Incentivizing Calculated Risk-Taking

Evidence from a Series of Experiments with Commercial Bank Loan Officers*

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Abstract

How do performance incentives in commercial lending affect risk-taking and lending decisions? This paper describes a series of experiments with commercial bank loan officers to answer this question. We analyze the underwriting process of small-business loans to entrepreneurs in an emerging market and test the impact of performance pay by comparing three commonly implemented classes of incentive schemes: incentives that reward origination, incentives that reward origination conditional on performance, and high-powered incentives that reward performance and penalize default. The results show strong and economically significant effects of performance pay on risk-assessment and lending behavior. Incentives that penalize bad lending decisions cause loan officers to exert significantly greater screening effort and lead to more profitable lending decisions. Loan officers who face high-powered incentives are more likely to outperform a statistical credit scoring model and provide risk-assessments that are more predictive of their lending decision and the probability of default. In additional treatments, we show that deferring performance pay significantly reduces the ability of high-powered incentives to induce screening effort. Finally, we document considerable heterogeneity in the effect of performance pay on loan officer behavior: more experienced loan officers exert greater screening effort, irrespective of the incentive scheme in place. The results from these experiments can provide guidance for lenders seeking to develop staff incentives to reduce bias and default-risk in lending.

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1 Introduction

> "An evaluation of compensation practices at banking organizations preceding the financial crisis reveals that they did, in fact, contribute to safety and soundness problems [...] For example, some firms gave loan officers incentives to write a lot of loans, or traders incentives to generate high levels of trading revenues, without sufficient regard for the risks associated with those activities. The revenues that served as the basis for calculating bonuses were generated immediately, while the risks might not have been realized for months or years [...]. When these or similarly misaligned incentive compensation arrangements were common in a firm, the very foundation of sound risk management could be undermined by the actions of employees seeking to maximize their own pay."[1]
>
> —*Daniel Tarullo, Board of Governors of the United States Federal Reserve*

In response to the global financial crisis, bank compensation has come under increased scrutiny. While much of this attention has focused on incentives for risk-taking provided to top management, there is growing recognition that non-equity incentives, such as commissions, provided to loan officers and risk-managers may share some of the blame. Providing incentives for loan officers and other front-line employees at commercial banks is a difficult problem: their very responsibility is to collect information that the bank cannot otherwise observe, making monitoring quite difficult, they enjoy limited liability, may be more risk-averse and have a shorter time horizon than the bank's shareholders.

This paper presents results from an experiment on the relationship between performance incentives and loan officer behavior. We study lending decisions in the Indian market for small-enterprise loans and analyze lending decisions made by loan officers with an average of more than ten years of experience. We focus on new applications for unsecured working capital loans to small entrepreneurs with limited credit histories –precisely the type of loans for which an accurate assessment of credit risk depends most crucially on the expertise of the bank's employees. We pay loan officers to review and assess actual loan applications, comparing three commonly implemented classes of incentive schemes: a bonus for origination, a low-powered incentive scheme that rewards origination conditional on performance, and high-powered incentives that reward performance and penalize default.[2]

We find a strong effect of performance incentives on screening effort, risk-assessment, and the profitability of lending. Loan officers who are incentivized based on lending volume rather than the quality of their lending portfolio approve a greater share of loans, and originate loans of lower average quality. By contrast, high-powered incentives that penalize bad lending decisions cause loan officers to exert greater screening effort and lead to significantly more profitable lending decisions. When

[1] In a speech entitled "Incentive Compensation, Risk Management, and Safety and Soundness" at the University of Maryland's Robert H. Smith School of Business. Washington, D.C., November 2, 2009.

[2] For a review of compensation practices in retail- and investment banking see also "Compensation in Financial Services: Industry Progress and the Agenda for Change" Washington, DC: Institute for International Finance, 2009.

the acquisition of information is costly, loan officers facing high-powered incentives are more likely to outperform a statistical credit scoring model and provide risk-assessments that are more predictive of the lending decision and the probability of default.

In a second set of experimental treatments, we explore how the time horizon of performance incentives affects screening effort and risk-taking. We find that, consistent with theoretical predictions, deferred compensation significantly weakens the effectiveness of high-powered incentives; when incentive payments are awarded with a three month delay, high-powered incentives do not induce greater screening effort than an origination piece rate. Finally, we document considerable heterogeneity in the response to performance pay: more experienced loan officers are less responsive to performance incentives and exert greater screening effort under both high- and low-powered incentive schemes.

These results are important for several reasons. There is very little institutional knowledge or academic evidence on what sorts of incentive contracts are most effective at aligning the behavior of the bank's front-line staff with the operational and strategic goals of the institution. We are aware of only four studies that link loan officer incentives to actual lending behavior. Hertzberg, Liberti, and Paravisini (2010) study how loan officer rotation induces loan officers to reveal bad information about borrowers, suggesting that communication problems exist even within a bank. Banerjee, Cole, and Duflo (2009) use data on all bank loans in India from 1981 to 2003 to explore the impact of agency problems and loan quality-based incentives on loan volume and risk-taking. The authors find that, when faced with increased monitoring, lending volume declines and loan officers take fewer risks. Cadena, Schoar, Cristea, and Delgado-Medrano (2011) study the effect of target-based incentives on goal achievement among loan officers in Colombia and find that the frequency and intensity of reminders about lending targets is effective at mitigating time inconsistency and procrastination problems. Agarwal and Wang (2009) take advantage of a natural experiment affecting the compensation structure of large commercial lender in the United States to investigate the impact of a piece-rate incentive scheme, based on the volume of loan origination, on loan officer decisions. They find that the share of loan applications approved increased, while the quality of lending decreased. Loan officers who are offered origination incentives book larger and longer-maturity loans, which the authors argue is driven by a mismatch in time horizons between the bank and its front office employees; when a longer term loan defaults, chances are small that the loan officer who originated the loan will still be on the job.

