Financial Incentives and Loan Officer Behavior:
Multitasking and Allocation of Effort under an Incomplete Contract[◊]

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This version: October 16, 2014

Abstract

We investigate the implications of providing loan officers with a compensation structure that rewards loan volume and penalizes poor performance versus a fixed wage unrelated to performance. We study transaction information for more than 45,000 loans issued by 240 loan officers of a large commercial bank in Europe. We examine the three main activities that loan officers perform: monitoring, originating, and screening. We find that when the performance of their portfolio deteriorates, loan officers increase their effort to monitor existing borrowers, reduce loan origination, and approve a higher fraction of loan applications. These loans, however, are of above-average quality. We also show that loan officers neglect activities that are not directly rewarded under the contract, but are in the interest of the bank. In addition, while the response by loan officers constitutes a rational response to a time allocation problem, their reaction to incentives appears myopic in other dimensions.

JEL Classifications: G21, J33
Keywords: Loan officer, incentives, monitoring, screening, loan origination

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[◊] We would like to thank Phil Dybvig, Mrdjan Mladjan, Lars Norden, Klaus Schaeck, Jerome Taillard, participants at the annual meetings of the European Finance Association and the Swiss Society for Financial Market Research, and seminar participants of the Annual Meeting on Risk, Financial Stability and Banking of the Brazilian Central Bank, Bank of Canada, Brazilian School of Public and Business Administration, Federal Reserve Bank San Francisco, Frankfurt School of Finance and Management, Fudan University, and World Bank for their comments. Part of this research was completed while Gropp was visiting the University of Amsterdam, the hospitality of which is greatly appreciated. A previous version of the paper was entitled "Financial Incentives and Loan Officer Behavior".

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1. Introduction

While most research on bank compensation focuses on equity-linked incentives for high-level managers, there seems to be a consensus that distorted financial incentives for lower-level employees, such as loan officers and loan originators, were one of the factors at the root of the 2008–2009 financial crisis. The role of loan officers' behavior in the crisis opened a controversial public debate that has already caused important changes in the regulatory framework.[1] The debate has also increased academics' and practitioners' interest in exploring the implications of incentive-based compensation for the cost of credit, the availability of credit, and the stability of financial institutions.

In this paper we use exogenous variation in the compensation structure of loan officers at a large international bank to study how financial incentives affect their behavior. At the beginning of the sample period, the bank used a variable compensation structure, in which loan officers received a monthly cash bonus proportional to their lending volume. However, the bonus was not paid in months when the value-weighted non-performing loans in the loan officer's portfolio of outstanding loans exceeded a certain threshold. During the sample period, this incentive-based compensation plan was replaced by a fixed salary for all loan officers. The change in the way in which loan officers were compensated, together with the non-linearity embedded in the variable compensation plan, enables us to identify the causal effect of incentives on behavior. The identification strategy, hence, rests on comparing the behavior of the same loan officer under the two regimes.

We start with the observation that loan officers perform three distinct but interrelated tasks, all of which affect the quality of the bank's loan portfolio. Loan officers monitor existing loans, they originate new loans (Heider and Inderst, 2012), and they screen loan

[1] See for example the Dodd–Frank Act, Title XIV, Subtitle A (loan origination of residential mortgages) and the Truth in Lending Act (Regulation Z).

applications. Given the richness of our data, we are able to identify the effects of financial incentives on loan officer behavior regarding the allocation of loan officers' effort to their different tasks. We find that loan officers tend to respond rationally to incentives. Loan officers faced with losing their bonus focus on reducing the defaults of the existing loans ("monitoring"). This is rational in the sense that enhanced monitoring yields the highest "bang for the buck" in terms of improving portfolio performance in the short run. Further, the increased monitoring effort of loan officers at risk is concentrated on reducing the defaults among larger loans, given that their bonus depends on value-weighted defaults.

The increased effort put into monitoring existing loans comes at the expense of the effort spent on originating loans and screening loan applications, rather than by increasing overall work effort: loan officers face fewer applications, which we interpret as exerting less effort on originating loan applications, but approving a higher fraction. The net effect is that the total number of new loans issued decreases significantly for loan officers faced with losing their bonus. Surprisingly, despite approving a higher fraction of applications, we show that these new loans are less likely to default. We interpret these findings as suggesting that loan officers use a pecking order based on applicant quality and process applications only for the very best clients when under pressure from the incentive-based compensation plan ("cherry picking"). This may imply that under the incentive-based contract some viable loan applicants no longer receive credit. The evidence is consistent with the idea that high-powered incentives to maximize short-term income in incomplete contracts carry the risk that loan officers respond by neglecting those tasks that are less well rewarded, but nevertheless are in the interest of the bank (Holmström and Milgrom, 1991).

We also examine other dimensions of the response by loan officers to the incentive-based contract. One, we show that loan officers do not change their behavior as they *approach* a level of defaults in their portfolio that would imply a loss of the bonus, but rather only react once they *reach or exceed* this level. Hence, while loan officers seem to rationally respond to a time allocation problem, their reaction to incentives appears myopic in other dimensions. Second, from the perspective of the bank, the losses associated with a given loan portfolio are minimized, if loan officers minimize the probability of default multiplied by the loss given default in their portfolio. The bonus, however, depends only on the probability of default, not on the loss given default. We show that consistent with the incentives of their contract, loan officers do not show any regard for the loss given default. They do not enhance their monitoring of less collateralized loans.[2]

The previous empirical work focuses primarily on the impact of performance-based compensation on loan officers' *screening* decisions.[3] For example, using data from a large U.S. commercial lender, Agarwal and Ben-David (2013) study how loan-volume-based compensation affects the loan volume and delinquency rates. They find that when the compensation rewards volume, loan officers generate more but lower-quality loans. Most closely related to our paper, Cole et al. (2014) study three different contract designs in a laboratory setting. They show that compensation that rewards loan volume, but penalizes poor loan performance, entails more screening effort and a higher-quality loan portfolio relative to other compensation packages. In order to rule out the multitasking problems studied in this paper, their set-up rules out other activities, such as origination or monitoring, that may also affect loan outcomes. Using data from a major European bank, Berg et al. (2013) study how automated lending decisions based purely on hard information influence loan officer behavior when the compensation depends on the loan volume generated and find that loan officers bias their assessment of the borrowers' risk to increase the pool of clients who are eligible to receive credit.

[2] These findings may also help to explain why the bank abandoned incentive-based contracts for loan officers in the first place. We were unable to obtain any formal documentation on why the loan officer compensation structure was changed. In discussions with the bank's management, we learnt that the change was intended to release loan officers from short-term pressure to issue (underperforming) loans.

[3] Most of the literature on risk taking in banks focuses on top executives (e.g., Bebchuk and Spamann, 2010; Bolton et al., 2010; Balachandran et al., 2011; Fahlenbrach and Stulz, 2011), rather than loan officers.

While this literature establishes an important causal relationship between financial incentives and screening, it is mute about the multitasking problems that loan officers face in their job. In addition to screening, monitoring and loan origination may also significantly affect the ultimate performance of loans and the risk of the bank. We emphasize the trade-off faced by loan officers in regard to where to increase their effort in the context of an incentive scheme that is incomplete in the sense that it rewards some activities more than others.[4]

The literature also analyzes other aspects of the role of loan officers in financial institutions. For instance, Drexler and Schoar (2013) study the importance of relationships between loan officers and borrowers for loan take-up and other loan outcomes. Fisman et al. (2012) show that cultural proximity matters for the efficiency of credit allocation. Qian et al. (2014) use Chinese data to examine the effects of increased accountability of loan officers on the assessment of credit risk. Finally, Beck et al. (2013a, 2014) analyze the impact of loan officer gender on portfolio performance and gender-based discrimination.

The remainder of the paper is structured as follows. In section two, we describe the identification strategy in detail and discuss the sample. In section three, we present the main empirical results. Section four shows that there may also be some unintended consequences of incentive-based contracts, while section five contains placebo test results. The last section concludes.

2. Identification Strategy and Data

2.1 Loan Officer Compensation

Our data come from a large for-profit international commercial lender serving mainly individuals and small- and medium-sized enterprises. The data set includes 55,946 loan applications and 43,063 loans issued by the lender between January 2003 and October 2007.

[4] Our paper is also related to the literature on the presence of agency problems within banks (e.g., Liberti and Mian, 2009; Hertzberg et al., 2010).

As the lender did not have any credit card business in the sample period, all loans in our dataset are either individual or small business loans. We have access to information on approved as well as rejected applications, and we use this information to construct measures of origination and screening effort. Further, we are able to construct a measure of monitoring, because we have monthly information on the default status of the loans. This is discussed in more detail below.

The bank had 22 branches and 268 loan officers at the beginning of the sample period. Loan officers have full authority over their tasks: they independently process loans for their pre-existing clients as well as actively seeking out new clients. In addition, they are responsible for monitoring the existing loans. For example, if a loan is in default, the officer can intensify the monitoring, for instance by calling the borrower, sending him a letter, or visiting him to inquire about the reasons for the delay. To make monitoring salient, loan officers can, for instance, threaten borrowers to deny them access to future credit. Finally, loan officers have discretionary power over loan terms, such as the interest rate and maturity.

In general, loan applications by new borrowers are randomly assigned to loan officers on a first-come, first-served basis. New clients who walk into a branch are allocated to the loan officer who is available at the time and assignment is not based on any particular characteristics of the loan officer. However, we do observe that some loan officers specialize in certain sectors. Whenever appropriate, we use loan officer or loan fixed effects to address this problem.

The results in the paper rest on the comparison of loan officer behavior under two compensation plans used by the lender during the sample period. The first compensation plan was used between January 2003 and October 2004 and consisted of a fixed salary and a monthly-paid cash bonus; in the rest of the paper, we refer to this period as the *bonus period*. The bonus was proportional to the loan officer's lending volume and the computation of the bonus was based on the standing of the loan portfolio at the end of each month. However, in months when the value-weighted defaults in the loan officer's portfolio were above 3 percent, the bonus was cancelled. "Defaults" are defined by the bank as a loan payment overdue for at least 30 days, consistent with the international practice.[5] The strict threshold for cancelling the bonus generates a non-linearity that is crucial in our identification strategy, which is described in the next section. Depending on the performance, the bonus constituted up to 150 percent of the loan officers' salary. Hence, the incentive to keep the bonus was substantial under the performance-based contract.

In November 2004, the bonus plan was adjusted and subsequently replaced with a fixed salary. Specifically, between November 2004 and December 2005, the cash bonus was limited to 50 percent of the fixed salary, and after January 2006, the salary of loan officers became independent of their lending volume and performance. In the paper, we refer to this last period as the *no-bonus* period. To facilitate the interpretation of the findings in the paper, we present a comparison between the bonus period and the no-bonus period. However, similar results are obtained when we compare the bonus plan with the mixed and fixed salary plans.

