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

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Abstract

We investigate the implications of providing loan officers with a non-linear compensation structure that rewards loan volume and penalizes poor performance. Using a unique data set provided by a large international commercial bank, we examine the three main activities that loan officers perform: loan prospecting, screening, and monitoring. We find that when loan officers are at risk of losing their bonuses, they increase prospecting and monitoring. In some specifications, screening also increases. We further show that loan officers adjust their behavior more towards the end of the month when bonus payments are approaching. These effects are more pronounced for loan officers with longer tenures at the bank. Overall, the evidence suggests that the contract is effective for stimulating overall greater effort to extend loans while maintaining loan quality.

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1. Introduction

While most research on bank compensation focuses on equity-linked incentives for high-level managers, there appears to be a consensus that distorted financial incentives for lower-level employees, such as loan officers and loan prospectors, were also an important factor in the 2007–2008 financial crisis. The role of loan officers' behavior in the crisis opened a controversial public debate and has resulted in important changes in the regulatory frameworks of many countries.[1] The debate also increased academics' and practitioners' interest in exploring the implications of incentive-based compensation for financial institutions.

Identification of causal effects of loan officer compensation contracts on behavior and banks' loan portfolios is difficult for several reasons. First, loan officers may select into certain contracts. Second, work effort of loan officers is difficult to measure and multi-dimensional. And third, if contracts are performance-based, treatment (i.e., the incentives under the contract) are a function of the loan officer's past behavior. In this paper, we use unique data on a non-linear, incentive-based compensation scheme for loan officers at a large international commercial bank to address the first two challenges. Under the scheme, which was mandatory for all loan officers, loan officers receive a monthly cash bonus proportional to their lending volume in addition to a fixed salary. However, the bonus is not paid in months when the value-weighted non-performing loans in a loan officer's portfolio exceed some threshold. We use this non-linearity in the contract to help us identify causal effects of the contract.

In addition to the non-linear compensation structure, the contract offers another important feature to identify how financial incentives affect loan officers' behavior: The bank classifies loans into six size and business sector categories and calculates monthly bonuses *by category*. All loan officers in our final sample handle loans in at least two of the loan categories used by the bank. Hence, identifying the effect of financial incentives on a loan officer's performance relies on comparing the behavior of the *same* loan officer at the *same* point in time in a loan category in which she was above the threshold in terms of her behavior in

[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).

another loan category in which she was below the threshold. To achieve this specific comparison, we include loan officer-by-month fixed effects in our regression specifications.

Furthermore, the data permit measurement of different tasks that loan officers perform. Often, loan officers must divide their time among three different but interrelated tasks, all of which affect the bank's loan portfolio quality: They engage in loan *prospecting* (Heider and Inderst, 2012), *screen* new loan applications, and *monitor* existing loans. While we do not have information on the exact time allocations of the loan officers in our sample, we can, given the richness of our data, define outcome variables for all three tasks: the total volume and the average size of originated loans as well as the number of new loan applications as proxies for loan prospecting; the proportion of accepted loans relative to all loan applications and time spent until a decision on a loan application is reached as a proxy for screening; and monthly payment patterns of existing loans as a proxy for monitoring.

Finally, we are faced with the problem that the treatment in our setup is endogenous in the sense that being close to the 3 percent default threshold in a given loan category is a function of past efforts of the loan officer in that loan category. We address this problem by estimating a set of instrumental variable models, in which we use the instruments to isolate the exogenous component of being at risk of losing the bonus.[2]

The results suggest that loan officers respond to financial incentives rationally. For example, while the contract exhibits a discrete jump at a 3 percent default rate in a loan category, we find that loan officers tend to react well before reaching this threshold. Furthermore, we find robust evidence that loan officers that were at risk of losing their bonuses in the previous month focus on generating more and larger loans. The evidence for screening is weaker. Loan officers, when they are at risk of losing their bonuses, appear to concentrate on activities that have the greatest impact on reducing defaults on existing loans in the current month. Because defaults are measured as the ratio of defaulting loans in a loan category to total loans outstanding in that loan category, loan officers aim to improve the numerator through more monitoring

[2] The instruments are related to the sentiment of the loan officer at the time she granted the loan and to the performance in that loan category of other loan officers.

(“getting borrowers to pay up”) and the denominator by extending more loans. This highlights the importance, when attempting to understand incentive contracts and loan officer behavior, of studying all major tasks loan officers perform. Finally, we show that loan officers who have longer tenure with the bank respond to incentives more than other loan officers and that most of the change in behavior comes in the second two weeks of the month, closer to the effective date of the bonus.

Our setting also permits us to examine the effect of the incentive scheme on the ex post performance of loans. We find that, overall, the contract had no significant effect on loan performance. Taken together with the evidence that the contract was effective in inducing officers to enhance their efforts in loan prospecting, we conclude that the incentive scheme was effective in increasing loan volume while maintaining loan quality.

Previous empirical work focuses primarily on the impact of performance-based compensation on loan officers’ *screening* decisions.[3] Most closely related to our paper, Cole et al. (2015) study three different contract designs in a laboratory setting under real-world conditions. They show that compensation that rewards loan volume but penalizes poor loan performance, much like the contract studied in this paper, entails more screening effort and a higher-quality loan portfolio relative to other compensation schemes. Using data from a large U.S. commercial lender, Agarwal and Ben-David (2017) study how loan volume-based compensation affects loan volumes and delinquency rates. They find that when compensation rewards volume, loan officers generate more loans but that the ex post default rate of these loans increases. They provide further evidence that loan officers make stronger use of loan applicants’ hard information while disregarding unfavorable soft information. Using data from a major European bank, Berg et al. (2016) study how automated lending decisions, based purely on hard information, influence loan officers’ behavior when compensation depends on the loan volume generated, finding that loan officers bias their assessments of borrowers’ risk to increase the pool of clients who are eligible to receive credit. Tzioumis and Gee (2013) document that mortgage officers increase their output towards the end of the month by reducing processing

[3] Most of the literature on risk taking in banks focuses on top executives (e.g., Bebchuk and Spamann, 2010; Bolton et al., 2015; Balachandran et al., 2011; Fahlenbrach and Stulz, 2011) rather than loan officers.

time and approving marginal loan applications. Loans made on the last day of the month have higher delinquency rates.

While this literature establishes an important causal relationship between financial incentives and screening, it is largely mute about the *multitasking* problem that loan officers face in their jobs. In this paper, we show that studying the three components together yields interesting new insights. We are the first to emphasize the trade-off faced by loan officers when they need to allocate effort across multiple tasks[4] but are compensated according to a contract that is incomplete in the sense that some activities are rewarded more than others.[5] Furthermore, how a non-linear compensation structure affects loan officer behavior has not been studied in a real-world setup in prior studies.

Our work also contributes to a strand of literature that 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. (2017), using data from India, show that cultural proximity matters for the efficiency of credit allocation. Qian et al. (2015) use Chinese data to examine the effects of increased accountability of loan officers on the assessment of credit risk. Beck et al. (2013) and Beck et al. (2016) analyze the impact of loan officer gender on portfolio performance and gender-based discrimination. Finally, Brown et al. (2017) show that the loan officers' numeracy level positively affects loan performance.

2. Data and identification strategy

2.1 Institutional background

Our data come from a large for-profit international commercial lender serving mainly individuals and small- and medium-sized enterprises. The data set includes 37,533 loan applications and 27,742 loans issued by the lender between January 1996 and October 2004. As the lender did not have any credit card business in

[4] We do not study the effect of financial incentives on the three tasks in a simultaneous regression setup but run separate regressions. This is similar in spirit to the approach of Griffith and Neely (2009).
[5] 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).

the sample period, all loans in our data set are either individual or small business loans. For all loans, we observe the payment history and the point in time when a loan went into default. “Defaults” are defined by the bank as a loan payment overdue for at least 30 days, consistent with international practice.[6]

The bank had 15 branches with 271 loan officers during the sample period. Loan officers have full authority over their tasks: they independently process loans for their pre-existing clients as well as actively seek out new clients.[7] In addition, they are responsible for monitoring existing loans. For example, if a loan payment is late, the loan officer can intensify monitoring by calling the borrower, sending her a letter, or visiting her 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 or give them unfavorable loan terms in subsequent loan applications.

Loan applications by new borrowers are 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 or borrower. The bank categorizes loans into six loan categories that are differentiated by loan size and a borrower’s sector of business activity. These six categories are small loans to private individuals for consumption purposes (up to 2,300 euros), very small business loans (up to 2,300 euros), small business loans (up to 10,000 euros), medium-sized business loans (up to 50,000 euros), large business loans (larger than 50,000 euros), and agricultural loans. Loan officers can and do handle loans of more than one category at the same time.

The incentive-based compensation scheme was structured such that the bonus was proportional to the loan officer’s lending volume as of the end of each month in a given loan category. However, in months when value-weighted defaults in the loan officer’s *loan category-specific* portfolio were above 3 percent, the bonus was cancelled for this loan category and month. Depending on the performance in each loan category, the bonus was summed over all well-performing loan categories the loan officer was covering

[6] 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.
[7] Gao et al. (2017) show that loan officers have a significant impact on lending decisions.

and constituted up to a maximum of 150 percent of the loan officers' fixed salary.[8] Hence, the incentive to keep the bonus was substantial under this performance-based contract.