Our results contribute to three literatures. First, the existing literature on entrepreneurship and economic growth suggests that access to finance is an important prerequisite for efficient capital allocation and firm growth (Levine 1997), and that cross-sectional differences in the ability of banks to finance the most promising entrepreneurs may lead to differences in productivity growth across countries (Greenwood and Jovanovic 1990, Guiso, Sapienza, and Zingales 2004).[3] We contribute to this strand of the literature by exploring how the structure of compensation can affect loan officers' ability to identify promising lending opportunities in an environment of high idiosyncratic risk.

Second, we contribute to the literature on lending relationships and the use of soft and relationship-specific information in a challenging informational environment. If performance incentives can affect the quality of project choice, this may occur either through the collection of additional borrower details or improvements in the analysis of existing information, each lending to a greater depth of the lending relationship. Studies measuring credit availability have consistently found that stronger banking relationships facilitate access to financing and relax collateral requirements (see Petersen and Rajan 1995; Berger and Udell 1995; Cetorelli 2001). More generally, marginally creditworthy borrowers may have improved financial access when loan officers exert greater effort in the evaluation of available information (Sharpe 1990, Rajan 1992). We demonstrate that the structure of performance pay affects both the type and the extent of information loan officers consider in assessing credit risk.

Finally, our paper contributes to the broader literature on performance-based compensation. The idea that targeted monetary incentives can alter an individual's effort choice is the generally accepted rationale behind 'pay for performance'. A classic example is the replacement of hourly wages with piece rates as a strategy meant to increase output by raising average worker productivity for simple tasks (Lazear 2000). There are, however, innumerable variations of incentive schemes, among them rank-based incentives, team incentives and conditional pay-for-performance, and choosing between them is of non-trivial importance to a firm (Lazear and Rosen 1981, Gibbons 1998). A more recent strand of the literature has used experiments inside the firm to highlight that even simple modifications to employee compensation can have relatively complex repercussions as they may affect performance through effort and selection effects (Bandiera, Barankay, and Rasul 2007; Bandiera, Barankay, and Rasul 2009). The experiments we carry out are similar in spirit, but adapt incentives and performance measures to the specific context of a financial intermediary seeking to incentivize its employees in ways that balance the competing goals of risk-management and revenue generation.

The remainder of the paper proceeds as follows. In the next section, we describe how standard incentive problems within the bank are likely exacerbated in emerging markets, in ways that may affect the performance of the lender and the provision of credit to marginal borrowers. We provide a simple theoretical framework for our experiments in section 3 and review the experimental design and procedures in sections 4 and 5. Section 6 presents our main results and section 7 concludes.

[3]Entrepreneurial firms with a limited history of fromal sector borrowing are more likely to face credit constraints and several studies show that deregulation and the resulting improvements in bank competition have a disproportionally larger positive impact on new firms (see Black and Strahan 2002; Cetorelli and Strahan 2006).

2 Performance Incentives in Commercial Lending

The literature on performance incentives within organizations has identified a range of constraints to the implementation of optimal incentive contracts (see Gibbons 1998), many of which are likely exacerbated in a banking context. While the literature on incentive design in banking has generally emphasized problems inherent in delegated monitoring, we focus on the role of performance pay as an instrument to incentivize efficient initial screening decisions.

2.1 Incentives and Agency Problems within the Bank

Emerging credit markets, such as the one we study, are characterized by particularly severe information asymmetries between borrowers and lenders. The absence of reliable credit information systems,[4] for instance, places significant limitations on the use of predictive credit scoring models and similar loan approval and risk-management technologies. This makes banks particularly reliant on the risk-assessment of its front-line employees and introduces a significant scope for moral hazard within the firm. The existing literature provides several striking examples of agency problems within lending institutions. Hertzberg, Liberti, and Paravisini (2010) use internal data from an Argentinean bank to show that, unless faced with the imminent threat of an audit, credit officers inflate the risk-assessment of their lending portfolio. Qian, Strahan, and Yang (2011) demonstrate the presence of agency problems in lending by showing that a policy reform in China that increased the accountability of individual loan officers improved the predictive content of loan officers' assessment of credit risk. Cadena, Schoar, Cristea, and Delgado-Medrano (2011) provide evidence of behavioral biases among bank employees that may reduce screening effort below the level desired by the bank.

Such evidence of moral hazard internal to the bank suggests that, in addition to improving the efficiency of information processing, an important role of performance pay in lending is to align the interests of the bank's employees with the risk-preferences and strategic goals of the organization. In practice, banks use a wide variety of incentive contracts to limit moral hazard and incentivize efficient screening decisions, including performance bonus schemes, origination piece rates and team incentives. However, there exists little systematic evidence to guide the choice of performance incentives in commercial lending. The experiments we present in this paper allow us to compare the effect of several exogenously assigned incentive schemes on measures of screening effort and loan performance.