We are faced with the problem that, when eliminating the bonus, the fixed salaries were increased. Unfortunately, we do not have loan officer-specific information on the extent of this increase. We only know that the overall salary bill of the bank did not change significantly after the elimination of the incentive scheme. It seems plausible, however, that the increase in the fixed salary of loan officers after the removal of the bonus corresponded to the average bonus level during the bonus period. We assume that the *increase* in the fixed salary by itself did not affect the incentives of the loan officer, arguing that it should not

[5] Non-performing loans are taken out of a loan officer's portfolio after being overdue for more than 60 days; these loans are then taken care of by special workout units.

distort our comparison between a loan officer being above or below the cutoff in the bonus versus the fixed-salary period.[6]

We were unable to obtain any formal documentation on why the loan officer compensation structure was changed. However, the management of the bank was emphatic that the switch was not a reaction to a change in market conditions or to a deterioration in the quality of the portfolio.[7] Rather, the change was intended to release loan officers from short-term pressure to issue (underperforming) loans. Furthermore, the change was implemented in all the bank branches and in all the countries where the bank was operating at the same time and was immediately binding for all loan officers. Hence, the compensation structure is independent of the choice of loan officers, eliminating one source of potential selection bias.[8] We discuss other selection problems that do arise in the context of our identification strategy below. Nevertheless, we feel that the modification of the salary structure implemented by the bank creates an interesting natural experiment to study the effect of performance-based compensation plans on loan officers' effort.[9]

2.2 Identification Strategy

During the bonus period, loan officers received a monthly-paid cash bonus only in the months when the value-weighted defaults in their portfolio were below the cutoff point of 3 percent of the total loan portfolio volume. We observe the performance of the same loan officer during the bonus period and the no-bonus period. We identify the effect of the incentive-based

[6] We cannot rule out that higher fixed salaries led to an increase in loan officer effort because of an increase in the cost of being fired. However, a higher effort in the no-bonus period should introduce a bias against finding differences between the bonus and the no-bonus period.

[7] Our research on bank competition in the region confirmed the statement of the bank management. Indeed, we found no changes in the bank competition measures, such as the number of banks and the number of bank branches, before the bonus plan was replaced.

[8] The total lending volume of the country that we analyze accounted for a minor share of the global lending volume of the bank at the time.

[9] The other dimension that can affect effort is the risk of being fired, which is also smaller for loan officers with low default frequencies. We do not study this dimension and we assume that this incentive mechanism does not change during the observation period. However, the econometric approach requires a weaker assumption. It only requires that any change in the probability of being fired is linear around the cutoff point.

compensation plan by comparing the change in the behavior of the same loan officer when she crossed the cutoff in the bonus period with the change in the behavior of the loan officer when she crossed the cutoff in the no-bonus period.

Given our approach, we can only focus on loan officers who worked for the lender during both the bonus and the no-bonus period. We are faced with a selection problem if, for example, poorly performing loan officers stayed with the bank and high performers left. In that case, our results would reflect the effect of incentive-based compensation plans on the performance of poorly performing loan officers only. Table 1 compares the observable characteristics of the loan officers who stayed with the bank with those who left, after the compensation scheme was changed. First, note that only 10 percent of the loan officers left the bank before the bonus plan was replaced. This suggests that any bias may be limited. We find that the departing loan officers were significantly more experienced, but the departing and staying loan officers do not differ significantly with respect to the performance of their loan portfolio. We further compare the group of loan officers who left the bank with an experience-matched group of loan officers who stayed (the top three deciles according to experience). The loan portfolio performance results remain similar. Thus, it does not seem to be the case that only poorly performing loan officers stayed after the bonus plan was replaced. Furthermore, given that it seems plausible that loan officers who prefer short-term financial incentives are more likely to leave the bank, one can view our results as a lower bound of the responsiveness of all loan officers to financial incentives.

We implement a difference-in-differences (DD) estimator by tracking loan officers above and below the cutoff and before and after the removal of the bonus plan. Specifically, we first measure the difference between the behavior of the loan officers below the cutoff and the behavior of the loan officers above the cutoff; this represents the first difference and is estimated separately during the bonus period and during the no-bonus period. Second, we measure the difference between the first difference estimated during the bonus period and the first difference estimated during the no-bonus period; this represents the second difference. The identifying assumption underlying the difference-in-differences approach is that the difference in the behavior of the loan officers below and above the cutoff is constant over time unless there is a change in the incentive compensation. Hence, while the loan officers may differ systematically due to a number of unobservable factors, the identification of the causal effect of the incentive plan on the loan officers' behavior will be robust as long as the difference in the behavior of the loan officers above and below the cutoff explained by unobservable characteristics does not change over time.[10]

Hence we estimate variants of the following specification:

$$(1) \qquad y_{ijt} = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt} * Bonus_t + \mathrm{B}X_{ijt} + \mathrm{A} + e_{ijt},$$

where y_{ijt} represents different outcome variables that reflect monitoring, loan originating, and screening for loan i, loan officer j, and month t. The monitoring analyses use data on the loan-month level and the origination analysis employs data on the loan officer-time level, while the other tests use data on the loan-level. A is a vector of fixed effects. Most specifications use time fixed effects and loan officer fixed effects. In some specifications, we include loan fixed effects, which permits us to identify coefficients based on within-loan variation, controlling for any unobserved variation in portfolio composition or loan officer characteristics, and in others, we use branch-by-time fixed effects in order to control for time-variant regional variation in economic activity.[11] X_{ijt} represents a vector of time-variant loan- or loan officer-level covariates that may differ depending on the specification. The sets of controls are

[10] We use placebo or falsification tests to validate our identifying assumption further. In these tests, we run the same set of regressions, maintaining the cutoff at the same level but arbitrarily changing the date when the bonus was removed. If our identification is capturing time-varying changes unrelated to the compensation plan, then we expect to find significant differences in the falsification tests. We do not find significant differences above and below the cutoff point in these tests, supporting our view that the findings in the paper are explained by the change in the compensation structure (see section 5).

[11] It may, however, be the case that there are loan officer-specific time-varying unobserved factors that influence their effort and thus the likelihood of their loan portfolio ending above or below the bonus threshold. While we view this as unlikely, we cannot fully rule out this possibility.

described in detail in Appendix Table A1, but may include the outstanding loan amount, the remaining time to maturity, the loan officer experience measured as the total number of loans processed by loan officer j since she started working at the bank, and her workload measured as the number of outstanding loans in her portfolio at time t. $Defaults_{jt}$ measures the proportion of defaults in the portfolio of loan officer j in month t and controls for the linear component of the effect of having higher defaults in a loan officer's portfolio on her monitoring effort.[12]

$Bonus_t$ is a dummy variable that takes the value of one if date t is from January 2003 to October 2004 (the period when the incentive-based contract was in place) and zero if it is from January 2006 to October 2007 (the period when loan officers were paid a fixed salary), and $AboveCutoff_{jt}$ is a dummy variable that takes the value of one if the value-weighted defaults in the portfolio of loan officer j were above the cutoff at t and zero otherwise. The coefficient of interest is α_4, which measures the difference-in-differences of loan officer behavior above and below the cutoff and under the bonus and no-bonus regimes as described above.[13]

2.3 Descriptive Statistics

All the variables used in the empirical analysis are defined in Appendix Table A1 and summary statistics for all the variables are reported in Appendix Table A2. Table 2 provides descriptive statistics for the monitoring analysis. The sample consists of 486,555 observations at the loan-month level; this number is the number of approved loans (n = 43,063) summed over the number of months for which the loans are present in the database during the sample

[12] We also run all the regressions using the second-order polynomial of the default frequency as an additional control variable to account for potential non-linearity in the effect of the default frequency on the different outcome variables. All the results remain unchanged.

[13] Another way to define the difference-in-differences estimator would be, for instance, to include buckets for loan officers with default rates of 0-1%, 1-2%, 2-3%, 3-4% and above 4%. While such an approach would allow us to analyze whether the effects differ with regard to the bucket, we cannot perform it due to the small number of observations in these buckets.

period. The sample period includes the bonus and no-bonus periods, but excludes the transition period. Out of the outstanding loans, on average 0.76% were overdue on a monthly basis and 6.3% of the observations are linked to loan officers that were above the 3% default threshold. On average, loan officers processed 439 applications during the sample period and monitored a portfolio consisting of 194 loans at any given time. The loans tended to be small and short term: the average outstanding loan amount was 3,555 euros and the average time to maturity was 10 months.

Figure 1 gives basic time series plots of some key variables that illustrate the developments in the loan portfolio of the bank and in the activities of the loan officers during the sample period. Some of these variables we use below in the empirical analysis. All the charts are divided into three periods: the bonus period, in which the variable compensation plan was operative, the transition period, in which a capped bonus system was operative and which we exclude from the empirical analysis below, and the no-bonus period, in which the loan officers received a fixed salary unrelated to their performance.

Overall, the loan officers appear to have worked harder under the incentive-based contract in the dimensions directly rewarded under the contract. The figure shows that the loan officers originated more loans in the bonus period relative to the no-bonus period (Figure 1.1) and also rejected fewer loan applications (Figure 1.2), consistent with the aggressive lending behavior under incentivized contracts documented by Agarwal and Ben-David (2013).

However, we also find that the quality of the loans extended was higher with the incentive contract than with the fixed contract (Figure 1.3), consistent with the laboratory evidence presented by Cole et al. (2014). As in one of the contracts studied by Cole et al. (2014), loan officers lose their bonus if the defaults exceed a threshold of defaults in their portfolio, which provides strong incentives not to exceed a certain level of risk.[14] We show below, however, that the improved performance does not come via better screening (loan officers rejected *fewer* applications), but through "cherry picking," i.e. concentrating on selected high-quality loan applications. As discussed above, our identification strategy relies on the non-linearity in the contract at the 3 percent threshold of defaults in the loan officer's portfolio. Figure 1.4 plots the proportion of loan officers exceeding the threshold during the different compensation regimes. The probability that a loan officer would exceed the threshold was around 4 to 11 percent in the bonus period and increased to 13 to 21 percent under the fixed-salary regime. The loan officers appear to have responded quite strongly to the incentives provided under their contract.

While these results are suggestive, they could be driven by changes in the economic environment and differences in the composition of loan officers and their quality over time. Hence, below, we report the results of specifications that, in addition to loan- and loan officer-level control variables, include time and loan officer fixed effects and in some cases loan fixed effects. Further, they explore the three main activities that loan officers typically perform in turn. Figure 1 also raises the question of why the variable compensation scheme was abolished in the first place, given that it seems to have worked well when in place. We attempt to explore this question in section 4 below.

