choises of the higher-order polynomial of the running variable (initial internal rating). The results for the 5th order polynomial is identical to Panel Ia from Table 6. Panel II reports a version with collapsed data where scoring trials are collapsed into distinct buckets based on the initial rating grade. Column (A) presents results for the period before January 2009, column (B) presents the results for the period after January 2009. Columns (A1) and (B1) report results for the estimate of the discontinuity, columns (A2) and (B2) report robust standard errors, columns (A3) and (B3) report the number of observations and columns (A4) and (B4) report the R-squared. All regression include our standard set of covariates which include customer, client and loan officer characteristics (which are not shown for reasons of brevity). ***, **, * denotes significance at the 1, 5 and 10 percent level, respectively.

	(A)				(B)			
	Before January 2009				After January 2009			
	(A1)	(A2)	(A3)	(A4)	(B1)	(B2)	(B3)	(B4)
Method	Initial rating > 14 (β)	(SE)	Observations	R^2	Initial rating > 11 (β)	t-stat	Observations	R^2
Panel I: Data not collapsed								
Order of polynomials								
1st order polynomial	0.404***	(0.0253)	61,065	19.73%	0.350***	(0.0108)	165,692	11.43%
3rd order polynomial	0.404***	(0.0431)	61,065	19.75%	0.337***	(0.0168)	165,692	11.45%
5th order polynomial	0.346***	(0.0551)	61,065	19.75%	0.328***	(0.0228)	165,692	11.46%
7th order polynomial	0.331***	(0.0726)	61,065	19.76%	0.291***	(0.0259)	165,692	11.47%
9th order polynomial	0.347***	(0.0711)	61,065	19.76%	0.317***	(0.0228)	165,692	11.47%
Panel II: Collapsed data								
Order of polynomials								
1st order polynomial	0.336***	(0.028)	714	67.96%	0.270***	(0.0144)	1,236	61.99%
3rd order polynomial	0.366***	(0.040)	714	68.30%	0.271***	(0.021)	1,236	62.03%
5th order polynomial	0.280***	(0.065)	714	68.47%	0.323***	(0.033)	1,236	62.49%
7th order polynomial	0.336***	(0.075)	714	68.61%	0.256***	(0.034)	1,236	62.72%
9th order polynomial	0.303***	(0.095)	714	68.84%	0.175***	(0.038)	1,236	63.52%