[4] For example, only 10% of Indian adults are included in a credit bureau database, compared to 60% of adults in OECD countries (World Bank, 2010).

2.2 Incentives and Lending

The design of optimal incentive contracts is a central issue in commercial lending that has been addressed by both theoretical and empirical studies (see e.g., Diamond 1984). The potential for poorly designed incentive schemes to induce privately beneficial but socially costly behavior, often in the form of excessive risk-taking, has long been documented (Holmström and Milgrom 1991, Kashyap, Rajan, and Stein 2008, Erkens, Hung, and Matos 2009). This is of particular concern to commercial banks in emerging markets that walk a fine line between expanding their loan portfolio in an environment of high idiosyncratic risk, while trying to maintain the asset quality of their lending. Much of the previous work in this area has focused on delegated monitoring contracts which enable financial intermediaries to control their risk-exposure through diversification. In contrast to this line of research, we focus on incentive contracts for loan offciers, designed to improve the quality of initial screening decision.

The question, then, becomes how to control the moral hazards inherent in lending other people's money in order to align the interests of the loan officers and the firm.[5] The discussion about bank compensation in the wake of the recent financial crisis has focused on two main challenges in the design of performance based incentive contracts in banking: the *incentive power* of compensation, which may lead to a mismatch between the risk-preferences of the bank and its employees and the often short *time-horizon* of compensation, which may lead to a similar mismatch in the time-horizon between the bank and its front-line employees. The experiments we present in this paper address both of these issues. We vary both the incentive power and the time-horizon of performance pay and find that both dimensions have important effects on loan officer decision-making.

What are the features of the optimal contract in this context and what are the barriers to its implementation in an emerging credit market, such as the lending environment we study? Hypothetically, if the bank were owned by a single individual who screened borrowers, made lending decisions there would be no incentive problem within the bank. Similarly, one might imagine simply giving the loan officer an equity stake in the loan, thus making her a fully liable residual claimant. That we do not observe this contract in practice suggests that a range of frictions prevents writing contracts that attain the first-best outcome. The need to delegate screening decisions leads to a host of potential problems, some standard to all incentive contracts, some particularly pronounced in banking:

- **Limited liability** loan officers take decisions on large amounts of money, typically much larger amounts than they could lend on their own.

[5] See also Heider and Inderst (2011) for a model relating the choice of loan officer incentives to the competitive position of banks and the severity of internal agency problems.

- **Asymmetric information** The loan officer observes information about the borrower that is not accessible to the bank. Moreover, the bank cannot observe the quality or quantity of effort loan officers put into underwriting decisions.

- **Noisy outcome signals** the loan officer may make a loan to a dubious borrower who miraculously repays, or an ex-ante profitable loan to a borrower who is hit with a negative shock.

- **Differential risk-aversion** Loan officers may be more (or less) risk-averse than the bank's equity holders.

- **Differential discount rates** Loan officers, especially in developing countries, may have a higher discount rate than the bank. It may therefore be more expensive to generate effort with deferred pay, i.e. pay that is conditioned on loan outcomes, than with immediate bonuses.

- **Multi-tasking** In contrast to simple production tasks, banks do not want to maximize lending volume, but instead seek to lend only to clients with a sufficiently high probability of repayment.

3 Theoretical Framework and Empirical Predictions

In this section, we develop a simple model that describes our empirical setting and approximates the decision problem faced by a loan officer. The goal of the model is to understand, in the simplest set-up possible, what frictions may prevent implementation of the optimal contract.

The model encompasses firms, loan officers, and the bank. Firms seek to borrow one unit of capital from the bank. They invest in a project, which either succeeds, generating income, or fails, leaving zero residual value. There are two types of firms: good firms of type θ_G with probability of success p, and bad firms of type θ_B, with probability of success 0, where $p > 0$. Type is not observed, but the loan officer can exert effort to obtain a signal, as described below. The ex-ante fraction of good firms is π. We assume banks have a net cost of capital normalized to 0, and charge interest rate $1 + r$. If a bank makes a loan that is repaid, it therefore earns a net interest margin r while if the loan defaults the bank loses the unit of capital. There is no time discounting in the model. If a bank were to lend one unit of capital to all applicants, a loan would be repaid with probability πp and the bank would earn, in expectation, $\pi p r + (1 - \pi p)$. We generally assume that this amount is negative, so that it is not profitable to lend to all applicants. The loan officer may scrutinize the client's application in an attempt to learn their type. This requires effort, which comes at private cost e to the loan officer. If a loan officer engages in screening, she gets a signal that the firm is bad, σ_B with probability

$$Pr\big(\sigma_B\big) = \begin{cases} \gamma & \text{if borrower is type } \theta_B \\ 0 & \text{if borrower is type } \theta_G. \end{cases}$$

Hence, the posterior probability that a firm is good, given a good signal, is

$$Pr\big(\theta_G|\gamma\big) = \frac{\pi}{\pi + (1-\pi)(1-\gamma)} \tag{3.1}$$

The bad signal is fully informative, so that the posterior probability that a firm is bad, given a bad signal, is 1. We further assume that, if there are no incentive problems within the bank, it is profitable to lend to a firm with a good signal, even when screening costs are taken into consideration,

$$\pi\big[pr + (1-p)(-1)\big] + (1-\pi)\big[\gamma \cdot 0 + (1-\gamma)(-1)\big] - e \geq 0 \tag{3.2}$$

The incentive problem for the bank is how to motivate the loan officer to exert costly effort e, and to lend only when no bad signal is observed. We assume that the bank can offer the loan officer a contract $\Omega\big(w_P$

Whereas the expected utility of screening a loan is

$$u_S = \pi\big[pw_P + (1-p)w_D\big] + (1-\pi)\big[\gamma\bar{w} + (1-\gamma)w_D\big] - e \tag{3.4}$$

We begin by remarking the efficient outcome can be obtained if the loan officer is risk-neutral, by setting $\bar{w} = 0, w_P = r$ and $w_D = -1$. The loan officer's incentives are then perfectly aligned with those of the bank. However, this hypothetical contract is expensive for the bank and generally infeasible, in the sense that it gives the entire expected net interest margin to the loan officer, and risky for the loan officer, who is obliged to reimburse the bank for the entire cost of the failed loan.