3. Empirical Results

In this section, we show the main results on how financial incentives influence loan officers' behavior in the three dimensions of their job: monitoring existing loans, loan origination, and screening loan applications.

[14] We discuss the calculation of the ex ante probability of default in detail below (see section 3.4). It is a measure calculated based on variables that were observable to the loan officer at the time when she extended the loan.

3.1 Monitoring

Like much of the previous empirical literature (see, for example, Mester et al., 2007, and Norden and Weber, 2010), we do not have access to direct measures of loan officer monitoring, such as communication with the borrower, meetings, phone calls, or emails. However, we can measure monitoring based on changes in the status of the loans in the loan portfolio of the loan officer. Our data set contains one-to-one matching between borrowers and loan officers, and for each loan we observe the issuing date and the date of any missed payments. These enable us to focus on the within-loan variation in monthly defaults. We assume that screening will only affect the overall and time-invariant riskiness of a loan, and not its time series variation. Hence, we can attribute any effect of financial incentives that we find in this set-up to changes in the extent (quality or intensity) to which loan officers monitor their borrowers.

We construct the variable $\Delta Default_{it}$, which takes the value of 1 if loan *i* was current in the previous month, but defaulted in the current month; it takes the value of -1 if it defaulted in the previous month but returned to being current in the current month; and it takes the value of 0 if there was no change in the default status of loan *i*. Hence, if the loan officer exerted more effort on monitoring, we would expect a higher proportion of loans to move from being in default to being current. Table 2 shows that the average monthly change in defaults is 0.13 percent, i.e. on average the loan portfolio of loan officers deteriorated slightly from month to month over the sample period.

Panel A in Appendix Table A3 presents the unconditional difference-in-differences estimates of the effect of the incentive-based compensation plan on the month-to-month changes in defaults. This estimation represents the difference between the monthly change in default frequency of the portfolio of loan officers above the cutoff and the monthly change in default frequency of the portfolio of loan officers below the cutoff during the bonus period compared with the same difference calculated during the no-bonus period.

During the bonus period, the average change in defaults is -0.0007 when a loan officer was above the cutoff, which means the loan performance improved on average, and it is 0.0011 when a loan officer was below the cutoff, which means the loan performance deteriorated on average. Consequently, the first difference in the DD estimation is -0.0018, which is statistically significant at the 1 percent level. On the other hand, the average change in defaults in the no-bonus period seems to be independent of the loan officer's position above or below the cutoff; the first difference is -0.0002 and it is not statistically significant. As a result, the difference-in-differences estimate is negative and statistically significant at the 5 percent level. We interpret these findings such that under the financial incentive plan, loan officers whose default frequency exceeded the cutoff increased their monitoring effort in order to reduce the average default frequency in their portfolio. However, when their salary was fixed, there was no change above or below the cutoff.

The univariate results may be driven by differences in the characteristics of the loan officers above the cutoff and the loan officers below the cutoff. Furthermore, the loans observed during the bonus period may be substantially different from the loans observed during the no-bonus period. Hence, we estimate a number of variants of equation (1) with $\Delta Default_{it}$ as the dependent variable. The unit of observation in these specifications is the loan-month and the parameter of interest is α_4 in equation (1). A negative value of α_4 indicates that the defaults on average decreased more when the loan officer exceeded the cutoff in the bonus period compared with the no-bonus period.[15] This would support our inference from the univariate result that loan officers increase their monitoring effort when they exceed the cutoff.

Table 3 presents the estimation of specification (1) along with the estimation of other specifications that test the robustness of the main finding to the inclusion of different control

[15] We present the results in this way to facilitate the interpretation, despite the bonus period being before the no-bonus period in the timeline of events.

variables and fixed effects. Column 1 presents the results including the full set of covariates (described in Table A1 of the appendix) and excluding the fixed effects. The point estimate of α_4 is -0.0055, which is significant at the 5 percent level. The next two columns add time and loan officer fixed effects. Column 4 includes the loan fixed effects that saturate the time-invariant loan-level characteristics; therefore, this column only includes the time-varying covariates outstanding loan amount, remaining time to maturity, loan officer experience, and loan officer workload.[16]

In all the regressions, we obtain a negative and highly significant estimate of α_4. Financial incentives seem to induce loan officers to change their monitoring behavior – they monitor more, more efficiently, or both – in order to reduce the proportion of the portfolio in default and maximize their income. It is important to emphasize that this result even holds when we include loan fixed effects (column 4). This rules out that borrower selection, for instance, differences in the quality of the screening of loan applications during the bonus and the no-bonus period, or unobserved (time-invariant) loan officer skills drive our findings. Furthermore, the economic effect is larger in this case and represents 0.2 standard deviations of the monthly change in defaults.

The metric that determines whether or not the loan officer received a bonus is the *value-weighted* defaults in her portfolio. Hence, when faced with losing the bonus, loan officers may have rationally focused on large loans in their enhanced monitoring effort. In addition, Cole et al. (2014) show that the likelihood of improving the performance of a loan is more limited in the case of small loans. Therefore, we expect the incentive effect on monitoring to be more pronounced for large loans.

[16] Any other time-invariant loan, borrower, or loan officer characteristics are saturated by the loan fixed effects. We cannot fully rule out that there are time-variant borrower characteristics that are correlated with the loan officer ending up below/above the cutoff value, although this does not seem to be very plausible.

To test this effect, we compute a dummy variable, $LargeLoan_{it}$, that takes the value of one if the outstanding amount of loan i is above the average outstanding amount across all the loans in period t and zero otherwise. We then estimate an extended version of equation (1) that includes $LargeLoan_{it}$, as well as its two- and three-way interaction with the already-defined variables $Bonus_t$ and $AboveCutoff_{jt-1}$. The coefficient of interest is the three-way interaction term $AboveCutoff_{jt-1}*Bonus_t*LargeLoan_{it}$ that quantifies the extent to which the increase in monitoring effort by loan officers above the cutoff during the bonus period compared with the increase in monitoring effort by loan officers above the cutoff during the no-bonus period depends on the size of the outstanding loan.

Column 1 of Table 4 shows the results, including loan officer fixed effects, while column 2 shows the estimation using loan fixed effects; both estimations include time-varying loan officer-level covariates and time fixed effects. The coefficient obtained on the three-way interaction term is negative and significant in both models, suggesting that the increase in the monitoring effort exerted by the loan officers above the cutoff in the bonus period is larger for larger loans.

Taken together, these results support the idea that financial incentives affect loan officers' monitoring behavior. Loan officers exert more monitoring effort when the performance of their loan portfolio is above the cutoff and they are concerned about losing the bonus payment. We next test whether the additional monitoring effort is due to an overall higher effort by loan officers when faced with losing the bonus or comes at the expense of the other two activities that loan officers typically perform: origination and screening.

3.2 Loan Origination

The data that we use for this test are at the loan officer-month level and include 5,476 observations. We define loan origination effort, $OriginationEffort_{jt}$, as the ratio of the origination volume (defined as the sum of the originated loan volume) divided by the outstanding loan volume of loan officer *j* in month *t*.[17] First, we consider the univariate results reported in Panel B of Appendix Table A3. We find that origination is lower above the cutoff both in the no-bonus and in the bonus period. However, the effect is significantly larger in the bonus period. The difference-in-differences term is negative and significant: when faced with losing their bonus, loan officers reduce the number of loans that they extend.

Next, we estimate a variant of equation (1) with loan origination as the dependent variable. Hence, as before, our coefficient of interest is α_4 in equation (1). We start with a basic OLS specification and gradually add different sets of covariates and fixed effects, including branch-by-time fixed effects, to control for time-variant determinants of loan origination at the branch level, such as regional changes in the loan demand.

Table 5 presents the results. Column 1 only controls for loan officer experience. The negative value of α_4 suggests that the loan officers who surpassed the cutoff point during the bonus period reduced their loan origination effort compared with the loan officers who surpassed the cutoff point during the no-bonus period. This result is both statistically and economically significant as the point estimate of -11.59 percent represents a difference of 0.7 standard deviations. Columns 2 and 3 show similar results for α_4 when we add time fixed effects and loan officer fixed effects. Column 4 shows that the results are robust to branch-by-time fixed effects. They address concerns that loan officer characteristics or regional changes in the loan demand may be driving the findings.[18]

3.3 Screening

[17] The loan origination of individual loan officers is strongly influenced by their experience. Experienced loan officers extend significantly more loans in any given month. Hence, in the baseline specifications, we scale new loans extended with the loan officer's volume of loans outstanding to control for this effect. Alternatively, we also run models on a sample of experience-matched loan officers and find that our findings are robust to this change. The results are not reported, but are available from the authors upon request.

[18] In unreported regressions, we show that within a given branch, the reduction in loan origination by loan officers above the cutoff was in part offset by an increase in loan origination by loan officers below the cutoff.

When faced with a loss of their bonus, loan officers increase their monitoring and reduce their loan origination effort. The third activity that we examine is screening. Hence, we estimate loan officers' rejection rates, again focusing on α_4 in equation (1). $RejectionRate_i$ is defined as a binary variable that takes the value of one if loan application i is rejected and zero otherwise.[19] Hence, the unit of observation is the loan application in these specifications. X_{ijt} is a vector of covariates including all the loan application-level covariates of Table A1 in the appendix (except the balance sheet and guarantee information in the first three specifications as these variables are often missing for rejected loan applications).

Panel C of Appendix Table A3 shows the univariate results. In contrast to the evidence from a lab experiment by Cole et al. (2014), loan officers above the cutoff are significantly *less* likely to reject a loan application in the bonus period than when subject to a fixed salary. This is confirmed in the regressions reported in Table 6. We obtain a significantly negative coefficient for all the specifications, regardless of which control variables we use or which fixed effects we include. The probability that a loan would be rejected was lower if the loan officer was about to lose her bonus. More loans were approved. We consider the most comprehensive specification in Column 3 of Table 6, using time and loan officer fixed effects. The reduction in the rejection rate is 1.7 percent, which represents 0.04 standard deviations of the unconditional rejection rate and is significant at the 10 percent level. Column 4 adds three balance sheet variables and information on whether or not the loan was guaranteed by a third party as further control variables, which we omit in the first three specifications because these variables are often missing for rejected loan applications. The results remain qualitatively unchanged.