2.2 Identification strategy

Our identification strategy relies on two distinctive features of the compensation scheme used by the bank in the sample period. The first feature is the non-linearity embedded in the incentive scheme, which specifies that in months when the value-weighted default rate in a given loan category is above 3 percent, the bonus is canceled. The second feature is that loan officers simultaneously handle loans in more than one category. These two features allow us to compare the behavior of the *same* loan officer at the *same* point in time in a loan category in which she is at risk of losing her bonus (or has already lost her bonus) with her behavior in another category in which she is not at risk of losing the bonus.[9]

Figure 1 plots two alternative responses to the contract by loan officers: a situation in which loan officers myopically change their behavior right at the cut-off point of 3 percent (solid line); and a situation in which loan officers change their behavior as they approach the cut-off point of 3 percent (dashed line). To allow for both possibilities, we test the following specification:[10]

$$(1) \qquad y = \alpha_1 Default_{jct\text{-}1} + \alpha_2 AtRisk_{jct\text{-}1} + \alpha_3 AboveCutoff_{jct\text{-}1} + bX + A + e,$$

where y represents the different outcome variables that capture loan prospecting, screening, and monitoring; $Default_{jct\text{-}1}$ is the value-weighted average default rate of loans of category c in the portfolio of loan officer j in month t-1, which controls for the linear effect of default on the effort employed in each task; $AtRisk_{jct\text{-}1}$ is a dummy variable that takes a value of one if the value-weighted average default rate on loans of category c in the portfolio of loan officer j in month t-1 was between 1.5 and 3 percent and captures the non-linear

[8] We do not have detailed information about the average size of the bonus across all months and loan officers. Some back-of-the envelope calculations suggest, however, that the average bonus size was between 75 and 95 percent of the fixed monthly salary. Hence, it is plausible that the bonus payments were salient.
[9] The third identification problem is addressed in Section 3.4. below, where we instrument for A*tRisk* and *Default* to control for potential endogeneity.
[10] Qualitatively similar results are obtained through a more general specification in which the different loan default groups can have not only different levels but also different slopes. For brevity, we only include the results for the more parsimonious specification with a uniform slope. All other results are available upon request.

effect of being at risk of losing the bonus; and $AboveCutoff_{jct\text{-}1}$ is a dummy variable that takes a value of one if the value-weighted average default rate on loans of category c in the portfolio of loan officer j in month t-1 was above the cut-off of 3 percent. This variable captures the non-linear effect of receiving no bonus because of a default rate that is too high.

In our specification, the omitted reference benchmark refers to loan officers' behavior in loan categories with a value-weighted average default rate below 1.5 percent; therefore, the coefficients of interest, α_2 and α_3, capture the effect of being at risk of losing the bonus and of being in the no-bonus zone, respectively. In unreported tests, we also estimated all regressions, controlling for loan officer performance measures that are lagged by two months and using different definitions of the *AtRisk* variable (1.25-3 percent and 1.75-3 percent). These tests, which are available upon request, yield qualitatively and quantitatively similar results.

Depending on the estimation, X represents a vector of control variables at the loan (application)-level (referred to as covariate set 1 in the regressions), loan officer characteristics that vary over time (covariate set 2a), loan officer characteristics that vary over time and by loan category (covariate set 2b), and loan covariates that vary over time (covariate set 3). For instance, the controls represented by X include the outstanding loan amount, the remaining time to maturity, loan officer experience measured as the total number of loans processed by loan officer j in loan category c since she started working at the bank and her workload measured as the number of outstanding loans in her overall portfolio at time t. All these controls are described in detail in Table 1.[11] Finally, A is a vector of fixed effects. Standard errors in the loan prospecting and screening regressions are clustered at the branch-month level, as we expect the quality of loans to be correlated with time and geographic location. In the monitoring regressions, we cluster standard errors at the branch-month and loan level (Thompson, 2011) to further correct for potential

[11] All regression results presented below are qualitatively and quantitatively similar if no further covariates are included in addition to the fixed effects.

autocorrelation.[12]

To compare the behavior of the *same* loan officer at the *same* point in time in loan categories close to or above the cut-off point with her behavior in a loan category where she was far away from the cut-off point, we include loan officer-by-month fixed effects, which control for loan officer-specific time-varying unobserved factors that may influence loan officers' efforts. In the monitoring analyses, we also add loan fixed effects in one specification to control for any unobserved variation in the portfolio composition.

To illustrate the approach: If in month t-1, a loan officer has a default rate of 1 percent in loan category A and 2 percent in loan category B, the coefficient α_2 would capture the difference between the monitoring effort (or other outcomes, depending on the regression) of the loan officer on loans that are unlikely to put her above the no-bonus threshold at time t and her monitoring effort on loans that are likely to put her above the no-bonus threshold at time t. An important contribution of our approach is that it is immune to time-varying loan officer characteristics, which are likely to be an important source of bias in extant empirical work on the subject. Furthermore, the non-linearity of the compensation scheme permits us to conduct a placebo analysis, using data from a period in which the bank compensated its loan officers based on a fixed wage contract (see Section 3.6). Given our setup, we drop loan officers who were active in only one loan category during the sample period (7 percent of the sample).

2.3 Descriptive statistics

All control variables used in the empirical analysis are defined in Table 1. In the regression tables, we indicate which of the covariates are included in which specification. Table 2, Panel A provides descriptive statistics for the main dependent variables used in the empirical analyses. We use three variables as proxies for loan prospecting. *Prospecting volume*$_{jct}$ denotes the total originated loan application volume in euros; *Average loan size*$_{jct}$ is the average size of all originated loans in euros; and *N applications*$_{jct}$ is the total number of received loan applications. All three variables are computed for loan category c, handled by loan

[12] All results are invariant to clustering at the loan officer level, and the monitoring results are invariant to clustering at the branch-month level only. The latter results have a higher statistical significance when Newey-West standard errors are used to correct for autocorrelation at the loan level.

officer *j* in month *t*.

To proxy for screening effort, we use two variables, which are standardized in different ways. The first variable is the ratio of the number of rejected loan applications to the number of received loan applications. To correct for months with extraordinarily many or few loan applications, we use the one-month average (*N rejected applications/N applications* (1-*month avg.*)), the three-month average (*N rejected applications/N applications* (3-*month avg.*)) and the six-month average (*N rejected applications/N applications* (6-*month avg.*)) of the variable. The second variable is processing time. Processing time is measured in days from the date the loan officer received the loan application until the date the loan application was either approved or rejected. To control for a mechanical increase in processing time because of a larger number of loan applications handled by loan officers, we standardized it by using the natural log of the prospecting volume (*Processing time/ln*(*Prospecting volume*)), the natural log of the average loan size (*Processing time/ln*(*Avg. loan size*)), and the natural log of the number of loan applications (*Processing time/ln*(*N applications*)). These variables are all computed at the loan officer-by-loan category-by-month level.

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 proxy for monitoring effort based on status changes of the loans in a loan officer's loan portfolio. Our data set contains one-to-one matching between borrowers and loan officers, and for each loan, we observe the application date, the issuing date and the dates of any missed payments. These data enable us to focus on the within-loan variation in monthly defaults. In line with the literature, 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 observe in this setup to changes in the extent (quality or intensity) to which loan officers monitor their borrowers.

Following this reasoning, we generate the variable $\Delta(Default)_{it-1,t}$, which takes a value of 1 if loan *i* was not in default in the month *t*-1 but is in default in the month *t*, a value of 0 if there was no change in the default status from month t-1 to month t, and a value of -1 if loan i was in default in the previous month but is not in default in the current month. This variable is constructed at the loan-by-month level (it), so that the maximum number of observations per loan is equal to the time to maturity of the loan, measured in months minus one.

On average, loan officers generated a loan volume of approximately 13,000 euros, the average loan size was 6,000 euros, and 3.5 loan applications were originated per month. The average rejection rate was 32 percent, if calculated for the current month (i.e., *N rejected applications*$_{jct}$/*N applications* (1-*month avg.*)). On average, processing time, which is standardized by using the natural log of the number of loan applications, is 6.3 days. The monitoring outcome variable, $\Delta(Default)_{it-1,t}$, has a mean of 0.08 percent, which implies a slight deterioration in the average loan's quality over its duration.

Panel B of Table 2 presents descriptive statistics for the main explanatory variables used in the loan prospecting analyses. On average, 0.4 percent of a loan officer's loans in a given category defaulted in the previous month, approximately 1.4 percent of loan officers had a category-specific portfolio default rate of between 1.5 and 3 percent, and 3 percent had a category-specific portfolio default rate above 3 percent. On average, loan officers had already processed 35 applications in a given loan category.

Table A1 in the appendix provides additional descriptive statistics for the control variables used in the screening and monitoring analyses.

3. Empirical results

In this section, we present the main results regarding how financial incentives influence loan officers' behavior in the three tasks of their job: prospecting for and screening new loan applications and monitoring existing loans. We first present the regression result for loan prospecting, then screening, and finally monitoring. We also present results for the instrumental variable approach, some results regarding heterogeneity across loan officers and time as well as the findings of additional tests.