Note that any contract that induces effort must satisfy two incentive constraints: $u_S \geq u_{NS}$ and $u_S \geq u_R$. The requirement, which states that screening must be more advantageous than not screening $u_S > u_{NS}$ simplifies to the condition

$$\gamma\big[(1-\pi)(\bar{w} - w_D)\big] > e \tag{3.5}$$

This is, however, not the only constraint that must bind to ensure the loan officer screens. It must also be more advantageous to screen than to simply reject loans, That is, $u_S > u_R$

$$\pi p w_P + (\pi\gamma - \pi p - \gamma)w_D - (1-\gamma)\bar{w} > e \tag{3.6}$$

Since both constraints are upper bounds for the cost of effort, only one will bind. If (3.6) binds, the following comparative statics hold: It is easier to induce effort when: i.) the cost of effort is lower, ii.) the faction of good firms in the pool increases, iii.) the reward for a loan that performs increases, iv.) the payment for a loan that fails becomes greater (or less negative) and v.) the probability a good firm repays increases. While the above comparative statics generate several testable predictions, for the purposes of the present paper, we focus on the following results:

Prediction 1: *An origination bonus scheme $w = w_P = w_D > 0$, as often employed by commercial banks, leads to indiscriminate lending, low e ort, and high defaults.*

Prediction 2: *With strictly limited liability, such that $w, w_R, w_P, w_D \geq 0$ and a risk-neutral loan o cer, if $e > 0$, there exists parameters such that the loan o cer cannot be induced to screen. The basic problem here is that if e ort is costly, and default su ciently rare, then loan o cers will prefer to lend to all applicants. While (3.5) can be made slack for any cost of e ort e, by increasing $\bar{w}$, increasing $\bar{w}$ has the opposite e ect of making (3.6) less likely to be satis ed.*

Prediction 3a: *High-powered incentives, including penalties for failure, can induce screening e ort. In the above parameter space, relaxing limited liability and providing penalty for default may induce screening. For example, by setting* $w_D = -1$ *(the entire principal of the loan), and* $w_P = r$*, the loan o cer will screen, as long as condition* (3.2) *is satis ed.*

Prediction 3b: *High-powered incentives result in more conservative lending. A corollary of* (3.6) *is that when loan o cers exert greater screening e ort, they are more likely to discover that a rm is bad, and thus less likely to make a loan.*

Finally, the model makes basic predictions about the effect of the *time horizon* of compensation on screening effort and lending decisions. To see this, assume that the outcome of a loan originated at time t is realized with some delay Δ, and that incentive payments are awarded at $t + \Delta$, once the outcome of the loan is observed. Letting $\delta > 0$ denote a loan officer's discount factor for payments made at time $t + \Delta$, the loan officer chooses screening effort according to:

$$e^*_{s,t+\Delta} = \pi\delta\big[pw_P + (1-p)w_D\big] + (1-\pi)\big[\gamma\bar{w} + (1-\gamma)\delta w_D\big] \tag{3.7}$$

and the difference in screening effort under immediate and deferred incentives is then,

$$e^*_{s,t+\Delta} - e^*_{s,t} = \pi(\delta-1)\big[pw_P + (1-p)w_D\big] + (1-\pi)\big[(1-\gamma)(\delta-1)w_D\big] \tag{3.8}$$

with $e^*_{s,t+\Delta} - e^*_{s,t} < 0$ and $\partial(e^*_{s,t+\Delta} - e^*_{s,t})/\partial\delta < 0$. This shows that, for any positive discount factor δ, deferrring incenive payments reduces a loan officer's expected utility thus attenuating incentives to exert costly screening effort. As we shall see, the results from the experiment provide compelling evidence in support of this prediction.

Prediction 4: *If loan o cers have a positive discount rate, any performance based incentive scheme will induce less e ort if payment is deferred. This follows from condition* (3.8)*, which shows that* $e^*_{s,t+\Delta} - e^*_{s,t}\ \forall\ \delta > 0$*. It also follows that the disincentive e ect of deferred compensation is greater for loan o cers with a higher discount factor, since* $\frac{\partial(e^*_{s,t+} - e^*_{s,t})}{\partial\delta} < 0,\ \forall\ \delta > 0$*.*