At first glance, the results seem surprising: loan officers faced with the prospect of losing their bonus due to too many defaults in their portfolio rejected fewer loans. However, from a

[19] Alternatively, we aggregate the data to the loan officer level and find consistent results. The aggregated approach has the disadvantage that we are unable to control for loan-level characteristics.

time allocation perspective, the results that we obtained for monitoring (increasing), originating (decreasing), and screening (decreasing) seem to reflect a rational adjustment of the relative share of time spent on each activity. Monitoring (especially the monitoring of large loans) immediately reduces the defaults among these loans and may bring loan officers' default share back below the threshold for the bonus in the very short run. Originating and screening, on the other hand, do not have an immediate effect on the default share in loan officers' portfolios; hence, loan officers rationally reduce their effort in this area. In order to underline this point, column 5 analyzes the average time that loan officers spent processing a loan application (measured in days). Consistent with the prior evidence, we obtain a negative coefficient of 0.7 days, which, however, is not significantly different from zero. This suggests that the time savings in loan origination and screening come largely from the number of loans processed, rather than the time spent on each loan application. The results suggest that loan officers seem to solve a time allocation problem rationally. Loan officers above the cutoff point during the bonus period reduced the time they spend on loan origination and screening and allocated additional time to monitoring in an attempt to maximize their bonus payments.

3.4 Ex Ante and Ex Post Loan Quality

Loan officers originate fewer loans and are less likely to reject applicants when at risk of losing their bonus, in order to spend more time monitoring the existing loans. In order to understand better whether this ultimately results in riskier or less risky loan portfolios, we check the quality of the loan portfolio of loan officers above the threshold upon the origination of the loan (ex ante) and ex post.

We examine the ex ante quality of loans extended first. We develop a simple statistical model that predicts the ex ante credit quality of selected loan applications using only the information available to the loan officer at the time of the loan origination. The characteristics that are observable (or easily verifiable) for loan officers at the time of the loan origination are: the business sector of the borrower, the applied loan amount, the leverage, the total assets, the cash over total assets, the applied loan amount over total assets, whether the borrower has an account at the bank, whether the borrower has ever applied for a loan at the bank before, the juridical form, and yearly country-specific macroeconomic variables like the GDP, inflation, and unemployment rate. The macroeconomic variables used in this analysis are extracted from the World Bank web page and are lagged by one year.

We then proceed to estimate an out-of-sample logit regression to explain the observed one-year-ahead defaults for loans issued during the sample period. We recalibrate the model on a yearly basis to include the most recent historical information. For example, for 2003, we include all the information from 1996 to 2002; for 2004, we include all the information from 1996 to 2003, etc. We use the coefficients obtained from these regressions to estimate each borrower's ex ante one-year-ahead probability of default (PD).[20] The estimated PDs are used as the dependent variable in the estimation of equation (1) presented earlier. As before, the coefficient of interest is the coefficient obtained on the difference-in-differences term, α_4.

Table 7 presents the results. We find negative and highly significant estimates for α_4 in all three specifications. Column 3, for instance, which includes loan officer fixed effects, shows that the ex ante PD of new borrowers was 0.5 percent lower when a loan officer was above the cutoff value during the bonus period compared with the no-bonus period. This represents a reduction in the unconditional ex ante PD of 0.19 standard deviations. These findings suggest that loan officers above the cutoff originate ex ante better loan applications than loan officers below the cutoff value in the bonus period vis-à-vis the same comparison in the no-bonus period. Even though the rejection rate for these loan officers was lower, they approved ex ante higher-quality loans. Combined with the finding that loan officers also originated fewer loans,

[20] The results of the logit estimation are shown in Table A4 in the appendix.

this suggests "cherry picking" behavior of loan officers in the case that their bonus was endangered.

We would like to perform one final test on this point. Even though the loans originated by loan officers at risk of losing their bonus may ex ante seem to be of higher quality, they may not necessarily turn out to be less likely to default ex post, for example if the loan officers manipulate the data (the same data that we observe) as in Berg et al. (2013). We test this idea using the sub-sample of approved loans and use their observed default during the next six months as the dependent variable in estimating equation (1).

Table 8 shows that the likelihood of a borrower defaulting within the first six months after the loan was granted is significantly lower when the issuing loan officer was above the cutoff during the bonus period, as indicated by the negative and significant coefficient of *AboveCutoff**Bonus*. This result holds when we include time fixed effects (column 2) and loan officer fixed effects (column 3). Columns 4 and 5 change the performance window to four and eight months and find similar but not statistically significant results.

Taken together, these results suggest that the performance of loans issued when the loan officers were above the cutoff value in the bonus period is of better quality than that of loans issued during the period without variable incentives, despite the lower rejection rate. As we also find that fewer loans were originated, we conclude that when faced with the risk of losing their bonus, loan officers concentrate on monitoring to improve the performance of the existing loans and reduce their effort spent on originating and screening. They reduce the effort exerted on screening, however, without compromising the quality of the loans extended; instead, they focus on granting credit to the very best borrowers only ("cherry picking").

3.5 Loan Contract Outcomes

Besides changing the effort exerted on loan monitoring, origination, or screening, loan officers can adjust the loan contract terms in order to increase the likelihood of receiving a bonus payment, for example by extending the term to maturity of loans or by charging lower interest rates. To explore this possibility, we analyze whether loan officers use their discretion to change important loan contract characteristics. Specifically, we study whether they modify the interest rate of the loan contract, the approved loan amount, the approved share defined as the approved loan amount over the applied loan amount, the term to maturity in days, and the existence of personal and/or mortgage guarantees. In order to avoid outliers driving our results, we replace the loan amount and maturity with their natural logs.

As this analysis is performed at the loan-level, the most comprehensive specification includes covariates, time fixed effects, and loan officer fixed effects.[21] The effect of incentive-based compensation plans on loan terms is obtained using specification (1) with one of the loan contract characteristics as the dependent variable. We can only use approved loans for these analyses, yielding an estimation sample of 43,063 approved loans.

Table 9 presents the OLS estimation of these specifications. We do not find significant changes in interest rates, loan amounts, loan maturity, or guarantees since the coefficient of interest, *AboveCutoff*Bonus*, is never significant. This result stands in contrast to the findings of Agarwal and Ben-David (2013), but may be explained by the use of a fundamentally different incentive scheme in their work. Note also that Drexler and Schoar (2013) find that loan officers adjust lending by cutting credit rather than adjusting the loan terms.

We do find that loan officers increased the approved share, i.e. they reacted more favorably to the loan size requests of borrowers who obtained loans during the bonus period

[21] We do not use the respective covariate as an explanatory variable in the case in which we use it as a dependent variable. For instance, when we analyze the loan amount, we do not include the applied loan amount as an explanatory variable.

and when the loan officers' defaults were above the cutoff value. This finding is consistent with the cherry-picking hypothesis; when loan officers are above the cutoff during the bonus period, they process loans for the very best clients who, compared with the average client, seem to obtain loan amounts that are much closer to their requested amount.

4. Other Incentive Effects of the Incentive-Based Contract

The results presented above largely seem to indicate that loan officers behave in a way that is desirable for the bank when faced with a performance-based incentive system. They attempt to maintain a certain quality of their portfolio while being incentivized to extend loans. Further, the bank-level time series evidence presented in section 2 pointed to an overall deterioration in loan quality after the removal of the incentive-based contract. This raises the question of why the bank abandoned the incentive-based contract and replaced it with a fixed salary. We discussed this question with the bank, but were unable to obtain formal documentation on the reasoning. Informally, bank managers told us that they wanted to remove any pressure on loan officers to issue loans. Whatever the stated reason, it is clear that the removal itself suggests that notwithstanding the observed loan officers' reaction to the incentive-based system being rational and possibly maximizing loan officers' compensation, it may not be optimal from the perspective of the bank. While we have insufficient information to answer this question comprehensively, in this section, we present some evidence that suggests that the incentive-based contract may have had unintended consequences in a number of dimensions.

4.1 Incomplete Contracts: Collateral and Loss Given Default

Above, we show that loan officers change their monitoring behavior when they are above the default threshold and that this improves the performance of the monitored loans. This seems to be an intended consequence of the contract and desirable from the perspective of the bank.

However, while the loan officers may be indifferent with regard to which loans they monitor more when several are in default at the same time, from the perspective of the bank, what matters is not the probability of default but rather the probability of default multiplied by the loss given default. Does it matter that only the probability of default, not the loss given default, is incentivized in the contract? While we do not have information on loan-by-loan loss given default, we do have some indication of whether the loan was collateralized or guaranteed by a third party. We conjecture that on average collateralized loans or loans that are guaranteed by a third party can be expected to have a lower loss given default than other loans. Hence, we can test whether loan officers take collateralization into account in their monitoring effort.

We construct a variable, *Unsecured*, that takes the value of one if a loan is secured neither by a personal guarantee nor by mortgage collateral. We then estimate a variant of equation (1) in which we include a triple interaction term with *Unsecured*, much like the specification that we estimated earlier when we were interested in whether loan officers disproportionately increase their monitoring of large loans. The optimal monitoring behavior from the viewpoint of the bank would require the coefficient of *AboveCutoff*Bonus*Unsecured* to be negative and significant, i.e. loan officers focus on those loans that have the highest potential to generate large losses for the bank.

Table 10 displays the results. We run the regression with and without loan fixed effects. The coefficient of the triple interaction term is positive in both specifications and weakly significant in the second. This suggests that loan officers do not focus on those loans that are less secured, as would be desirable from the bank's perspective.[22] Hence, while the observed loan officer behavior may be rational and optimal individually, this test suggests that it may

[22] The coefficient for *AboveCutoff*Bonus* is negative but insignificant in column 1. However, an unreported Wald test shows a significant difference (at the 5 percent level) between unsecured and secured loans for loan officers who were above the bonus cutoff.

not necessarily be optimal for the bank. The evidence is consistent with the theoretical literature on incentive-based contracts and multitasking. For example, Holmström and Milgrom (1991) show that incentives in incomplete contracts carry the risk that agents will neglect those tasks that are less well rewarded or are not part of the incentive structure at all, but nevertheless are in the interest of the bank.

4.2 Do Loan Officers Respond Rationally to Incentives?

Our identification strategy so far has built on the idea that loan officers change their behavior significantly once the value-weighted defaults in their loan portfolio exceed the threshold. While we would expect changes in behavior at that point, it would be rational for loan officers to adjust their behavior *as they approach* the threshold as well. Indeed, rational loan officers may intensify their monitoring or engage in cherry picking before they even reach the 3 percent threshold, in order to make sure that they do not lose their bonus.

To explore this question, we construct an additional dummy variable, *AtRisk*, that takes the value of one if the default frequency of a loan officer's portfolio was above 1.5 percent but below the cutoff value of 3 percent and zero otherwise. We then interact the *AtRisk* variable with *Bonus* to analyze whether the financial incentives already have an impact before loan officers actually cross the 3 percent threshold. All the other variables are defined as before. We proceed to re-estimate equation (1) for all our outcome variables (monitoring, origination, screening, and ex ante and ex post loan quality).