3.1 Loan prospecting

The data that we use for this test are at the loan officer-loan category-month level and include 10,202 observations. The coefficients of interest are α_2 and α_3 in equation (1). We estimate equation (1) using OLS and cluster standard errors at the branch-month level. The regressions include loan category fixed effects, loan officer-by-month fixed effects, and loan officer experience. The fixed effects permit identification of the same loan officer at the same time in two different loan categories. As we do not observe any loan officers moving across branches, this specification also subsumes branch-by-month fixed effects that control for time-variant determinants of loan prospecting at the branch level, such as regional changes in loan demand.

Table 3 presents the results. In column (1), with the natural log of the loan prospecting volume as the dependent variable, we find a highly significant, positive coefficient for $AtRisk_{jct-1}$, indicating that a loan officer who was at risk of losing her bonus in the previous month in a given loan category generated significantly more new loan application volume in this particular loan category than she generated in other loan categories, in which she was far away from losing her bonus in the previous month. The results are robust to using the natural log of the average loan size in column (2) or the natural log of the number of loan applications, although the coefficient in column (3) is only significant at the 10 percent level. These three point estimates are highly significant in economic terms: loan officers who are at risk of losing their bonus almost double their total origination volume; most of this effect is driven by larger loan sizes (+83 percent) and less by an increase in the number of new loan applications (+12 percent). In contrast, the coefficients for $AboveCutoff_{jct-1}$ and $Default_{jct-1}$ are insignificant in all three specifications.

These results suggest that loan officers increase effort in loan prospecting to maximize the likelihood of receiving a bonus payment. Interestingly, our evidence suggests that loan officers already react to financial incentives when they are at risk of losing their bonuses rather than when they have already lost their bonuses. Originating more and larger new loans makes sense from the perspective of the loan officer because a new loan is less likely to default at the beginning of its maturity and dilutes the default rate in the short run.

In a second set of tests, we analyze the time variation of this effect within any given month. The bonus for any given month is decided by the default rate in a loan segment for a given loan officer *at the end of a* *given month.* As time passes during a given month, loan officers continuously update their beliefs about the likelihood of receiving bonuses in a given loan segment. To investigate this, we split the sample into the first ($\tau = 1$) and second ($\tau = 2$) half of the month and rerun the regressions for all three outcome variables. To account for information acquired during these months, we also include a contemporaneous variable for the default rate and at risk and above cutoff dummies as of the last day of the first half of the current month (first three columns) and the end of the current month (last three columns).

Table 4 contains the results. The $AtRisk_{jct-1}$ variable is not significant in any of the three regressions, using data for the first half of the month, but it is significant in two of the three regressions for the second half of the month. The coefficient size for originated loan volume and average loan size is approximately twice as large in the second half as in the first half. However, because of the large standard errors, the differences in the coefficients are not significant. Contemporaneous effects tend to be insignificant. Overall, loan officers tend to increase their efforts in meeting their bonus targets in the second half of the month when more information is available, and/or the urgency of taking action seems more immediate.[13]

3.2 Screening

The second activity that we examine is screening. We proxy screening by the rejection rate and the time it takes a loan officer to process a loan application in days. We calculate the rejection rate by dividing the number of rejected loan applications by one-month, three-month, and six-month averages of the number of loan applications. Processing time is scaled by dividing it by the natural log of the originated loan volume, the natural log of the average loan size, and the natural log of the number of loan applications. We then estimate equation (1) with OLS, using the three versions of both variables as outcomes, and cluster standard errors at the branch-month level. In these tests, the data are at the loan officer-category-month level. We estimate all regressions, including fixed effects, for the loan category, loan officer-by-month fixed effects,

[13] We also performed an analysis in the spirit of Tzioumis and Gee (2013) and investigated whether the results differ between the last week of the previous month, i.e., the week just before the cutoff, and the first week of the current month. The unreported results, available upon request, show that the effect appears to be equally strong in the last week and the first week of the month. Hence, there is no indication of "gaming" of the incentive scheme.

and loan officer experience. The results are displayed in Table 5.

In Panel A of Table 5, we report the results for the scaled rejection rate as a dependent variable. The table shows that neither the coefficient for $AtRisk_{jct\text{-}1}$ nor the coefficient for $AboveCutoff_{jct\text{-}1}$ are significant at conventional levels in any of the specifications. These results suggest that while loan officers appear to increase their efforts to originate more loan volume, they do not change their behavior with regard to decisions to accept or reject loan applications. Similarly, in Panel B of Table 5, we do not find that scaled processing time changes, as evidenced by the non-significant coefficients for the $AtRisk_{jct\text{-}1}$ and $AboveCutoff_{jct\text{-}1}$ variables in all three specifications in the table.[14]

Overall, in these baseline specifications, loans are equally likely to be accepted when loan officers are at risk of losing their bonuses. Thus, loan officers do not attempt to reduce the riskiness of their loan portfolio by increasing their standards for accepting loans. As we will see below, in the IV specifications, we find some evidence that loan officers also tighten lending standards when at risk of losing their bonuses.

3.3 Monitoring

The final task of a loan officer we explore is monitoring existing loans. We use the change in loan *i*'s default status from *t*-1 to *t* as a measure of how successful the loan officer was in convincing the borrower to remain or become current on her payments to the bank. We estimate two specifications of this variable, denoted as $\Delta(Default)_{it\text{-}1,t}$. The first specification includes loan fixed effects, loan officer-by-month fixed effects, and covariate set 3. The second specification includes loan category fixed effects, loan officer-by-month fixed effects, and covariate sets 1-3.[15] In both specifications, we use two-way clustered standard errors at the branch-by-month and loan level, first, because we expect the quality of loans to be correlated with time and geographic location and, second, because we aim to correct for potential serial correlation at the loan level. Data are at the loan-by-month level, which explains the increase in the number of observations. As before, the coefficients of interest are α_2 and α_3 from equation (1). The results are displayed in Table 6.

[14] The results remain qualitatively unchanged if we use non-logarithmized versions of the dependent variables.
[15] Refer to Table 1 for a list of the covariates included in covariate sets 1-3 and their definitions.

In both specifications, we find a weakly significant coefficient for the $AtRisk_{jct\text{-}1}$ variable, with the coefficient size varying from -0.0024 to -0.0032, and an insignificant coefficient for the $AboveCutoff_{jct\text{-}1}$ variable. The magnitude in the former case amounts to a moderate 0.104-0.139 standard deviations of the monthly change in defaults.

These results suggest that financial incentives induce loan officers to change their monitoring behavior – they monitor more, more effectively, or both – to reduce the proportion of the portfolio in default and maximize their income. Moreover, as in the case of loan prospecting, loan officers react when they are at risk of losing their bonuses but not when they have already lost them. Finally, the increase in loan prospecting effort documented above does not appear to come at the expense of reduced monitoring effort, and vice versa.

3.4 Instrumental variables

Our identification strategy so far relies on saturating linear probability models with high dimensional fixed effects and further covariates to focus on the effects of the incentive scheme on our outcome variables. Nevertheless, a treatment – e.g., a loan officer being at *AtRisk* – is not exogenously imposed, as it is a function of past loan officer behavior in that loan category. To address this concern, we use a sentiment-based indicator and the occurrence of many defaults in a given loan category as instruments for loan officer performance.

We first build a sentiment indicator based on workdays before major holidays. Figure 2 illustrates the construction of this instrument. Our approach rests on the argument that upcoming holidays are associated with an upbeat mood. Agarwal et al. (2012), using this instrument, find that positive sentiment events are associated with a higher loan approval rate and higher defaults ex post. In our setting, this corresponds to less scrutiny in screening of loan applications (at time t-n) because of the upbeat mood before holidays compared with loans that are screened further away from holidays. Because of less intense screening, these pre-holiday loans are of lower quality and thus more likely to default in month t-1. A loan officer with many pre-holiday/low-quality loans is thus more prone to be *AtRisk* (or *AboveCutoff*) in month t-1, which may induce greater effort in our three tasks of interest in month *t*. Specifically, we aggregate the loan level sentiment information at the loan officer-loan category-month level. *Pre holiday* ranges between zero (i.e., no loan in the portfolio was granted on the two workdays preceding holidays) and one (i.e., all loans in the portfolio were granted on the two workdays preceding holidays).

The second instrument is based on the category-specific loan performance of loan officers outside officer *j*'s bank branch. This variable should capture macroeconomic shocks that drive up a loan officer's default rate independently of the loan officers' efforts and may exogenously push loan officers to be at risk (or above the cutoff). We construct the dummy variable *Many defaults*, which equals one if the average default rate of loan officers outside officer *j*'s bank branch is between 0.25 and 2.5 percent in loan category *c* in month *t*-1.[16]

We argue that excluding these two variables from the second stage is valid. For instance, it should not matter for the intensity with which a loan officer monitors her current loan portfolio whether there was an upcoming holiday many months ago when a loan was granted. Additionally, our instruments appear to be valid because they do not share the same reasoning. This fact is confirmed by the negative correlation between *Pre holiday* and *Many defaults*. Because our main specification includes three potentially endogenous variables, *Default*, *AtRisk*, and *AboveCutoff*, we opt to instrument two of them in three possible combinations.