4 Experimental Incentive Schemes

We take these predictions to the data using a framed field experiment with commercial bank loan officers, in which participants evaluated loan applications under exogenously assigned monetary incentive schemes. Each incentive scheme consists of three conditional payments; a payment w_P made when a loan is approved and performs, the payment w_D, made when a loan is approved and defaults and the outside payment $\bar{w}$ that is made when a loan is declined. As in the real lending environment, the bank does not observe the outcome of loans that were declined and can therefore incentivize loan officers only based on realized outcomes. Letting x denote the profitability of the lending decision from the perspective of the bank, loan officers face payoffs:

$$w_{il} = \begin{cases} w_P & \text{if } x_l > 0 \mid \textit{approved} \\ w_D & \text{if } x_l < 0 \mid \textit{approved} \\ \bar{w} & \text{if } \textit{declined} \text{ and } x_l = 0 \end{cases} \tag{4.1}$$

where $x = 0$ if a loan is declined. Throughout the paper, we remind the reader of the structure of incentive payments in place by denoting the payment schedule as the triple $\mathbf{w}_l = [w_P, w_D, \bar{w}]$. All payoffs are denominated in Indian rupees and calibrated to the hourly wages of participating loan officers to ensure that monetary incentives are perceived as meaningful by the experimental subjects. Table I summarizes the experimental incentive schemes. An obvious feature of incentive schemes C to E is that they provide very little incentive for a loan officer to exert effort in making the right decision. In fact, under these schemes, accepting every loan application is a (weakly) dominant strategy for the loan officer. Yet, such schemes have often observed in consumer lending, and for that reason we include them among the first set of incentive schemes we test. Indeed, we find that loan officers exert effort and decline loan applications under these incentives. This suggests that, even in the absence of monetary rewards, factors such as career concerns cause loan officers to invest in making the right decision. Another possibility is that loan officers attain some intrinsic utility from properly allocating capital. If, building on the simple framework laid out in the previous section, we abstract from these factors and assume that loan-officers care exclusively about minimizing effort and maximizing financial reward, we can make the following intuitive predictions.

First, incentives awarded for origination will lead to excessive risk-taking. Indeed, purely rational and profit-maximizing loan officers should indiscrimiately approve all applications under scheme C, D and E and exert minimal screening effort *Second*, High-powered incentives will increase effort by increasing the rewards for a profitable lending decision and increasing the penalty for originating a loan that ultimately becomes delinquent. Thus, the amount of effort exerted under various treatment can be ranked $B > A > C, D, E$. *Third*, High-powered incentives will induce more conservative lending behavior by increasing the loan officer's liability for making a bad lending decision. *Fourth*, if a loan

Table I: Summary of Experimental Incentive Schemes

Incentive Scheme		Payments $\mathbf{w}=[w_P,\ w_D,\ \bar{w}]^a$	Description
A	Low-Powered[a,b]	20, 0, 10	This incentive scheme, used as the baseline throughout the experiment, rewards loan officers with a payoff of Rs 20 for approving a loan that performs, Rs 0 for approving a loan that defaults and an outside option of Rs 10 for declining a loan.
B	High-Powered[a,b,c]	50,-100, 0	The *High-powered* incentive rewards participants with Rs 50 for approving a loan that performs, but carries significant penalty for approving loans that become delinquent. Note that loan officers still enjoy limited liability; in case their total incentive payment for a session is negative, no penalty is collected.
C	Origination Bonus[a,b]	20, 20, 0	The *Origination Bonus* scheme provides loan officers with a reward for originating a loan, irrespective of performance.
D	Performance Bonus, Low[a]	50, 0, 0	The *Performance Bonus (low)* scheme provides a bonus of Rs 50 in case an approved loan performs, and no payment otherwise.
E	Performance Bonus, High[a]	100, 0, 0	The *Performance Bonus (high)* scheme provides a bonus of Rs 100 in case an approved loan performs, and no payment otherwise.

Notes: All incentive schemes refer to the payoffs for an individual lending decision. [a] A subset of observations was implemented with an *information credits* feature, which endowed credit officers with Rs 60 information credits and charged Rs 10 for reviewing each section of the loan file beyond the basic client information. [b] A subset of observations under this incentive scheme was implemented with the *deferred payment* feature. Payoffs under this subset of treatments were identical to those listed in the table, but the payout of earned incentives was deferred by 30 days. [c] A subset of observations under this treatment was implemented with the *shared liability* feature. In this subset of observations, payoffs were identical to those listed in the table, and participants were additionally provided with an initial endowment of Rs 200, which they could lose if they made a series of unprofitable lending decisions.

officer's discount rate is greater than zero, the amount of effort induced by incenties F and G will be less than the amount of effort induced by A and B. If, however, credit officers are intrinsically motivated, or erroneously believe that their performance on this task may affect their reputation, they may invest in scrutinizing loan applications even when such scrutiny will not yield additional remuneration.

5 Experimental Design and Procedures

We study loan officer decision-making, using a framed field experiment in the Indian market for small-enterprise loans. In the experiment, loan officers, recruited from leading Indian commercial banks, process a set of credit applications from a database of real historical loans. While lending decisions in the experiment are hypothetical in the sense that the loans have been made and their performance has been observed, all participants are active credit officers and face meaningful monetary incentives, conditional on the loan officer's decision and the eventual outcome of the loan.

The database of loans used in the experiment was constructed in collaboration with the risk-analytics team of a leading commercial lender in Mumbai, India (hereafter "the Lender"). We assembled a database of 635 historical loans, comprising pre-sanction information and at least five quarters of monthly repayment history for each loan. Within our partner firm's range of retail lending products, we limit our attention to uncollateralized small business loans to self-employed individuals with a ticket size between Rs 150,000 (US$ 3,300) and Rs 500,000 (US$ 11,000). We consider only term loans to new borrowers, many of whom are first-time applicants for a formal sector loan.[7] The median loan in our database has a tenure of 36 months, a ticket size of Rs 283,214 (US$ 6,383) and a monthly installment of Rs 9,228 (US$ 208).