The results are presented in Table 11. For all the outcome variables but ex post loan performance (column 5), we find a significant effect only for *AboveCutoff*Bonus*, and not for *AtRisk*Bonus*. This suggests that loan officers seem to react only once they have crossed the 3 percent threshold, rather than as they approach the threshold. In contrast to our results that show loan officers responding rationally to incentives in their allocation of effort across different tasks, the "late" reaction to incentives that we document here suggests myopic loan officer behavior. While somewhat unexpected, this result is in line with the recent literature investigating procrastination in the workplace (e.g., Cadena et al., 2011; Kremer et al., 2013). Whether or not this is optimal from the perspective of the design of the incentive contract is not entirely clear. It does suggest that in designing incentives, banks may want to set thresholds that are tighter than optimal, anticipating procrastination and myopic behavior by loan officers.

5. Placebo Tests

In any difference-in-differences regression set-up, the identification is based on the assumption of a parallel trend over time. In our case, this assumption would require that (in the absence of a compensation change) the difference between loan officers' behavior above the cutoff and that below the cutoff is constant over time; this condition would be violated, for example, if the pool of loan officers above and below the cutoff changes over time.

Our identification strategy relies on less stringent assumptions. By including loan officer fixed effects, we hold the loan officer constant and therefore we do not require the pool of loan officers above and below the cutoff to be similar over time; instead, we identify the effect of differences in compensation from within loan officer variation in behavior. The non-linearity of the compensation plan also helps the identification; for instance, given this non-linearity, we do not require the change in the performance of the loan officer when she crosses the cutoff to be constant over time; instead, we only need the change not to be discontinuous. Both of these refinements make our identification strategy quite robust.

Nonetheless, it is still possible that other non-linearities exist around the cutoff point that affect the behavior of the loan officer. To confirm that such non-linearities are not present in the data, we run a placebo test in which we repeat the estimations in the paper but we arbitrarily shift the date of the exogenous variation. For brevity, we use only the preferred specifications for each dependent variable: monitoring (column 4 of Table 3), loan origination (column 4 of Table 5), screening (column 3 of Table 6), and ex ante loan quality (column 3 of Table 7).

Specifically, we only focus on observations from the no-bonus period and assume that the change in compensation structure was in the middle of the no-bonus period. Therefore, the *PlaceboBonus* treatment variable equals one for observations from the first half of the no-bonus period and zero otherwise. As there was no change in the incentive compensation plan in the no-bonus period, we should not find any differential effect of being above or below the cutoff in the placebo test unless there are other non-linear effects around the cutoff.

Table 12 displays the results of this test. None of the estimates, denoted as *AboveCutoff**PlaceboBonus* in the table, are statistically different from zero. These results confirm our expectation that there are no other non-linear differential effects associated with being below or above the cutoff during the no-bonus period.[23]

In a second, unreported placebo test, we focus on observations from the bonus period only. Again, we split the bonus period into two sub-periods of approximately equal length and construct a placebo treatment variable that takes the value of one if the observation is from the first half of the bonus period and zero otherwise. We then re-estimate the regressions using the same four outcome variables. As expected, and similar to the first test, all the estimates for the placebo treatment dummies are close to zero and are not statistically significant. Finally, our results from Section 4.2 suggest that loan officers only change their behavior when really faced with a loss of the bonus payment, but not when they are already close to losing the bonus. Another way to interpret this result is as a cross-sectional placebo test that implies that the effects we identified above are really caused by a change in the incentive scheme.

[23] In further, unreported tests, we vary the threshold for the placebo bonus period on a monthly basis using the months June 2006 to April 2007 for this variation (that is, the first placebo bonus period stretches from January-June 2006, the second from January-July 2006, etc.). We then rerun all regressions for these placebo bonus periods. This gives ten coefficients for the *AboveCutoff**PlaceboBonus* variable for all four outcome variables. None of the resulting coefficients is significant in these tests.

Together, these tests validate our identifying assumption and suggest that we are indeed capturing the causal effect of the change in the incentive compensation structure.

6. Conclusion

We study the behavior of loan officers at a large international bank before and after the elimination of a performance-based compensation plan. What makes our setting particularly interesting is that the original compensation plan is highly non-linear. In particular, it rewards the loan officer with a bonus that increases monotonically with the loan volume as long as the proportion of the portfolio in default is below 3 percent, but the bonus is cancelled once the proportion of the portfolio in default surpasses that threshold.

Our results indicate that when loan officers have an underperforming portfolio that would result in the cancellation of the bonus, they allocate more time to monitoring, reduce loan origination, and approve a larger share of loan applications. This behavior results in a higher rate of repayment of the existing loans in the loan portfolio of the loan officer and also to an increase in the quality of approved loans. The effect on the repayment of existing loans is larger for larger loans. Hence, loan officers focus on activities that maximize their salary in the short term and reduce their effort on those that do not.

Our findings allow us to make the general causal claim that financial incentives for loan officers (for example like the one described in the paper) are effective in improving loan quality. The results may also be interpreted as cautioning banks to replace incentive-based contracts that penalize defaults with fixed salaries. However, the evidence also shows that such incentive-based contracts, by rewarding certain activities over others, may not necessarily result in outcomes that are preferable from a bank perspective. One bank-managerial implication of our results is to contract on all dimensions that are relevant for the bank, but any incentive-based contract is necessarily incomplete and therefore risks rewarding some activities "too little" that would also be in the interest of the bank. For example, loan officers rationally focus on the probabilities of default, rather than the loss to the bank, which is a combination of default probability and loss given default. Loan officers also “cherry pick” customers when at risk of losing the bonus, which may result in some customers not receiving credit who from the perspective of the bank (and the economy as a whole) should receive credit. Finally, loan officers may rationally reallocate their time in response to incentives, but our evidence suggests that they do so in a myopic way, i.e. they only react once they have already exceeded the threshold and not as they approach it.

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Figure 1: Time series graphs

This figure shows the time series graphs of the key variables. The data for Figures 1.1, 1.3, and 1.4 are at the loan-month level, while the data for Figure 1.2 are at the loan-level. The data are restricted to loan officers who were active before and after the removal of the bonus. *Bonus* indicates observations from January 2003 to October 2004, *transition* marks observations from November 2004 to December 2005, and *no-bonus* indicates observations from January 2006 to October 2007. Figure 1.1 shows the originated loan volume over the total outstanding loan volume (per loan officer). Figure 1.2 plots the rejection rate, which is calculated as the number of rejected loan applications over all the loan applications. Figure 1.3 depicts the average volume-weighted default frequency of loan officers' portfolio. Figure 1.4 shows the average fraction of loan officers whose volume-weighted default frequency was above the threshold of 3 percent.

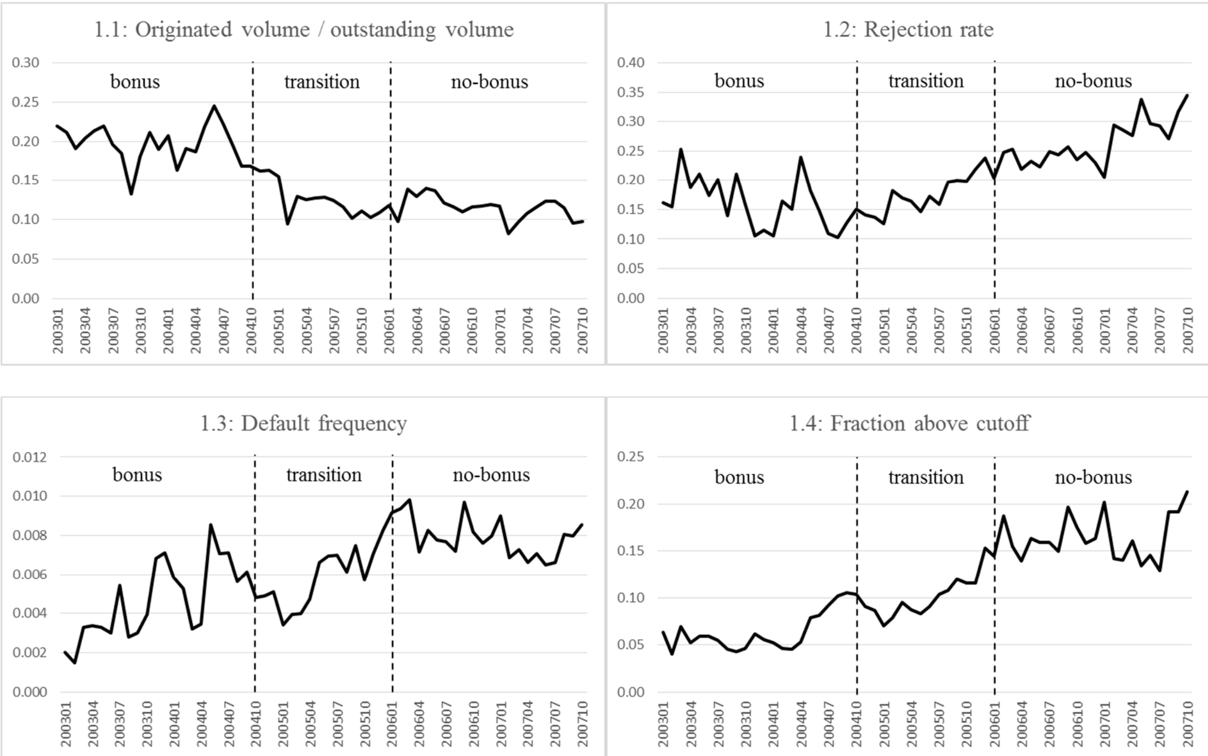

Table 1: Loan officer selection

This table tests for loan officer selection. We compare the characteristics of loan officers who left the lender before the variable compensation plan was replaced, group (I), with loan officers who stayed, group (II). Only the latter group is included in our DD estimations below. The loan officers who left the lender were more experienced than the loan officers who stayed. We thus form a third group (III), including an experience-matched group of loan officers who stayed at the bank (the top three experience deciles). We compare the average of several characteristics of loan officers in the period from January 2003 to October 2004, when the variable compensation plan was still in place. *Loan officer experience* refers to the number of loan applications that were already being handled by a loan officer in the bonus period. *Defaults* are a loan officer's average loan portfolio frequency of defaults in the bonus period. *AboveCutoff* is a dummy variable that takes the value of one if the defaults were above the cutoff value of 3 percent in month *t* and zero otherwise. Column 4 shows the differences between loan officers who left the lender and loan officers who stayed at the bank. Column 5 shows the differences between the loan officers who left the lender and a group of loan officers with similar experience who stayed at the bank. Statistical inference is based on standard t-tests. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively.