We first instrument *Default* and *AtRisk* with these two variables. Table 7 shows the results. The first stage always reveals a positive relationship between the two instruments and *AtRisk*, while we obtain less conclusive results in the case of *Default*. The p-value of the first stage Kleibergen-Paap rk Wald F statistic is always below 1 percent, which indicates sufficient correlation between the endogenous variables and the instruments. The two-stage least squares results show a positive *AtRisk* coefficient for the first two measures of loan prospecting, while the third coefficient is negative. Thus, we find consistent evidence that loan officers originate larger loan volumes if they are at risk of losing their bonuses in the previous month. They

[16] The results are robust to reasonable variations in the lower and upper thresholds. See Table A2 in the appendix for descriptive statistics.

appear to grant larger loans on average rather than handle more loan applications. Furthermore, we find positive *AtRisk* coefficients for the standardized rejection rate and processing time. This may indicate that loan officers intensify screening once they are at risk of losing their bonuses. We are, however, cautious about these results, as they are at odds with our fixed effects results above, and the point estimates are extremely large compared with those in Table 5. The last row of Table 7 shows the monitoring results. They indicate that loan officers intensify monitoring when they are at risk of losing their bonuses in the previous month.

Table A3 in the appendix further shows IV regression results for the two other combinations of our two instruments with the three endogenous variables. Panel A shows the case where we instrument *Default* and *AboveCutoff*. In general, the first-stage results appear weak, with insignificant F statistics. Origination and screening results for the *AboveCutoff* variable enter the two-stage least squares estimations as statistically significant. Panel B shows the case where we instrument *AtRisk* and *AboveCutoff*. The first stage results are comparable with those in Table 7. For two of the origination measures and the screening and monitoring regressions, the coefficient for *AtRisk* is statistically significant, but only one coefficient for *AboveCutoff* enters the regressions significantly. We thus argue that loan officers anticipate upcoming loan performance issues by increasing origination and intensifying screening and monitoring. Overall, these IV results support our finding that the compensation scheme appears to work.

3.5 Heterogeneous results

The next set of tests explores some heterogeneous dimensions of the effects documented so far. We first explore whether loan officer tenure affects the results. We hypothesize that loan officers who have been working for the bank longer should have a better idea of how and which of the three tasks they can influence best through a change in behavior to maximize their bonus payments. We define loan officer tenure as the date of the current loan application less the date of the first loan application in the dataset. The mean and median tenures of loan officers are both approximately two years. We then compute the median across all loan officers in a certain month and split the sample into observations below (short tenure) and above (long tenure) the median. We run split regressions for the three loan prospecting outcome variables, for two of the six screening outcome variables[17] and for the monitoring outcome. The results are shown in Table 8.

Panel A of the table shows that for loan prospecting volume and average loan size, the coefficient for $AtRisk_{jct\text{-}1}$ is highly significant among loan officers with long tenure, while it is not significant among loan officers with short tenure. On the other hand, there is no difference between short- and long-tenured loan officers when the number of loan applications is used.

Panel B shows the results for screening and monitoring. As before, we do not find any significant results for screening effort, irrespective of loan officer tenure. In contrast, we observe a larger monitoring effect for loan officers with a longer tenure with the bank. The effect of financial incentives on loan officers' loan prospecting behavior appears to be more pronounced for loan officers who have more experience with the contract and the job. These results are consistent with Griffith and Neeley (2009), who find that more experienced managers react more strongly to the introduction of an incentive-based compensation scheme.

In unreported results, we also tried the number of outstanding loans, the volume of the outstanding loan portfolio, and loan officer experience (proxied by the total number of loan applications handled so far) as a source of heterogeneity across loan officers. The results are qualitatively similar to those for loan officer tenure, as these variables are highly correlated. Finally, we tested whether results differ between first-time and repeat borrowers. We find some weak evidence that loan officers focus more on originating loans from new clients. All results are available upon request.

3.6 Additional tests

In a final set of analyses, we discuss the results from a placebo test and the results of the effect of a change in loan officer behavior on loan performance.

Our identification compares the same loan officer across different loan categories at the same point in time, as described above. This prevents unobserved differences in loan officer characteristics and time

[17] The results for the other four screening variables not shown here are qualitatively and quantitatively similar. We omit the results to save space. They can be obtained from the authors upon request.

effects from driving our results. Nevertheless, it may be instructive to observe loan officers in an environment without any incentive pay. Our data permit us to examine this because the bank under study in this paper introduced a fixed wage system without incentive pay two years after the end of the sample period (by the end of December 2005).[18] We use this change in the bank's bonus system to perform a placebo test. Specifically, we collect data from January 2006 through September 2007 and re-run all outcome regressions, using this time period and the same identification. The results, provided in Table 9, show that we do not obtain any significant coefficients for $AtRisk_{jct\text{-}1}$ and $AboveCutoff_{jct\text{-}1}$ in any of the specifications.

Finally, we investigate whether loan performance changed as a result of changed behavior during the bonus period. For this test, we measure loan performance as the default likelihood between month t and month $t+n$, where n represents different time buckets, and t is the time period when the loan was extended. The time buckets we use are the loan performance for 1 to 4 months after month t, 5 to 8 months, 9 to 12 months, and beyond 12 months. If loan officer behavior not only achieved a higher likelihood of receiving a bonus payment but also better loan performance, this should be in the interest of the bank. The results are provided in Table 10. The table shows that loan performance remained unchanged as a result of the financial incentive scheme, as the coefficient for the $AtRisk_{jct\text{-}1}$ and $AboveCutoff_{jct\text{-}1}$ variables are not significant in any of the four regressions. The results suggest that loan quality was not a function of the incentive scheme. The quality of loans being extended when loan officers were at risk of losing their bonuses in that loan category, despite their increased focus on loan prospecting, was no worse than in other loan categories.

4. Conclusion

We study how the behavior of loan officers at a large international commercial bank responds to a performance-based compensation scheme. What makes our setting particularly interesting is that the

[18] Conversations with bank management revealed that the major reason for abandoning the incentive contract was that it appeared to undermine teamwork within and across branches, with negative consequences for bank profitability. Hence, while the incentive contract appeared to have worked well at the individual level, it may not have been optimal from the perspective of the bank.

compensation plan studied is highly non-linear. In particular, it rewards loan officers with bonuses that increase monotonically with loan volume, provided the proportion of the portfolio in default in a given loan category is below 3 percent but with bonuses canceled once the proportion of the portfolio in default surpasses that threshold. Our empirical setup and data further allow us to compare the behavior of the same loan officer at the same point in time when she is at risk of losing her bonus in one loan category as opposed to another loan category in which she is far from the risk of losing her bonus.

The results indicate that when loan officers are at risk of losing their bonuses, they allocate more effort to two of the three activities of a loan officer in the current month: loan prospecting and monitoring. In IV specifications, we also find tentative evidence for a tightening of loan standards. The results suggest that overall, the contract is effective in increasing loan officer effort and overall loan volume for the bank without compromising quality.

We also find that these effects are more concentrated among loan officers that have a longer tenure with the bank and that loan officers appear to increase their efforts in the second half of each month, when the effective date for the bonus is approaching. Finally, we provide evidence from a placebo test in which the bank's loan officers were given a fixed wage contract and show that none of the effects exist in that setting.

The results of our study improve our understanding of loan officer behavior when loan officers are faced with an incentive contract. Crucially, focusing on analyzing single tasks only when loan officers perform several tasks at the same time may lead to results that do not fully capture how loan officers react to different incentive schemes. Accounting for multi-dimensionality is thus essential in the current debate about compensation schemes in financial institutions.

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Figure 1: Functional form of the loan officers' responses to the financial incentives
This figure plots two alternative responses by loan officers. The solid line represents a hypothetical situation in which loan officers change their behavior right at the punishment zone of 3 percent. The dashed line illustrates a situation in which loan officers have already changed their behavior as they get closer to the punishment zone. The latter is the functional form we test in the main econometric specifications in this paper.

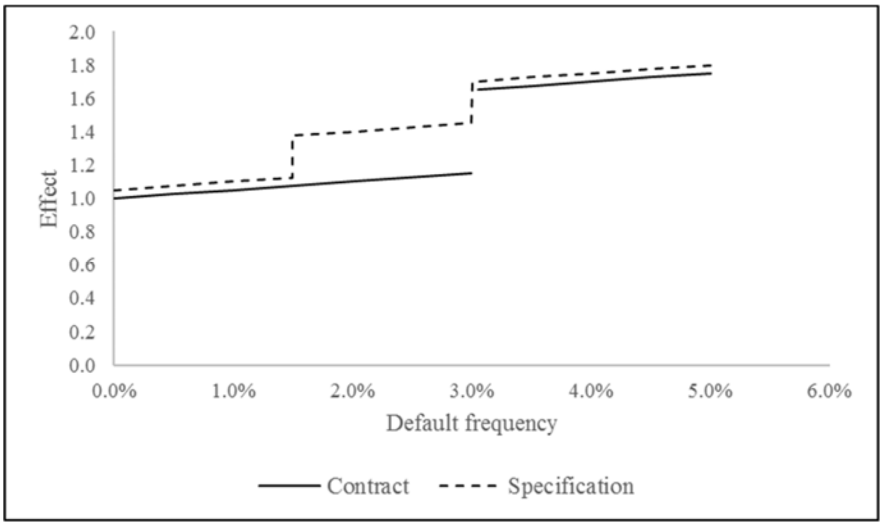

Figure 2: Construction of the sentiment-based instrument

This figure illustrates how we construct the sentiment-based instrument, *Pre holiday*. We argue that upcoming holidays are associated with an upbeat mood (Agarwal et al., 2012). In our setting, this corresponds to lower scrutiny in screening loan applications (at time *t-n*), which are thus more likely to default in month *t*-1. A loan officer is thus more prone to be *AtRisk* (or *AboveCutoff*) in month *t*-1 and may make greater effort in our three tasks of interest in month *t*. We aggregate the loan level sentiment information on the loan officer-loan category-month level. *Pre holiday* ranges between zero (i.e., no loan in the portfolio was granted on the two workdays preceding holidays) and one (i.e., all loans in the portfolio were granted on the two workdays preceding holidays).