To ensure consistency in the quality of loans used in the experiment, and the screening criteria applied when the loans were first evaluated by the Lender, we restricted our sample to loans originated during 2008 Q1 and 2008 Q2. Based on the Lender's proprietary data on the repayment history of each loan, we then classified credit files into performing and non-performing loans. Following the standard definition, we classify a loan as delinquent if it has missed two monthly payments and remains 60+ days overdue, and as performing otherwise. To achieve as representative a sample as possible, we also include credit files from clients who applied, but were rejected by the Lender. In the experiment and empirical analysis, we classify loans that were rejected by the Lender as non-performing loans. In additional robustness checks, not separately reported here, we exclude the subsample of loans rejected by the Lender and show that our main results remain qualitatively unaffected.

All experimental sessions were conducted at two designated experimental labs in the western Indian city of Ahmedabad. Experimental subjects were recruited from the staff of five leading Indian commercial banks. Participants were invited to attend an introductory session and were then given the opportunity to sign up for sets of 15 experimental sessions, completed over a time period of two months. Loan officers were first given an introduction to the software and a non-recorded practice exercise. They were then contacted a week in advance and given a choice of three dates and times to attend a session. Upon arriving at the experimental lab, participants were me by a lab assistant and received an individual introduction to the day's incentive scheme, based on a standardized presentation and a set of instruction cards summarizing the conditions and conditional payoffs for the treatment in place. Prior to the exercise, participants were further asked to complete a brief questionnaire to verify their understanding of the incentive scheme in place. We report summary statistics for the pool of participants in Table 2. In Appendix B, we additionally compare the demographics of loan offciers who participated in our experiment to the employee population of a large Indian commercial bank and show that the pool of participating loan officers is quite representative of this reference population.

[7]Since none of the loans in our sample are collateralized, they are priced at an annual interest rate of between 15 and 30 per cent. We control for the variation in interest rates by including loan fixed effects throughout the analysis.

The experiment was implemented using a customized software interface. The software allowed loan officers to review all applicant information available to the bank at the time the loan was originated. Loan officers were able to navigate between different sections of the credit application, with each tab on the evaluation screen corresponding to a particular section of the loan application (such as a description of the applicant's business, balance sheet, trade reference verification, site visit report, document verification and credit bureau report for the few businesses that have a documented history of formal sector borrowing). While reviewing this information, participants were asked to assess the applicant's credit risk along a set of 15 risk-rating criteria. The list of rating criteria was adapted from the internal credit assessment format of a leading Indian commercial bank and grouped under the categories *personal risk*, *business risk*, *management risk* and *nancial risk* (See Appendix B for a screenshot of the loan evaluation interface).

In each session of the experiment, participating loan officers were asked to evaluate six credit files. Within each experimental session, the sequence of files was randomly assigned, but the ratio of performing, non-performing and declined loans was held constant at four performing loans, one non-performing loan and one loan declined by the Lender. Loan officers were asked to evaluate these loans based on their best judgment and all available information, but neither had any prior information about the ratio of good, bad and declined loans nor the outcome of the loans under evaluation.

Participating loan officers received a fixed compensation of Rs 100 per experimental session to cover time and travel costs. In addition, each incentive scheme offered participants the opportunity to win additional incentive payments, which varied according to the treatment in place and the participant's performance. To ensure that participants perceived conditional payoffs as salient, we calibrated the mean payout of experimental incentive schemes to roughly 1.5 times the hourly wage of the median participant in our experiment, a Level 2 public sector credit officer with an annual income of Rs 240,000 (US$ 5,400) and an approximate hourly wage of Rs 125.

This experimental design offers us the unique opportunity to collect data both on actual lending decisions as well as subjective risk-assessment and the behavior of loan officers during the exercise. In addition to performance measures, required to test our basic hypotheses, we collected data on a set of subjective risk assessment rankings, as well as indicators of behavior during the exercise, such as total viewing time for each file and viewing time for each sub-category, and information credits spent, which we use as a measure of screening effort in the empirical analysis. All participants further completed an exit survey, which included demographics, measures of risk-aversion, time preference and self control.

6 Empirical Strategy and Results

In order to present formal evidence on the effect of monetary incentives on loan officer behavior, we compare screening effort, risk perception, lending decisions and the profitability of lending under each incentive scheme. We estimate treatment effect regressions of the form:

$$y_{il} = \sum_{k=1}^{K} \beta_k T_{ilk} + \theta_i + \theta_l + \zeta' \mathbf{R}_{il} + \xi' \mathbf{X}_{il} + \varepsilon_{il} \tag{6.1}$$

where y_{il} is an outcome of interest for loan officer i and loan l, T_{il} is a treatment vector, taking on a value of one for loan officer-loan combinations rated under the incentive scheme that is being compared to the baseline and zero for loan officer-file combinations rated under the baseline. We additionally control for loan officer fixed effects, θ_i, loan file fixed effects θ_l and a matrix of randomization conditions $\mathbf{R}_{il}$ and additional controls $\mathbf{X}_{il}$. The omitted category in all regressions is the treatment vector T_0, which corresponding to an indicator for the basic *low-powered* incentives treatment, and ε_{il} is a stochastic error term, which we cluster at the session and loan officer level to account for time- and individual-specific shocks to loan officer productivity.