	Loan officer type			Differences	
	(I) Left	(II) Stayed	(III) Stayed High experience	(I)–(II)	(I)–(III)
Loan officer experience	156.58	56.20	155.15	100.38***	1.4345
Defaults	0.0038	0.0046	0.0043	-0.0008	-0.0005
AboveCutoff	0.0168	0.0245	0.0315	-0.0077	-0.0147
N	28	240	72		

Table 2: Monitoring – Descriptive statistics

This table shows the descriptive statistics for the variables used in the monitoring analysis. The data are at the loan-month level. The first row shows the dependent variable, Δ*Default*, which takes the value of 1 if the loan was not in default in the previous month but is in default in the current month; it takes the value of 0 if there was no change in the default status; and it takes the value -1 if the loan was in default in the previous month but is not in default in the current month. Rows two to four present time-variant loan officer characteristics. *Defaults* are the loan officer's average loan portfolio defaults. *AboveCutoff* is a dummy variable that takes the value of one if the defaults in a loan officer's portfolio were above the cutoff value of 3 percent in the previous month and zero otherwise. *Loan officer experience* is the number of loan applications handled until the current month. *Number of outstanding loans* is the loan officer's number of outstanding loans, which we use as a proxy for the loan officer's workload. The last two rows present time-variant loan characteristics. *Outstanding amount* is the loan's outstanding amount in euros, while *Remaining maturity* is the remaining loan maturity in months.

Variable	Mean	N	Std dev	Min	p25	p50	p75	Max
ΔDefault	0.0013	486,555	0.0478	-1.0000	0.0000	0.0000	0.0000	1.0000
Loan officer characteristics								
Defaults	0.0076	486,555	0.0188	0.0000	0.0000	0.0008	0.0085	1.0000
AboveCutoff	0.0627	486,555	0.1790	0.0000	0.0000	0.0000	0.0000	1.0000
Loan officer experience	439	486,555	284	0	221	408	608	1,474
Number of outstanding loans	194	486,555	108	1	109	195	269	545
Loan characteristics								
Outstanding amount	3,555	486,555	14,324	0	447	1,029	2,312	1,300,000
Remaining maturity	10	486,555	9	0	3	8	14	87

Table 3: Monitoring – Baseline results

This table shows the results of the OLS regression

$$\Delta Default_{it} = \alpha_1 Defaults_{jt\text{-}1} + \alpha_2 AboveCutoff_{jt\text{-}1} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt\text{-}1} {*} Bonus_t + \mathrm{B}X_{ijt} + e_{it}$$

and examines whether an incentive-based compensation plan affects the changes in monitoring effort. The data are at the loan-month level and are restricted to loan officers who were active before and after the removal of the bonus. $\Delta Default_{it}$ takes the value of one if loan i was not in default in the previous month (t-1) but is in default in the current month t, the value of zero if there was no change in the default status, and the value of minus one if the loan was in default in the previous month but is not in default in the current month. $Defaults_{jt\text{-}1}$ is the default frequency of loan officer j's portfolio in the previous month and $AboveCutoff_{jt\text{-}1}$ is a dummy variable that takes the value of one if the defaults in loan officer j's portfolio were above the cutoff value of 3 percent in the previous month and zero otherwise. $Bonus_t$ is a dummy variable that takes the value of one if the observation is from January 2003 to October 2004 and zero otherwise. The covariate sets (X) are defined in Table A1 in the appendix; the first set includes time-invariant covariates at the loan-level, the second set includes time-variant covariates at the loan officer level, and the third set includes time-variant covariates at the loan-level. We gently add fixed effects on the time (t), loan officer (j), and loan (i) levels in columns 2 to 4. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively. Standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)	(3)	(4)
Defaults	-0.0124	-0.0122	-0.0276	-0.0779***
	(0.0133)	(0.0135)	(0.0168)	(0.0274)
AboveCutoff	0.0002	0.0003	-0.0011	-0.0003
	(0.0010)	(0.0010)	(0.0012)	(0.0016)
Bonus	-0.0003			
	(0.0003)			
AboveCutoff*Bonus	-0.0055**	-0.0055**	-0.0045*	-0.0096**
	(0.0021)	(0.0022)	(0.0027)	(0.0048)
Time fixed effects	No	Yes	Yes	Yes
Loan officer fixed effects	No	No	Yes	No
Loan fixed effects	No	No	No	Yes
Covariate set 1	Yes	Yes	Yes	No
Covariate set 2	Yes	Yes	Yes	Yes
Covariate set 3	Yes	Yes	Yes	Yes
Observations	486,555	486,555	486,555	486,555
Adj. R square	0.0019	0.0024	0.0025	0.0013

Table 4: Monitoring – Loan size interactions

This table shows the results of the OLS regression

$$\Delta Default_{it} = \alpha_1 Defaults_{jt\text{-}1} + \alpha_2 AboveCutoff_{jt\text{-}1} + \alpha_3 LargeLoan_{it} + \alpha_4 AboveCutoff_{jt\text{-}1}{*}Bonus_t + \alpha_5 AboveCutoff_{jt\text{-}1}{*}LargeLoan_{it} + \alpha_6 LargeLoan_{it}{*}Bonus_t + \alpha_7 AboveCutoff_{jt\text{-}1}{*}Bonus_t{*}LargeLoan_{it} + \mathrm{B}X_{ijt} + e_{it}$$

and examines whether the increase in the monitoring effort of loan officers who surpassed the cutoff was focused on larger loans. The variables are defined as in Table 3, except that we use the variable *LargeLoan* that takes the value one if a loan's outstanding amount is above the median outstanding loan amount of the current month and zero otherwise. The covariate sets are defined in Appendix Table A1. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)
Defaults	-0.0272*	-0.0768***
	(0.0165)	(0.0268)
AboveCutoff	-0.0008	0.0028*
	(0.0012)	(0.0016)
LargeLoan	0.0016***	0.0002
	(0.0003)	(0.0003)
AboveCutoff*Bonus	-0.0012***	0.0011
	(0.0004)	(0.0009)
AboveCutoff*LargeLoan	0.0014	0.0048
	(0.0018)	(0.0030)
LargeLoan*Bonus	-0.0006	-0.0051***
	(0.0010)	(0.0013)
AboveCutoff*Bonus*LargeLoan	-0.0092**	-0.0229***
	(0.0042)	(0.0065)
Time fixed effects	Yes	Yes
Loan officer fixed effects	Yes	No
Loan fixed effects	No	Yes
Covariate set 1	Yes	No
Covariate sets 2 and 3	Yes	Yes
Observations	486,555	486,555
Adj. R square	0.0019	0.0015

Table 5: Loan origination effort

This table shows the results of the OLS regression

$$OriginationEffort_{jt} = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt}{*}Bonus_t + \mathrm{B}X_{jt} + e_{jt}$$

and examines whether an incentive-based compensation plan affects the loan origination effort. The data are at the loan officer-month level and are restricted to loan officers who were active before and after the removal of the variable compensation plan. We measure loan origination effort, $OriginationEffort_{jt}$, as the volume of originated loans over the volume of outstanding loans per loan officer for every month. *Defaults* are the default frequency of a loan officer's portfolio and *AboveCutoff* is a dummy variable that takes the value of one if the defaults in a loan officer's portfolio were above the cutoff value of 3 percent and zero otherwise. *Bonus* is a dummy variable that takes the value of one if the observation is from January 2003 to October 2004 and zero otherwise. The regressions control for loan officer experience and include different combinations of fixed effects as indicated in the table. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)	(3)	(4)
Defaults	0.0287	0.0360	-0.2297*	-0.2823**
	(0.1547)	(0.1398)	(0.1230)	(0.1144)
AboveCutoff	-0.0446***	-0.0431***	0.0176	0.0271*
	(0.0146)	(0.0132)	(0.0156)	(0.0144)
Bonus	0.1228***			
	(0.0096)			
AboveCutoff*Bonus	-0.1159***	-0.1039***	-0.1058***	-0.0762**
	(0.0393)	(0.0391)	(0.0351)	(0.0306)
Time fixed effects	No	Yes	Yes	No
Loan officer fixed effects	No	No	Yes	Yes
Time-by-branch fixed effects	No	No	No	Yes
Loan officer experience	Yes	Yes	Yes	Yes
Observations	5,476	5,476	5,476	5,476
Adj. R square	0.2803	0.2971	0.4220	0.3666

Table 6: Rejection rate and processing time

This table shows the results of the OLS regressions

$$RejectionRate_i = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt}{*}Bonus_t + \mathrm{B}X_{ijt} + e_i \quad \text{(a)}$$
$$ProcessingTime_i = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 AboveCutoff_{jt}{*}Bonus_t + \mathrm{B}X_{ijt} + \alpha_t + \alpha_j + e_i \quad \text{(b)}$$

and examines whether an incentive-based compensation plan affects loan rejection probability (specification a: columns 1 to 4) and respectively processing time (specification b: column 5). The data are at the loan application level and are restricted to loan officers who were active before and after the removal of the bonus scheme. The dependent variable in the first four columns is the rejection rate of the 55,946 loan applications in the period from January 2003 until October 2007. The dependent variable for the fifth column is the processing time, which is measured as the days a loan officer needs to evaluate a loan application. *Defaults* are the default frequency of a loan officer's portfolio and *AboveCutoff* is a dummy variable that takes the value of one if the default frequency of a loan officer was above the cutoff value of 3 percent and zero otherwise. *Bonus* is a dummy variable that takes the value of one if the observation is from January 2003 to October 2004 and zero otherwise. We include the covariate sets 1 and 2 of Table A1 in the appendix. The reduced covariate set 1 excludes *Guarantee*, *Leverage*, *Cash over total assets*, *Total assets*, ln(*Applied maturity*), and *Applied loan over total assets*, which are often missing for rejected loan applications. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. Standard errors in parentheses are clustered at the loan officer level.