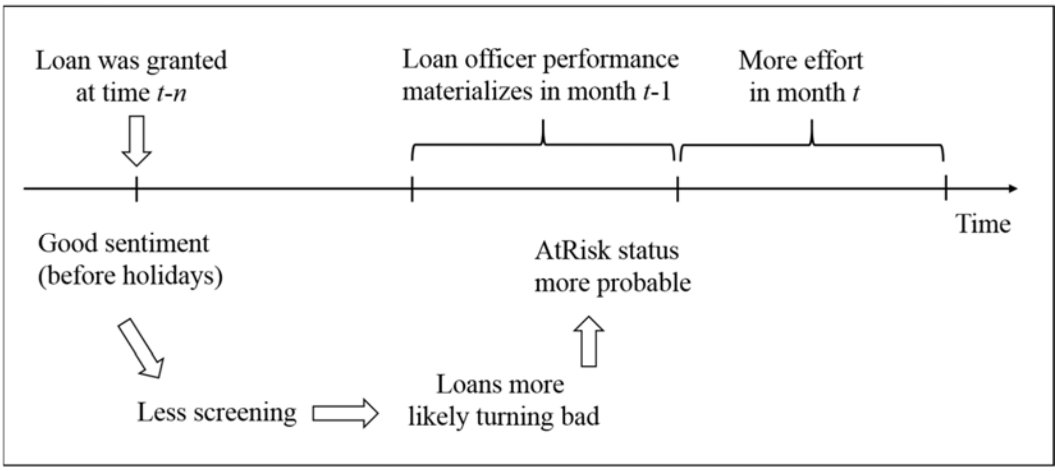

Table 1: List of covariates
This table shows the covariates used in the different regressions.

Covariate	Description
Covariate set 1: Loan (application) 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 a 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 a 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 on 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.
Past experience	1 if the borrower had past experience with the loan officer and 0 otherwise
Loan category	Size- and sector-specific categories
Loan destination	Loan used for working capital, fixed assets, mixed working capital and fixed assets, real estate, consuming, or other
Business sector	Agriculture, production, construction, transport, trade, other services, or other
Covariate set 2a: Loan officer*time level	
Number of outstanding loans	Number of outstanding loans per loan officer (approximates workload)
Covariate set 2b: Loan officer*loan category*time level	
Loan officer experience	Number of loan applications already handled by a loan officer in a loan category
Covariate set 3: Loan*month 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 2: Descriptive statistics

Panel A shows descriptive statistics for the main dependent variables. The first three variables are used to measure loan prospecting effort: *Prospecting volume*$_{jct}$ denotes the originated loan volume in euros in loan category *c* originated by loan officer *j* in month *t*; *Average loan size*$_{jct}$ is the average loan size in euros in loan category *c* originated by loan officer *j* in month *t*; *N applications*$_{jct}$ denotes the number of loan applications in loan category *c* originated by loan officer *j* in month *t*. These three variables are specified as 1 plus their natural logarithm in the regressions. The next three variables represent our first measure of screening effort (rejection rates). We standardize the number of rejected loan applications in loan category *c* originated by loan officer *j* in month *t* by three different averages (one-month, three-month, and six-month) of the total number of received loan applications. The next three variables represent our second measure of screening effort (processing time). We standardize the average processing time of loan applications in loan category *c* originated by loan officer *j* in month *t* by three different measures of work load (prospecting volume, average loan size, and number of loan applications; we always use the natural logarithm). The last measure approximates monitoring effort: $\Delta(Default)_{it-1,t}$ takes a value of 1 if loan *i* was not in default in the previous month but is in default in the current month; it takes a value of 0 if there was no change in the default status; and it takes a value of -1 if loan *i* was in default in the previous month but is not in default in the current month. Panel B comprises descriptive statistics for the explanatory variables used in the loan prospecting analysis. *Default*$_{jct-1}$ is loan officer *j*'s average loan portfolio default frequency in loan category *c* in month *t*-1. *AtRisk*$_{jct-1}$ is a dummy variable that takes a value of one if the default frequencies in loan officer *j*'s portfolio in loan category *c* were between 1.5 and 3 percent in month *t*-1. *AboveCutoff*$_{jct-1}$ is a dummy variable that takes a value of one if the default frequencies in loan officer *j*'s portfolio in loan category *c* were above the cut-off value of 3 percent in month *t*-1. *Loan officer experience*$_{jct}$ is the number of loan applications in loan category *c* handled by loan officer *j* up to month *t*.

Variable	Data level	Mean	N	Std. dev.	Min.	p50	Max.
Panel A: Main dependent variables							
Prospecting volume$_{jct}$	Officer*category*month	12,736	10,202	24,512	0	4,564	461,742
Average loan size$_{jct}$	Officer*category*month	6,117	10,202	15,172	0	1,659	342,855
N applications$_{jct}$	Officer*category*month	3.59	10,202	3.60	1	2.00	38.00
N rejected applications$_{jct}$/N applications (1-month avg.)	Officer*category*month	0.3193	7,889	0.3693	0	0.2000	1.0000
N rejected applications$_{jct}$/N applications (3-month avg.)	Officer*category*month	0.4328	7,889	0.6410	0	0.2000	3.0000
N rejected applications$_{jct}$/N applications (6-month avg.)	Officer*category*month	0.5006	7,889	0.8550	0	0.2143	6.0000
Processing time$_{jct}$/ln(Prospecting volume$_{jct}$)	Officer*category*month	0.7552	7,889	0.5854	0	0.6136	3.8513
Processing time$_{jct}$/ln(Average loan size$_{jct}$)	Officer*category*month	0.8406	7,889	0.6220	0	0.7017	3.8868
Processing time$_{jct}$/ln(N applications$_{jct}$)	Officer*category*month	6.3344	7,889	6.8529	0	3.9068	28.8539
Δ(Default)$_{it-1,t}$	Loan*month	0.0008	241,510	0.0393	-1	0	1
Panel B: Explanatory variables for the loan prospecting analysis							
Default$_{jct-1}$	Officer*category*month	0.0040	10,202	0.0304	0	0	1
AtRisk$_{jct-1}$	Officer*category*month	0.0140	10,202	0.1176	0	0	1
AboveCutoff$_{jct-1}$	Officer*category*month	0.0300	10,202	0.1706	0	0	1
Loan officer experience$_{jct}$	Officer*category*month	35	10,202	37	1	22	281

Table 3: Loan prospecting
This table shows the results of the OLS regression

$$Y_{jct} = \alpha_c + \alpha_{jt} + \alpha_1 Default_{jct\text{-}1} + \alpha_2 AtRisk_{jct\text{-}1} + \alpha_3 AboveCutoff_{jct\text{-}1} + \alpha_4 Loan\ officer\ experience_{jct} + e_{jct},$$

and examines whether an incentive-based compensation plan affects loan prospecting effort. The data are at the loan officer-by-loan category-by-month level (*jct*). *Y* denotes the three different measures of loan prospecting effort: *Prospecting volume*$_{jct}$ denotes the total loan volume in euros in loan category *c* originated by loan officer *j* in month *t*; *Average loan size*$_{jct}$ is the average loan size in euros in loan category *c* originated by loan officer *j* in month *t*; *N applications*$_{jct}$ denotes the number of loan applications in loan category *c* originated by loan officer *j* in month *t*. These three variables are specified as 1 plus their natural logarithm. *Default*$_{jct\text{-}1}$ is loan officer *j*'s average loan portfolio default frequency in loan category *c* in month *t*-1. *AtRisk*$_{jct\text{-}1}$ is a dummy variable that takes a value of one if the default frequency in loan officer *j*'s portfolio in loan category *c* was between 1.5 and 3 percent in month *t*-1. *AboveCutoff*$_{jct\text{-}1}$ is a dummy variable that takes a value of one if the default frequency in loan officer *j*'s portfolio in loan category *c* was above the cut-off value of 3 percent in month *t*-1. *Loan officer experience*$_{jct}$ is the number of loan applications in loan category *c* handled by loan officer *j* up to month *t*. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Standard errors in parentheses are clustered at the branch-month level.

	ln(Prospecting volume$_{jct}$)	ln(Average loan size$_{jct}$)	ln(N applications$_{jct}$)
Default$_{jct-1}$	1.5069	2.1076	-0.3433
	(1.6525)	(1.5980)	(0.4138)
AtRisk$_{jct-1}$	0.9649***	0.8278***	0.1194*
	(0.3013)	(0.2781)	(0.0669)
AboveCutoff$_{jct-1}$	-0.0885	-0.0652	-0.0289
	(0.3134)	(0.2978)	(0.0621)
Loan category FE	Yes	Yes	Yes
Loan officer*Month FE	Yes	Yes	Yes
Loan officer experience	Yes	Yes	Yes
Data level	Officer*category*month	Officer*category*month	Officer*category*month
Observations	10,202	10,202	10,202
Adj. R square	0.3447	0.3072	0.3756

Table 4: Time-variation of loan prospecting

This table shows OLS regression results that extend the Table 3 specification by using a bimonthly data frequency. We calculate the three measures of loan prospecting separately for the first half (τ equals 1, first three columns) and second half (τ equals 2, latter three columns) of the month. We further use contemporaneous loan officer performance measures as of the end of the first half of the current month (first three columns) and as of the end of the current month (last three columns). All other variables are defined in Table 1. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Standard errors in parentheses are clustered at the branch-month level.