We estimate equation (6.1) using data on a total of 14,369 lending decisions, representing 206 unique subjects across five basic treatments: *Low-powered* incentives, which we use as the baseline throughout the empirical analysis; *High-powered* incentives, which reward loan officers for approving loans that perform and penalizes the origination of loans that default; an *Origination bonus*, which rewards the loan officer for every originated loan, regardless of decision or loan performance and two linear incentive schemes, which reward loan officers for every successful loan made, but do not penalize unprofitable decisions. In a second set of treatments, we first add information credits to these four basic treatments to obtain an additional measure of screening effort. Second, we consider a subset of treatments which relaxes the participants' limited liability constraint by providing an initial endowment that can be lost if a loan officer makes a series of unprofitable lending decisions. Randomization checks comparing observable participant characteristics across treatments are reported in Table A.3.

To test our hypotheses, we consider three groups of outcomes: (i) measures of screening effort, (ii) measures of subjective risk-assessment, (iii) actual lending decisions and the profitability of originated loans. We construct four separate measures of screening effort. We begin by measuring each loan officer's total evaluation time per credit file, as well as the evaluation time for the sub-sections of the credit files containing basic client information. We additionally construct a variable indicating the number of credit file sections reviewed by a credit officer. We obtained an additional proxy of costly screening effort by conducting a subset of treatments in which loan officers were charged information credits for each section of the credit file they reviewed. From these treatments, we construct a variable measuring the number of information credits spent for each evaluated loan. To measure loan officers' subjective assessment of credit risk, we record internal risk ratings assigned to each of the 15 credit rating questions and calculate the rating assigned to each loan evaluated in the exercise on a scale from 0 (high risk) to 100 (low risk). To evaluate loan officer decisions and performance under alternative incentive schemes, we match the loan officer's lending decision to the loan's historical delinquency status, obtained from the Lender's proprietary data on repayment history. This allows us to calculate the net profit of each loan, and assess the quality of loans originated under each incentive treatment.

6.1 Incentivizing Screening Effort

We first analyze the effect of incentives on screening effort. Performance incentives can affect the quality of lending decisions if it induces a loan officer to choose higher screening effort, and translates into the collection of borrower information that was not previously available or a more thorough evaluation of available information. The design of our experiment provides us with several straightforward measures of screening effort. First, we record the total time a loan officer spends reviewing each credit file. Second, we record how many of the ten sections of the credit file the loan officer chooses to review before making a decision. Third, in a separate set of treatments loan officers were provided with an endowment of Rs 18 at the beginning of each loan evaluation, which they could either take home, or use to purchase access to additional information sections of the credit file under review. Under this treatment, the sections of the loan file containing basic information about each client were 'free', but loan officers had to pay to review additional sections, such as the applicant's credit bureau report or detailed balance sheet. We use the number of information credits spent as an additional measure of screening effort, which captures the notion of costly information. However, since screening effort is not observable to the bank, we do not tie bonus payments to measures of effort observed in the experiment.

Table 8 reports treatment effects of performance pay on screening effort, as proxied by (log) evaluation time, (columns 1 and 2), the number of loan file sections reviewed (columns 3 and 4), and our measure of costly screening effort, the number of information credits spent reviewing the loan application (columns 4 and 5). Compared to the ***Baseline*** treatment, we see that the time spent evaluating each credit file declines by up to 14% under incentives that reward origination but have no downside risk for the loan officer. By contrast, under ***High-powered*** incentives which reward for profitable lending decisions and penalize the origination of loans that default, evaluation time does not differ significantly from the baseline while the number of credit file sections reviewed and information credits spent is significantly higher. On average, loan officers facing high-powered incentives were 41% more likely to review an additional section of the credit file above the mean and spent .77 additional information credits. Both effects are statistically significant at the 1% level. In line with the predictions of the theoretical framework (i) loan officers exert less effort per loan when the incentive is placed on lending volume, and (ii) exert greater screening effort under incentives that penalize bad lending decisions. Taken together, these results confirm that loan officers strongly adapt their effort in response to monetary incentives, and suggest that performance pay can serve as a useful tool to incentivize effort in the collection and review of borrower information.

6.2 Risk-Assessment and Risk-Taking

How does the structure of performance incentives affect risk-taking and the assessment of credit risk? In this section, we address these questions using the internal risk-ratings assigned to each loan evaluated in the exercise. Before participants made a decision to approve or decline a loan application, we asked each loan officer to assess the merit of the application along 15 risk-rating criteria based on a list of standard credit scoring formats used by an Indian commercial bank (a higher score indicates higher credit quality). We emphasized that, in contrast to what is common practice for larger loans, the ratings are not binding for the officer's decision. That is, an applicant did not have to attain a minimum score to be considered for a loan. Table 5 provides summary statistics of risk-rtings by incentive, Figure 4 plots the distribution of risk-ratings for the sample of performing and non-performing loans, respectively.

We first explore how performance incentives affect the assessment of credit risk. We compare the internal risk-ratings assigned under each incentive scheme. Figure 7, Panel (a) depicts Epanechnikov kernel density estimates for risk-ratings under the *Baseline* treatment, *Origination bonus* and *High-powered* incentives. The density plots reveal that, relative to the *Baseline* incentives, loan officers assign significantly higher risk-ratings when they face incentives that reward origination and assign significantly more conservative riskratings when they face incentives that penalize default. A Kolmogorov-Smirnov test rules out the equality of distributions for the *Baseline* incentive versus *Origination bonus* and *High-powered* incentives at the 1% level, respectively.