	Rejection rate				Processing time
	(1)	(2)	(3)	(4)	(5)
Defaults	0.0537	0.0536	0.0371	0.0332	1.7303
	(0.0483)	(0.0486)	(0.0409)	(0.0440)	(2.7087)
AboveCutoff	0.0026	0.0022	0.0026	0.0033	-0.3034
	(0.0049)	(0.0049)	(0.0034)	(0.0043)	(0.2285)
Bonus	-0.0114***				
	(0.0025)				
AboveCutoff*Bonus	-0.0265***	-0.0266***	-0.0174*	-0.0202**	-0.6663
	(0.0095)	(0.0094)	(0.0090)	(0.0080)	(0.8312)
Time fixed effects	No	Yes	Yes	Yes	Yes
Loan officer fixed effects	No	No	Yes	Yes	Yes
Reduced covariate set 1	Yes	Yes	Yes	No	No
Covariate set 1	No	No	No	Yes	Yes
Covariate set 2	Yes	Yes	Yes	Yes	Yes
Observations	55,946	55,946	55,946	45,826	45,826
Adj. R square	0.9731	0.9731	0.9722	0.9141	0.2286

Table 7: Ex ante quality of originated loans

This table shows the results of the OLS regression

$$PD_i = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt}{*}Bonus_t + \mathrm{B}X_{ijt} + e_i$$

and examines whether an incentive-based compensation plan affects the quality of the originated loans. The data are at the loan application level and are restricted to loan officers who were active before and after the removal of the bonus compensation plan. We measure loan quality as the predicted ex ante credit risk based on historical information. The credit risk measure is annually calibrated using variables that are observable (or easily verifiable) for loan officers at the time of loan origination: the business sector of the borrower, the loan amount needed, the leverage, the total assets, the cash over total assets, the applied loan amount over total assets, whether the client had an account at the bank, whether the client had ever applied for a loan at the bank, the juridical form, and the three yearly macroeconomic variables GDP, inflation, and unemployment rate (see Appendix Table A4). The dependent variable, ex ante probability of default (*PD*), is based on a logit regression using the aforementioned variables. *Defaults* are the default frequency of a loan officer's portfolio and *AboveCutoff* is a dummy variable that takes the value of one if the defaults in a loan officer's portfolio were above the cutoff value of 3 percent and zero otherwise. *Bonus* is a dummy variable that takes the value of one if the observation is from January 2003 to October 2004 and zero otherwise. We include the covariate sets 1 and 2 of Table A1 in the appendix, excluding those used to calculate the ex ante PD. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)	(3)
Defaults	-0.0034	0.0012	-0.0044
	(0.0137)	(0.0134)	(0.0113)
AboveCutoff	0.0031*	0.0036**	0.0015
	(0.0018)	(0.0016)	(0.0012)
Bonus	-0.0204***		
	(0.0005)		
AboveCutoff*Bonus	-0.0076***	-0.0077***	-0.0049**
	(0.0025)	(0.0026)	(0.0020)
Time fixed effects	No	Yes	Yes
Loan officer fixed effects	No	No	Yes
Covariates	Yes	Yes	Yes
Observations	45,826	45,826	45,826
Adj. R square	0.3910	0.4099	0.3208

Table 8: Ex post loan performance

This table shows the results of the OLS regressions

$$DefaultLikelihood_i = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt} * Bonus_t + \mathrm{B} X_{ijt} + e_i$$

and examines whether an incentive-based compensation plan affects the ex-post loan performance. The data are at the loan-level and are restricted to loan officers who were active before and after the removal of the bonus plan. The default likelihood is 1 if a loan missed a payment for more than 30 days at least once within the first 6 months after it was granted. We exclude loans with maturities below 6 months and loans for which the 6-month period overlaps the bonus and the no-bonus periods. We use either a 6-month (columns 1 to 3), 4-month (column 4), or 8-month (column 5) time window. *Defaults* are the default frequency of a loan officer's portfolio and *AboveCutoff* is a dummy variable that takes the value of one if the default frequency of a loan officer was above the cutoff value of 3 percent and zero otherwise. *Bonus* is a dummy variable that takes the value of one if the observation is from January 2003 to October 2004 and zero otherwise. We include the covariate sets 1 and 2 of Table A1 in the appendix. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

Default likelihood	6 months	6 months	6 months	4 months	8 months
	(1)	(2)	(3)	(4)	(5)
Defaults	0.1032*	0.1026*	-0.0039	0.0353	-0.0263
	(0.0533)	(0.0540)	(0.0553)	(0.0636)	(0.0428)
AboveCutoff	-0.0039	-0.0039	-0.0132**	-0.0083	-0.0076
	(0.0052)	(0.0053)	(0.0055)	(0.0053)	(0.0059)
Bonus	-0.0034*				
	(0.0019)				
AboveCutoff*Bonus	-0.0213***	-0.0211***	-0.0155*	-0.0068	-0.0120
	(0.0056)	(0.0056)	(0.0087)	(0.0086)	(0.0158)
Time fixed effects	No	Yes	Yes	Yes	Yes
Loan officer fixed effects	No	No	Yes	Yes	Yes
Covariate set 1	Yes	Yes	Yes	Yes	Yes
Covariate set 2	Yes	Yes	Yes	Yes	Yes
Observations	27,606	27,606	27,606	34,299	22,591
Adj. R square	0.0216	0.0212	0.0176	0.0307	0.0050

Table 9: Loan contract outcomes

This table shows the results of the OLS regression

$$y_i = \alpha_1 Defaults_{jt} + \alpha_2 AboveCutoff_{jt} + \alpha_3 Bonus_t + \alpha_4 AboveCutoff_{jt} * Bonus_t + \mathrm{B} X_{ijt} + e_i$$

and examines whether an incentive-based compensation plan affects the interest rate, loan size, approved share (approved over applied loan amount), loan maturity, and existence of (personal and/or mortgage) guarantees for all approved loans. Loan size and maturity are replaced with their natural logs. *Defaults* are the default frequency of a loan officer's portfolio and *AboveCutoff* is a dummy variable that takes the value of one if the default frequency of a loan officer was above the cutoff value of 3 percent and zero otherwise. *Bonus* is a dummy variable that takes the value of one if the observation is from January 2003 to October 2004 and zero otherwise. We include the covariate sets 1 and 2 of Table A1 in the appendix. The loan size control is excluded from the estimation in column 2, and the loan maturity control is excluded from the estimation in column 4. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	Interest rate	ln(Loan size)	Approved share	ln(Maturity)	Guarantee
Defaults	0.0063	0.2215	0.0791	-0.0053	0.2191
	(0.0132)	(0.2078)	(0.0649)	(0.1086)	(0.1964)
AboveCutoff	-0.0009	-0.0216	-0.0017	-0.0066	0.0072
	(0.0019)	(0.0161)	(0.0075)	(0.0102)	(0.0162)
AboveCutoff*Bonus	0.0022	0.0179	0.0349***	0.0242	-0.0108
	(0.0026)	(0.0487)	(0.0124)	(0.0192)	(0.0325)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Loan officer fixed effects	Yes	Yes	Yes	Yes	Yes
Covariate set 1	Yes	Yes	Yes	Yes	Yes
Covariate set 2	Yes	Yes	Yes	Yes	Yes
Observations	43,063	43,063	43,063	43,063	43,063
Adj. R square	0.4889	0.8914	0.1324	0.8266	0.3004

Table 10: Incomplete contracts: Collateral and loss given default

This table shows the results of the OLS regression

$$\Delta Default_{it} = \alpha_1 Defaults_{jt-1} + \alpha_2 AboveCutoff_{jt-1} + \alpha_3 Unsecured_i + \alpha_4 AboveCutoff_{jt-1} {*} Bonus_t \\ + \alpha_5 AboveCutoff_{jt-1} {*} Unsecured_i + \alpha_6 Unsecured_i {*} Bonus_t \\ + \alpha_7 AboveCutoff_{jt-1} {*} Bonus_t {*} Unsecured_i + \mathrm{B}X_{ijt} + \alpha_t + \alpha_j + e_{it}$$

and examines whether the increase in the monitoring effort of loan officers who surpassed the cutoff was focused on unsecured loans. The variables are defined as in Table 3. We include the individual and interaction effects of the variable *Unsecured*. It is defined as 1 – *Guarantee* and takes the value of one if a loan does not come with a personal and/or mortgage guarantee and zero otherwise. The covariate sets are defined in Appendix Table A1. The specification of column 2 uses loan fixed effects (α_i) instead of loan officer fixed effects (α_j) and thus saturates the time-invariant *Unsecured* variable. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)
Defaults	-0.0265	-0.0760***
	(0.0166)	(0.0269)
AboveCutoff	-0.0037**	-0.0053**
	(0.0016)	(0.0021)
Unsecured	-0.0001	
	(0.0003)	
AboveCutoff*Bonus	-0.0056	-0.0125*
	(0.0042)	(0.0067)
AboveCutoff*Unsecured	0.0033**	0.0068***
	(0.0013)	(0.0016)
Unsecured*Bonus	0.0002	-0.0068***
	(0.0004)	(0.0020)
AboveCutoff*Bonus*Unsecured	0.0064	0.0153*
	(0.0047)	(0.0081)
Time fixed effects	Yes	Yes
Loan officer fixed effects	Yes	No
Loan fixed effects	No	Yes
Covariate set 1	Yes	No
Covariate set 2	Yes	Yes
Covariate set 3	Yes	Yes
Observations	486,555	486,555
Adj. R square	0.0019	0.0015

Table 11: Do loan officers respond rationally to incentives?

This table shows the OLS regressions of the most saturated specifications of the previous tables and investigates whether loan officers act myopically. We introduce another dummy variable *AtRisk* that takes the value of one if the default frequency of a loan officer was above 1.5 percent and below the cutoff value of 3 percent and zero otherwise. The data are at the loan officer-month level and are restricted to loan officers who were active before and after the removal of the variable compensation plan. The first column resembles the specification of column 4 of Table 3; *ΔDefault* takes the value of one if the loan was not in default in the previous month but is in default in the current month, the value of zero if there was no change in the default status, and the value of minus one if the loan was in default in the previous month but is not in default in the current month. The second column corresponds to the specification of column 4 of Table 5; *OriginationEffort* is the volume of loan applications over the volume of outstanding loans per loan officer for every month. The third column corresponds to the specification of column 3 of Table 6; *RejectionRate* equals one if a loan application was rejected and zero otherwise. The fourth column resembles the specification of column 3 of Table 7; *PD* is the predicted ex ante credit risk based on historical information. The last column resembles the specification of column 3 of Table 8; *DefaultLikelihood* measures ex post loan performance and equals one if a loan was in default at least once within the first 6 months after it was granted. The covariates are used according to the mentioned specification. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	ΔDefault	Origination Effort	Rejection Rate	PD	Default Likelihood
	(1)	(2)	(3)	(4)	(5)
Defaults	-0.0776***	-0.0703	0.0365	-0.0054	-0.0042
	(0.0273)	(0.1072)	(0.0408)	(0.0113)	(0.0551)
AtRisk	-0.0004	-0.0026	-0.0013	-0.0004	0.0073**
	(0.0005)	(0.0067)	(0.0013)	(0.0005)	(0.0033)
AboveCutoff	-0.0001	0.0075	0.0034	0.0018	-0.0170***
	(0.0016)	(0.0150)	(0.0036)	(0.0012)	(0.0059)
AtRisk*Bonus	0.0020	0.0058	0.0004	-0.0018	-0.0049
	(0.0022)	(0.0282)	(0.0065)	(0.0014)	(0.0053)
AboveCutoff*Bonus	-0.0103*	-0.1177***	-0.0178**	-0.0044**	-0.0120
	(0.0054)	(0.0328)	(0.0086)	(0.0020)	(0.0095)
Loan officer fixed effects	No	Yes	Yes	Yes	Yes
Loan fixed effects	Yes	No	No	No	No
Time fixed effects	Yes	No	Yes	Yes	Yes
Time-by-branch fixed effects	No	Yes	No	No	No
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	486,555	5,476	55,946	45,826	27,606
Adj. R square	0.0013	0.3678	0.9722	0.3246	0.0179

Table 12: Placebo tests

This table shows the OLS regression of a placebo test in which we repeat the estimations from the previous tables considering only the no-bonus period and arbitrarily shifting the date of the change in the compensation plan. The placebo treatment variable, *PlaceboBonus*, equals 1 for observations from the first half of the no-bonus period. Covariates and fixed effects are included in the regressions as specified in the table. *, **, and *** indicate significance at the 10, 5, and 1 percent level, respectively. The standard errors in parentheses are clustered at the loan officer level.