	First half of the month (τ = 1)			Second half of the month (τ = 2)		
	ln(Prospecting volume$_{jc\tau}$)	ln(Average loan size$_{jc\tau}$)	ln(N applications$_{jc\tau}$)	ln(Prospecting volume$_{jc\tau}$)	ln(Average loan size$_{jc\tau}$)	ln(N applications$_{jc\tau}$)
Default$_{jct-1}$	-0.7214	-0.9312	0.2891	4.0896***	4.0448***	-0.0008
	(1.8148)	(1.7973)	(0.2083)	(1.1693)	(1.1507)	(0.1551)
AtRisk$_{jct-1}$	0.3532	0.3216	0.0646	0.6384**	0.5672**	0.0180
	(0.3575)	(0.3338)	(0.0454)	(0.2739)	(0.2587)	(0.0427)
AboveCutoff$_{jct-1}$	0.6231*	0.6355*	0.0167	0.1934	0.1553	0.0317
	(0.3482)	(0.3360)	(0.0382)	(0.2825)	(0.2719)	(0.0363)
Default$_{jct}$	-2.6902*	-2.3901	-0.3342	-5.2011***	-5.1765***	0.0511
	(1.6108)	(1.5763)	(0.2239)	(1.7011)	(1.6946)	(0.2135)
AtRisk$_{jct}$	0.1848	0.1891	-0.0460	0.4484	0.3762	0.0465
	(0.2409)	(0.2316)	(0.0315)	(0.2785)	(0.2589)	(0.0377)
AboveCutoff$_{jct}$	0.1598	0.1431	-0.0086	0.3250	0.4479	-0.0936***
	(0.2921)	(0.2795)	(0.0322)	(0.2889)	(0.2823)	(0.0324)
Loan category FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer experience	Yes	Yes	Yes	Yes	Yes	Yes
Data level	Officer*category* bimonthly	Officer*category* bimonthly	Officer*category* bimonthly	Officer*category* bimonthly	Officer*category* bimonthly	Officer*category* bimonthly
Observations	8,547	8,547	8,547	9,271	9,271	9,271
Adj. R square	0.2778	0.2605	0.2645	0.2411	0.2276	0.2734

Table 5: Screening

This table shows the results of the OLS regression

$$Y_{jct} = \alpha_c + \alpha_{jt} + \alpha_1 Default_{jct\text{-}1} + \alpha_2 AtRisk_{jct\text{-}1} + \alpha_3 AboveCutoff_{jct\text{-}1} + \alpha_4 Loan\ officer\ experience_{jct} + e_{jct},$$

and examines whether an incentive-based compensation plan affects screening effort. The data are at the loan officer-by-loan category-by-month level (*jct*). *Y* denotes six different measures of screening effort, as described in Table 1. In Panel A, we use three different variations of the standardized rejection rate. In Panel B, we show results for the standardized processing times. The other variables are also defined in Table 1. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Standard errors in parentheses are clustered at the branch-month level.

Panel A: Standardized rejection rate

	N rejected applications$_{jct}$ standardized by		
	N applications (1-month avg.)	N applications (3-month avg.)	N applications (6-month avg.)
Default$_{jct-1}$	0.0681	0.3839	0.3862
	(0.1964)	(0.3722)	(0.5331)
AtRisk$_{jct-1}$	-0.0298	-0.0438	-0.0531
	(0.0396)	(0.0659)	(0.0933)
AboveCutoff$_{jct-1}$	-0.0058	-0.0342	-0.0635
	(0.0414)	(0.0660)	(0.0808)
Loan category FE	Yes	Yes	Yes
Loan officer*Month FE	Yes	Yes	Yes
Loan officer experience	Yes	Yes	Yes
Data level	Officer*category*month	Officer*category*month	Officer*category*month
Observations	7,889	7,889	7,889
Adj. R square	0.4721	0.4022	0.3275

Panel B: Standardized processing time

	Processing time$_{jct}$ standardized by		
	ln(Prospecting volume$_{jct}$)	ln(Average loan size$_{jct}$)	ln(N applications$_{jct}$)
Default$_{jct-1}$	0.1250	0.1243	5.4138
	(0.3369)	(0.3540)	(4.7299)
AtRisk$_{jct-1}$	-0.0353	-0.0112	-1.0706
	(0.0654)	(0.0700)	(0.7611)
AboveCutoff$_{jct-1}$	-0.0329	-0.0327	-0.7885
	(0.0499)	(0.0543)	(0.6388)
Loan category FE	Yes	Yes	Yes
Loan officer*Month FE	Yes	Yes	Yes
Loan officer experience	Yes	Yes	Yes
Data level	Officer*category*month	Officer*category*month	Officer*category*month
Observations	7,889	7,889	7,889
Adj. R square	0.5458	0.5574	0.5242

Table 6: Monitoring

This table shows the results of the OLS regressions

$$\Delta(Default)_{it\text{-}1,t} = \alpha_i + \alpha_{jt} + \alpha_1 Default_{jct\text{-}1} + \alpha_2 AtRisk_{jct\text{-}1} + \alpha_3 AboveCutoff_{jct\text{-}1} + bX + e_{it} \qquad \text{(column 1)}$$

$$\Delta(Default)_{it\text{-}1,t} = \alpha_c + \alpha_{jt} + \alpha_1 Default_{jct\text{-}1} + \alpha_2 AtRisk_{jct\text{-}1} + \alpha_3 AboveCutoff_{jct\text{-}1} + bX + e_{it} \qquad \text{(column 2)}$$

and examines whether an incentive-based compensation plan affects changes in monitoring effort. The data are at the loan-by-month level (*it*). $\Delta(Default)_{it\text{-}1,t}$ takes a value of 1 if loan *i* was not in default in the previous month but is in default in the current month; it takes a value of 0 if there was no change in default status; and it takes a value of -1 if loan *i* was in default in the previous month but is not in default in the current month. All other variables are defined in Table 1. The covariate sets (*X*) are also defined in Table 1; the first set includes time-invariant covariates at the loan level, the second set includes time-variant loan officer characteristics, and the third set includes time-variant covariates at the loan level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Standard errors in parentheses are clustered in two dimensions: at the branch-month and loan level.

	(1)	(2)
$Default_{jct\text{-}1}$	-0.1786***	-0.1298***
	(0.0401)	(0.0281)
$AtRisk_{jct\text{-}1}$	-0.0032*	-0.0024*
	(0.0018)	(0.0015)
$AboveCutoff_{jct\text{-}1}$	-0.0028	-0.0009
	(0.0028)	(0.0021)
Loan category FE	No	Yes
Loan FE	Yes	No
Loan officer*Month FE	Yes	Yes
Covariate set 1	No	Yes
Covariate set 2	No	Yes
Covariate set 3	Yes	Yes
Data level	Loan*month	Loan*month
Observations	241,510	241,510
Adj. R square	0.0140	0.0644

Table 7: Instrumental variables

This table shows two-stage least squares results for the analyses of Tables 3, 5, and 6. A loan officer sentiment indicator, *Pre holiday*, and an indicator of poor loan performance of loan officers outside officer *j*'s bank branch, *Many defaults*, are used as instruments for *Default* and *AtRisk*. For a detailed description of the instruments, refer to Figure 2 and text. We report the Kleibergen-Paap rk Wald F statistic to test for weak identification. We cluster at the branch-month level in the first five columns and at the loan level in the last column. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Dependent variable:	ln(Prospecting volume$_{jct}$)	ln(Average loan size$_{jct}$)	ln(N applications$_{jct}$)	N rejected applications$_{jct}$ / N applications$_{jct}$	Processing time$_{jct}$ / ln(Prospecting volume$_{jct}$)	Δ(Default)$_{it-1,t}$
First stage for Default:						
Pre holiday$_{jct-1}$	-0.0113***	-0.0113***	-0.0113***	-0.0099***	-0.0099***	-0.0102***
	(0.0030)	(0.0030)	(0.0030)	(0.0033)	(0.0033)	(0.0017)
Many defaults$_{jct-1}$	0.0014*	0.0014*	0.0014*	0.0009	0.0009	-0.0007***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0002)
First stage for AtRisk:						
Pre holiday$_{jct-1}$	0.0150*	0.0150*	0.0150*	0.0178	0.0178	0.0638***
	(0.0085)	(0.0085)	(0.0085)	(0.0109)	(0.0109)	(0.0071)
Many defaults$_{jct-1}$	0.0112***	0.0112***	0.0112***	0.0107***	0.0107***	0.0147***
	(0.0024)	(0.0024)	(0.0024)	(0.0028)	(0.0028)	(0.0010)
Two-stage least squares:						
Default$_{jct-1}$	20.2931	40.5945	-14.0796**	11.1598	45.5733*	-0.1324
	(44.3352)	(46.6355)	(6.8758)	(7.4348)	(23.7898)	(0.2022)
AtRisk$_{jct-1}$	36.0956***	45.1190***	-5.4119***	3.0960**	17.3474***	-0.0450**
	(10.0649)	(11.3871)	(1.9339)	(1.2822)	(5.1743)	(0.0202)
F statistic	7.8162	7.8162	7.8162	6.0269	6.0269	8.6056
F statistic, p-value	0.0004	0.0004	0.0004	0.0026	0.0026	0.0002
Covariates	Loan officer experience	Loan officer experience	Loan officer experience	Loan officer experience	Loan officer experience	Sets 1-3
Data level	Officer*category*month	Officer*category*month	Officer*category*month	Officer*category*month	Officer*category*month	Loan*month
Observations	10,202	10,202	10,202	7,889	7,889	241,510