	ΔDefault	Origination Effort	Rejection Rate	PD	Default Likelihood
	(1)	(2)	(3)	(4)	(5)
Defaults	-0.0509***	-0.2034**	-0.0134	0.0086	-0.0080
	(0.0161)	(0.0928)	(0.0268)	(0.0164)	(0.0719)
AboveCutoff	-0.0022**	0.0040	0.0022	-0.0011	-0.0195**
	(0.0011)	(0.0104)	(0.0031)	(0.0017)	(0.0090)
AboveCutoff*PlaceboBonus	-0.0003	-0.0058	-0.0015	0.0023	0.0050
	(0.0011)	(0.0158)	(0.0043)	(0.0022)	(0.0080)
Loan officer fixed effects	No	Yes	Yes	Yes	Yes
Loan fixed effects	Yes	No	No	No	No
Time fixed effects	Yes	No	Yes	Yes	Yes
Time-by-branch fixed effects	No	Yes	No	No	No
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	438,971	3,308	39,132	30,956	21,001

Appendix

Table A1: List of covariates

This table shows the covariates that are used in the different regressions.

Covariate	Description
Covariate set 1: Loan-level	
Leverage	Total liabilities/total assets
Cash over total assets	Liquid assets/total assets
Total assets	In euros
ln(Applied amount)	Natural logarithm of the loan size applied for by the borrower in euros
ln(Applied maturity)	Natural logarithm of the loan maturity the borrower applied for in days
Applied loan over total assets	Loan size applied for by the borrower in euros/total assets
Juridical form business	1 if the client is a legal entity and 0 if the client is a natural person
Available account	1 if the client has other accounts (checking, savings, etc.) at the bank at the time of the loan application and 0 otherwise
Guarantee	1 if the client provides personal or mortgage guarantees and 0 otherwise
Has been in default	1 if the client has been in default with a previous loan
Has been rejected	1 if the client had submitted a previous loan application that was rejected
Last week of the month	1 for loans applied for in the last week of the month and 0 otherwise
Number of loan applications	1 for the first loan application, 2 for the second loan application, etc.
Loan destination	Loan used for working capital, fixed assets, mixed working capital and fixed assets, real estate, consuming, or others
Loan category	Size- and sector-specific categories
Business sector	Agriculture, production, construction, transport, trade, other services, or others
Covariate set 2: Loan officer-by-time level	
Loan officer experience	Number of loan applications that were already handled by a loan officer
Number of outstanding loans	Number of outstanding loans per loan officer (approximate workload)
Covariate set 3: Loan-by-time level	
ln(Outstanding amount)	Natural logarithm of the outstanding loan amount in euros
ln(Remaining maturity)	Natural logarithm of the remaining maturity in months

Table A2: Additional descriptive statistics of further dependent variables

This table shows the descriptive statistics for the dependent variables of Tables 5, 6, 7, 8, 11, and 12. O*riginationEffort* is the volume of originated loans over the volume of outstanding loans per loan officer-month observation. We winsorize this measure at the 2.5/97.5 percent level (Table 5). *RejectionRate* reflects the percentage of rejected loan applications, while *ProcessingTime* is measured as the number of days elapsed from the day when the loan application was submitted until the rejection/approval decision was made (Table 6). *PD* (probability of default) provides the observable ex ante borrower riskiness (Table 7). *DefaultLikelihood, 6 months* equals 1 if a loan was in default for more than 30 days at least once in the first 6 (4, 8) months after it was issued (Table 8). *Interest rate* is the loan contract interest rate, ln(*Loan size*) is the natural logarithm of the approved loan size in euros, *Approved share* is the approved over the applied loan amount (winsorized at the 2.5/97.5 percent level), ln(*Approved maturity*) is the natural logarithm of the loan maturity in days, and *Guarantee* takes the value 1 if the borrower pledged personal and/or mortgage guarantees and 0 otherwise (Table 9).

Variable	Mean	N	Std dev.	Min.	p25	p50	p75	Max.
OriginationEffort	0.1646	5,476	0.1750	0.0087	0.0549	0.1077	0.1951	0.7941
RejectionRate	0.2289	55,946	0.4201	0.0000	0.0000	0.0000	0.0000	1.0000
ProcessingTime	3.1063	45,989	4.5238	0.0000	0.0000	2.0000	4.0000	30.0000
PD	0.0535	45,826	0.0254	0.0016	0.0378	0.0488	0.0631	0.6313
DefaultLikelihood, 6 months	0.0067	27,606	0.0818	0.0000	0.0000	0.0000	0.0000	1.0000
DefaultLikelihood, 4 months	0.0054	34,299	0.0732	0.0000	0.0000	0.0000	0.0000	1.0000
DefaultLikelihood, 8 months	0.0058	22,591	0.0762	0.0000	0.0000	0.0000	0.0000	1.0000
Interest rate	0.1266	43,063	0.0272	0.0249	0.1078	0.1322	0.1410	0.2520
ln(Loan size)	7.5328	43,063	1.0635	3.9773	6.7036	7.3941	8.0827	14.0779
Approved share	0.9248	43,063	0.1533	0.5000	0.8750	1.0000	1.0000	1.1765
ln(Approved maturity)	6.3488	43,063	0.4610	4.0943	6.0403	6.2916	6.5793	8.5942
Guarantee	0.1824	43,063	0.3862	0.0000	0.0000	0.0000	0.0000	1.0000

Table A3: Univariate DD results

This table shows the univariate difference-in-differences (DD) results for the dependent variables of Tables 3, 5, and 6. ΔDefault takes the value of one if the loan was not in default in the previous month but is in default in the current month, the value of zero if there was no change in the default status, and the value of minus one if the loan was in default in the previous month but is not in default in the current month (Table 3). *OriginationEffort* is the volume of originated loans over the volume of outstanding loans per loan officer-month observation (Table 5). We winsorize this measure at the 2.5/97.5 percent level. *RejectionRate* reflects the percentage of rejected loan applications, while *ProcessingTime* is measured as the number of days elapsed from the day on which the loan application was submitted until the rejection/approval decision was made (Table 6). The table shows the average for loan officers below and above the cutoff and during the bonus and the no-bonus period. Statistical inference is based on OLS regressions that use standard errors clustered at the loan officer level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Period	Below cutoff	Above cutoff	Difference
Panel A: ΔDefault			
Bonus	0.0011	-0.0007	-0.0018***
No-bonus	0.0014	0.0012	-0.0002
DD			-0.0016**
Panel B: OriginationEffort			
Bonus	0.2682	0.1501	-0.1180***
No-bonus	0.1080	0.0820	-0.0260***
DD			-0.0921***
Panel C: RejectionRate			
Bonus	0.1532	0.1215	-0.0317
No-bonus	0.2560	0.2994	0.0434**
DD			-0.0751**
Panel D: ProcessingTime			
Bonus	4.2027	4.2794	0.0767
No-bonus	2.4691	3.1589	0.6897***
DD			-0.6131

Table A4: Ex ante PD estimation

This table shows the results for the ex ante PD estimation. This risk measure is used in Tables 7, 11, and 12. It is calibrated annually using variables that are observable (or easily verifiable) by loan officers at the time of loan origination: the loan amount needed, leverage, total assets, cash over total assets, applied loan amount over total assets, whether the client had an account at the bank, whether the client had ever applied for a loan at the bank, juridical form, three-yearly macroeconomic variables GDP, inflation, and unemployment rate, as well as the business sector of the borrower. The table provides the coefficients from logit regressions with a loan's default status (1 if in default, 0 otherwise) as the dependent variable. The coefficients are used to calculate the ex ante PD for each loan. Statistical inference is based on logit regressions that use standard errors clustered at the loan officer level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

	Default, loan applications prior to				
	2003	2004	2005	2006	2007
Intercept	-2.9000***	-4.5597***	-2.6725***	-3.0272***	-3.7942***
	(0.6480)	(0.6107)	(0.3954)	(0.3214)	(0.2823)
ln(Applied amount)	0.1805***	0.2380***	0.2655***	0.3044***	0.3610***
	(0.0347)	(0.0306)	(0.0225)	(0.0194)	(0.0176)
Leverage	1.2093***	1.2865***	1.2492***	1.4537***	1.5766***
	(0.3546)	(0.3001)	(0.2093)	(0.1706)	(0.1500)
Cash over total assets	-0.1653	-0.4037	-0.1790	-0.1610	-0.1458
	(0.3138)	(0.2865)	(0.1916)	(0.1626)	(0.1448)
Total assets	-0.0008**	-0.0014***	-0.0018***	-0.0018***	-0.0020***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
Applied loan over total assets	-0.0039	-0.0066	-0.0105**	-0.0163***	-0.0249***
	(0.0057)	(0.0055)	(0.0052)	(0.0053)	(0.0056)
Available account	-0.0447	-0.0815	0.1249*	0.0555	-0.0978**
	(0.1701)	(0.1350)	(0.0656)	(0.0483)	(0.0407)
Juridical form business	0.4846***	0.5384***	0.5049***	0.3453***	0.3062***
	(0.1257)	(0.1158)	(0.0978)	(0.0906)	(0.0824)
Number of loan applications	-0.0023	0.0052	0.0251	0.0167	0.0349***
	(0.0357)	(0.0292)	(0.0203)	(0.0157)	(0.0121)
GDP (previous year)	0.0150	0.0427***	0.0459***	0.0453***	0.0366***
	(0.0110)	(0.0108)	(0.0108)	(0.0107)	(0.0104)
Inflation (previous year)	-0.0042	0.0022	-0.0088	-0.0092*	-0.0104*
	(0.0058)	(0.0056)	(0.0055)	(0.0055)	(0.0053)
Unemployment rate	-0.0922***	-0.0592**	-0.1679***	-0.1739***	-0.1481***
(previous year)	(0.0296)	(0.0302)	(0.0232)	(0.0204)	(0.0186)
Sector fixed effects	Yes	Yes	Yes	Yes	Yes
N	12,855	20,217	38,147	55,829	75,378