Table 8: Heterogeneous effects - Loan officer tenure

This table explores whether loan officer tenure affects the results with respect to loan prospecting (Panel A), screening, and monitoring (Panel B). We rerun the specifications detailed in Tables 3, 5, and 6 and split the samples at loan officers' median tenure. Loan officer tenure is measured as the number of days between the current and first loan application per loan officer. Short (long) tenure indicates loan officers with a tenure below (above) the median tenure across all loan officers in a certain month. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Loan prospecting

Dependent variable:	ln(Prospecting volume$_{jct}$)		ln(Average loan size$_{jct}$)		ln(N applications$_{jct}$)	
Loan officer tenure:	Short	Long	Short	Long	Short	Long
Default$_{jct-1}$	1.9749	0.7129	2.4765	1.4100	-0.2778	-0.3658
	(1.6096)	(3.6958)	(1.5502)	(3.4725)	(0.5543)	(0.5628)
AtRisk$_{jct-1}$	0.3332	1.0412***	0.0929	0.9303***	0.1566	0.1084
	(0.5821)	(0.3513)	(0.4415)	(0.3273)	(0.2055)	(0.0697)
AboveCutoff$_{jct-1}$	-0.2131	-0.1091	-0.1824	-0.0653	-0.0218	-0.0537
	(0.3567)	(0.4689)	(0.3321)	(0.4451)	(0.1026)	(0.0754)
Further specification details	Table 3	Table 3	Table 3	Table 3	Table 3	Table 3
Observations	5,240	4,962	5,240	4,962	5,240	4,962

Panel B: Screening and monitoring

Dependent variable:	N rejected applications$_{jct}$ / N applications$_{jct}$		Processing time$_{jct}$ / ln(Prospecting volume$_{jct}$)		Δ(Default)$_{it-1,t}$	
Loan officer tenure:	Short	Long	Short	Long	Short	Long
Default$_{jct-1}$	-0.1108	0.2568	0.1132	0.1128	-0.1398***	-0.1274***
	(0.1525)	(0.5000)	(0.3377)	(0.7609)	(0.0432)	(0.0394)
AtRisk$_{jct-1}$	0.0449	-0.0453	-0.0508	-0.0319	-0.0001	-0.0034*
	(0.0692)	(0.0479)	(0.1398)	(0.0747)	(0.0014)	(0.0021)
AboveCutoff$_{jct-1}$	0.0144	-0.0120	-0.0255	-0.0373	0.0009	-0.0019
	(0.0498)	(0.0606)	(0.0816)	(0.0707)	(0.0033)	(0.0029)
Further specification details	Table 5	Table 5	Table 5	Table 5	Table 6	Table 6
Observations	4,069	3,820	4,069	3,820	124,581	116,929

Table 9: Placebo test

This table shows results from OLS regressions of a placebo test in which we repeat the estimations from Tables 3, 5, and 6, using only observations from January 2006 to September 2007, a period in which the bank did not have an incentive-based compensation plan in place. Covariates and fixed effects are included in the regressions, as specified in the table. All variables and covariate sets are defined in Table 1. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Standard errors in parentheses are clustered at the branch-month level in the case of the loan prospecting and screening analyses and at the branch-month and loan level in the case of the monitoring analysis.

Panel A: Loan prospecting

	ln(Prospecting volume$_{jct}$)	ln(Average loan size$_{jct}$)	ln(N applications$_{jct}$)
Default$_{jct-1}$	-1.0515	-1.3429	0.4573
	(2.6165)	(2.6386)	(0.3043)
AtRisk$_{jct-1}$	0.2055	0.1354	0.0750
	(0.3060)	(0.2830)	(0.0558)
AboveCutoff$_{jct-1}$	0.3000	0.3302	-0.0069
	(0.4299)	(0.4191)	(0.0583)
Loan category FE	Yes	Yes	Yes
Loan officer*Month FE	Yes	Yes	Yes
Loan officer experience	Yes	Yes	Yes
Data level	Officer*category*month	Officer*category*month	Officer*category*month
Observations	8,079	8,079	8,079
Adj. R square	0.4153	0.3564	0.5124

Panel B: Screening and monitoring

	Screening		Monitoring
	N rejected applications$_{jct}$ / N applications$_{jct}$	Processing time$_{jct}$ / ln(Prospecting volume$_{jct}$)	Δ(Default)$_{it-1,t}$
Default$_{jct-1}$	0.0472	0.0359	-0.1803***
	(0.1781)	(0.2547)	(0.0442)
AtRisk$_{jct-1}$	-0.0330	0.0114	-0.0009
	(0.0325)	(0.0331)	(0.0010)
AboveCutoff$_{jct-1}$	-0.0396	0.0445	0.0018
	(0.0380)	(0.0525)	(0.0028)
Loan category FE	Yes	Yes	Yes
Loan officer*Month FE	Yes	Yes	Yes
Covariate set 1	No	No	Yes
Covariate set 2a	No	No	Yes
Covariate set 2b	Yes	Yes	Yes
Covariate set 3	No	No	Yes
Data level	Officer*category*month	Officer*category*month	Loan*month
Observations	6,522	6,522	460,776
Adj. R square	0.4992	0.4176	0.0536

Table 10: Ex post loan performance

This table shows the results of the OLS regression

$$DefaultLikelihood_i = a_c + a_{jt} + \alpha_1 Defaults_{jct\text{-}1} + \alpha_2 AtRisk_{jct\text{-}1} + \alpha_3 AboveCutoff_{jct\text{-}1} + bX + e_i,$$

and examines whether an incentive-based compensation plan affects ex post loan performance. The data are at the loan level (i). The default likelihood is 1 if a loan missed a payment for more than 30 days at least once within various time periods after the loan was granted. In the first column, we concentrate on the first 4 months after the loan was granted; in the second column, we use months 5 to 8; in the third column, we use months 9 to 12; and in the last column, we use all observations with a maturity over 12 months. All other variables and covariate sets are defined in Table 1. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively. Standard errors in parentheses are clustered at the branch-month level.

Maturity range (in months)	1-4	5-8	9-12	> 12
$\text{Default}_{jct\text{-}1}$	-0.0192	0.5511***	0.4526***	0.3509
	(0.0274)	(0.1613)	(0.1691)	(0.2698)
$\text{AtRisk}_{jct\text{-}1}$	0.0077	0.0007	0.0110	0.0189
	(0.0054)	(0.0127)	(0.0097)	(0.0229)
$\text{AboveCutoff}_{jct\text{-}1}$	0.0027	-0.0042	0.0204	-0.0047
	(0.0060)	(0.0136)	(0.0142)	(0.0218)
Loan category FE	Yes	Yes	Yes	Yes
Loan officer*Month FE	Yes	Yes	Yes	Yes
Covariate set 1	Yes	Yes	Yes	Yes
Covariate set 2b	Yes	Yes	Yes	Yes
Data level	Loan	Loan	Loan	Loan
Observations	26,351	20,662	13,574	6,934
Adj. R square	0.0955	0.3197	0.4351	0.3035

APPENDIX

Table A1: Descriptive statistics covering other explanatory variables

The table shows descriptive statistics for the explanatory variables used in the screening analysis (Panel A) and the monitoring analysis (Panel B).

Variable	Data level	Mean	N	Std. dev.	Min.	p50	Max.
Panel A: Explanatory variables for the screening analysis							
$Default_{jct-1}$	Officer*category*month	0.0035	7,889	0.0272	0.0000	0.0000	1.0000
$AtRisk_{jct-1}$	Officer*category*month	0.0147	7,889	0.1204	0.0000	0.0000	1.0000
$AboveCutoff_{jct-1}$	Officer*category*month	0.0289	7,889	0.1675	0.0000	0.0000	1.0000
Loan officer experience$_{jct}$	Officer*category*month	38	7,889	38	1	26	281
Panel B: Explanatory variables for the monitoring analysis							
$Default_{jct-1}$	Loan*month	0.0040	241,510	0.0230	0.0000	0.0000	1.0000
$AtRisk_{jct-1}$	Loan*month	0.0248	241,510	0.1555	0.0000	0.0000	1.0000
$AboveCutoff_{jct-1}$	Loan*month	0.0351	241,510	0.1841	0.0000	0.0000	1.0000
$Leverage_{i}$	Loan*month	0.0442	241,510	0.0960	0.0000	0.0000	0.5802
Cash over total assets$_{i}$	Loan*month	0.0954	241,510	0.1334	0.0009	0.0442	0.7004
Total assets$_{i}$	Loan*month	47,848	241,510	107,694	601	18,005	937,947
ln(Applied amount$_{i}$)	Loan*month	8.2592	241,510	1.4593	1.3821	8.1587	16.5236
ln(Applied maturity$_{i}$)	Loan*month	6.3877	241,510	0.5495	3.4012	6.3969	8.1887
Applied loan over total assets$_{i}$	Loan*month	0.3513	241,510	0.3937	0.0041	0.2268	2.0404
Juridical form business$_{i}$	Loan*month	0.0803	241,510	0.2718	0.0000	0.0000	1.0000
Available account$_{i}$	Loan*month	0.0909	241,510	0.2875	0.0000	0.0000	1.0000
Guarantee$_{i}$	Loan*month	0.5624	241,510	0.4961	0.0000	1.0000	1.0000
Has been in default$_{i}$	Loan*month	0.0111	241,510	0.1049	0.0000	0.0000	1.0000
Has been rejected$_{i}$	Loan*month	0.1303	241,510	0.3366	0.0000	0.0000	1.0000
Last week of the month$_{i}$	Loan*month	0.2780	241,510	0.4480	0.0000	0.0000	1.0000
Number of loan applications$_{i}$	Loan*month	1.7561	241,510	1.1698	1.0000	1.0000	15.0000
Past experience$_{i}$	Loan*month	0.1350	241,510	0.3417	0.0000	0.0000	1.0000
Number of outstanding loans$_{jt}$	Loan*month	108	241,510	65	4	100	387
Loan officer experience$_{jct}$	Loan*month	63	241,510	51	2	49	281
ln(Outstanding amount$_{it}$)	Loan*month	7.4277	241,510	1.3948	0.0000	7.4052	12.7393
ln(Remaining maturity$_{it}$)	Loan*month	2.0072	241,510	0.8650	0.0000	2.0794	4.4773

Table A2: Instrumental variables: description and descriptive statistics

Panel A of this table describes our instrumental variables. For further discussion with respect to the timing of the sentiment-based instruments, refer to Figure 2. Panel B includes the respective descriptive statistics.

Instrument	
Panel A: List of instruments	
Pre holiday	Average frequency at which loans in the portfolio of loan officer *j* in loan category *c* in month *t*-1 were granted on the two working days preceding national holidays
Many defaults	1 if the loan performance of loan officers outside officer *j*'s bank branch were above 0.25 and below 2.5 percent in loan category *c* in month *t*-1 and 0 otherwise

Panel B: Descriptive statistics	Data level	Mean	N	Std. dev.	Min.	p50	Max.
B1: Loan prospecting							
Pre holiday$_{jct-1}$	Officer*category*month	0.0632	10,202	0.0893	0.0000	0.0417	1.0000
Many defaults$_{jct-1}$	Officer*category*month	0.3910	10,202	0.4880	0.0000	0.0000	1.0000
B2: Screening							
Pre holiday$_{jct-1}$	Officer*category*month	0.0645	7,889	0.0862	0.0000	0.0476	1.0000
Many defaults$_{jct-1}$	Officer*category*month	0.3865	7,889	0.4870	0.0000	0.0000	1.0000
B3: Monitoring							
Pre holiday$_{jct-1}$	Loan*month	0.0644	241,510	0.0614	0.0000	0.0571	1.0000
Many defaults$_{jct-1}$	Loan*month	0.4233	241,510	0.4941	0.0000	0.0000	1.0000

Table A3: Instrumental variables – Further specifications

This table shows two-stage least squares results for the analyses of Tables 3, 5, and 6. A loan officer sentiment indicator, *Pre holiday*, and an indicator of poor loan performance of loan officers outside officer *j*'s bank branch, *Many defaults*, are used as instruments for *Default* and *AboveCutoff* (Panel A) and *AtRisk* and *AboveCutoff* (Panel B). For a detailed description of the instruments, see Figure 2 and the text. We use the Kleibergen-Paap rk Wald F statistic to test for weak identification. We cluster at the branch-month level in the first five columns and at the loan level in the last column. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Panel A: *Default* and *AboveCutoff* are instrumented

Dependent variable:	ln(Prospecting volume$_{jct}$)	ln(Average loan size$_{jct}$)	ln(N applications$_{jct}$)	N rejected applications$_{jct}$ / N applications$_{jct}$	Processing time$_{jct}$ / ln(Prospecting volume$_{jct}$)	Δ(Default)$_{it-1,t}$
First stage for Default:						
Pre holiday$_{jct-1}$	-0.0113***	-0.0113***	-0.0113***	-0.0099***	-0.0099***	-0.0102***
	(0.0030)	(0.0030)	(0.0030)	(0.0033)	(0.0033)	(0.0017)
Many defaults$_{jct-1}$	0.0014*	0.0014*	0.0014*	0.0009	0.0009	-0.0007***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0002)
First stage for AboveCutoff:						
Pre holiday$_{jct-1}$	-0.0503***	-0.0503***	-0.0503***	-0.0498***	-0.0498***	-0.0476***
	(0.0135)	(0.0135)	(0.0135)	(0.0159)	(0.0159)	(0.0093)
Many defaults$_{jct-1}$	0.0128***	0.0128***	0.0128***	0.0102**	0.0102**	-0.0032**
	(0.0041)	(0.0041)	(0.0041)	(0.0044)	(0.0044)	(0.0014)
Two-stage least squares:						
Default$_{jct-1}$	-353.8455*	-427.0732*	42.0155	-26.6971	-166.5439	7.8149
	(211.9287)	(247.0420)	(29.2625)	(23.9444)	(126.9912)	(26.4261)
AboveCutoff$_{jct-1}$	73.1799**	91.4738**	-10.9720**	6.4521*	36.1521*	-1.6457
	(37.0566)	(43.8199)	(5.2899)	(3.8167)	(20.6428)	(5.7436)
F statistic	1.7881	1.7881	1.7881	1.0500	1.0500	0.0412
F statistic, p-value	0.1681	0.1681	0.1681	0.3506	0.3506	0.9596
Covariates	Loan officer experience	Loan officer experience	Loan officer experience	Loan officer experience	Loan officer experience	Sets 1-3
Data level	Officer*category*month	Officer*category*month	Officer*category*month	Officer*category*month	Officer*category*month	Loan*month
Observations	10,202	10,202	10,202	7,889	7,889	241,510

Panel B: *AtRisk* and *AboveCutoff* are instrumented

Dependent variable:	ln(Prospecting volume$_{jct}$)	ln(Average loan size$_{jct}$)	ln(N applications$_{jct}$)	N rejected applications$_{jct}$ / N applications$_{jct}$	Processing time$_{jct}$ / ln(Prospecting volume$_{jct}$)	Δ(Default)$_{it-1,t}$
First stage for AtRisk:						
Pre holiday$_{jct-1}$	0.0150*	0.0150*	0.0150*	0.0178	0.0178	0.0638***
	(0.0085)	(0.0085)	(0.0085)	(0.0109)	(0.0109)	(0.0071)
Many defaults$_{jct-1}$	0.0112***	0.0112***	0.0112***	0.0107***	0.0107***	0.0147***
	(0.0024)	(0.0024)	(0.0024)	(0.0028)	(0.0028)	(0.0010)
First stage for AboveCutoff:						
Pre holiday$_{jct-1}$	-0.0503***	-0.0503***	-0.0503***	-0.0498***	-0.0498***	-0.0476***
	(0.0135)	(0.0135)	(0.0135)	(0.0159)	(0.0159)	(0.0093)
Many defaults$_{jct-1}$	0.0128***	0.0128***	0.0128***	0.0102**	0.0102**	-0.0032**
	(0.0041)	(0.0041)	(0.0041)	(0.0044)	(0.0044)	(0.0014)
Two-stage least squares:						
AtRisk$_{jct-1}$	34.1378***	41.2026***	-4.0535**	2.1833*	13.6203***	-0.0443**
	(11.5593)	(12.1672)	(1.8494)	(1.2395)	(4.2916)	(0.0194)
AboveCutoff$_{jct-1}$	3.9692	7.9401	-2.7539**	1.9020	7.7673**	-0.0274
	(8.5215)	(8.7381)	(1.2072)	(1.1897)	(3.4917)	(0.0426)
F statistic	7.2106	7.2106	7.2106	5.6935	5.6935	4.6888
F statistic, p-value	0.0008	0.0008	0.0008	0.0035	0.0035	0.0092
Covariates	Loan officer experience	Loan officer experience	Loan officer experience	Loan officer experience	Loan officer experience	Sets 1-3
Data level	Officer*category*month	Officer*category*month	Officer*category*month	Officer*category*month	Officer*category*month	Loan*month
Observations	10,202	10,202	10,202	7,889	7,889	241,510