In Table 9 we report treatment effects of performance incentives on internal risk-ratings. In line with the 'cognitive consonance' result suggested by the kernel density estimates, the results show that loan officers inflate risk-ratings under incentive schemes that reward loan officers based on lending volume. Moreover, the degree of risk-rating inflation is roughly proportional to the magnitude of the performance bonus. In the loan officer and loan fixed effect specification (column 2), we see that the size of the coefficient increases in direct proportion to the incentive that is placed on origination. When separated into subsamples of performing loans and non-performing loans, we find that under the high performance treatment, loan officers inflate risk ratings for both categories of loans, but more so for non-performing loans. Under the low performance bonus, for instance, loan officers inflate their risk ratings only for non-performing loans. These results provide evidence that the structure of performance incentives have a significant effect on the perception of credit risk.

We next turn to the effect of performance pay on actual risk-taking. Because the realized outcome of a loan may be a poor proxy of perceived credit risk at the time of its origination, we construct a measures of risk-taking from the distribution of internal risk-ratings assigned to the loan under the *Baseline* incentive. Specifically, we assume that loans deemed safer at the time of origination are characterized by a higher mean and a lower dispersion of risk-ratings assigned under the *Baseline* incentive. We therefore calculate for each loan l the mean of all risk ratings it received under the baseline μ_l, restricting the sample to loans that received at least ten evaluations under the *Baseline* incenitve. We measure the dispersion in risk-ratings, which may be interpreted as risk stemming from disagreement about the interpretation of information in a loan application, as the coefficient of variation of all risk-ratings assigned to loan l under the *Baseline* $cv_l = \frac{\mu_l}{\sigma_l}$. Here, μ_l is the sample mean and σ_l is the standard deviation of all internal risk-ratings assigned to loan l under the *Baseline* incentive. Intuition suggests that, if high-powered incentives are effective in incentivizing more discerning lending decisions, loan officers will approve loans with higher mean and a lower variance of this measure of perceived asset quality under high-powered incentives.

Figure 7b and Table 10 test this hypothesis. Figure 7b depicts Epanechnikov kernel densities of our measure of perceived credit risk for loans originated under the *Baseline* incentive, the *Origination bonus* incentive and *High-powered* incentives. Figure 7b reveals that, consistent with our hypothesis, loans originated under *High-powered* incentives are characterized by lower perceived credit risk and a smaller dispersion in loan officers' assessment of the credit risk under the *Baseline*. The opposite is the case for loans originated under the *Origination bonus* treatment: compared to *High-powered* incentives, loan officers facing a bonus for origination approve loans with higher perceived ex-ante credit risk. A Kolmogorov-Smirnov test rejects equality between the *Baseline* and *High-powered* incentives as well as between *High-powered* incentives and *Origination bonus* at the 1% level (p=.0052 and p=.0174). Table 10 presents the corresponding treatment effect estimates. The results are striking. In line with the non-parametric evidence, we find that loan officers facing high-powered incentives originate loans that appear significantly less risky ex-ante. When we distinguish between sub-components of the risk-rating related to personal and management risk (columns 3 and 4) and components related to business and financial risk (clumns 5 and 6), we see that the effect of high-powered incentives on risk-taking appears to be more pronounced when there is uncertainty that relating to 'hard information' about a loan, such as the applicant's audited financials.

6.3 Lending Decisions and the Profitability of Lending

How does the provision of performance incentives affect the portfolio of originated loans and the profitability of lending from the perspective of the bank? To address this question, Table 11, reports treatment effects of performance pay on loan approvals. The dependent variable in all regressions is a dummy equal to one if a loan was approved, so that the coefficient estimates measure the percentage change in approved applications relative to the *Baseline* incentive. We present results for the entire sample of loans, as well as three subsamples: performing loans (columns 3 and 4), non-performing loans (columns 5 and 6), and loans that were originally declined by the Lender (columns 7 and 8). The results show an economically and statistically significant effect of performance incentives on loan approvals. In Table 11, columns (1) and (2), we see that the switch from the *Baseline* to *High-powered* incentives leads to slightly more conservative lending decisions and a decline in loan approvals of .7 to 4% However, this effect is statistically significant at the 10% level only in the basic specification (column 1) and does not attain statistical significance when we account for loan officer and loan file fixed effects. The switch from the baseline to incentive schemes that reward origination, however, leads to a steep increase in the probability of approval, irrespective of loan quality. Under the *origination bonus* treatment, loan approvals increase by approximately 8 percentage points over the baseline acceptance rate of 71%. The coefficient estimate is identical in both specifications and statistically significant at the 1% level. The probability of approval increases monotonically for the two *performance bonus* incentives with the probability of approval increasing by 10% and 13%, respectively. In columns (3) to (10) we disaggregate these changes in lending volume and distinguish between the subsample of performing, non-performing and declined loans. These results indicate that in the absence of a penalty for bad lending decisions, the probability of approving a 'bad' loan is increasing in the magnitude of the origination incentive.

We turn to the effect of performance pay on the profitability of lending decisions in Table 12. We consider two measures of loan-level profit: the Lender's net profit per *approved loan* and the Lender's net profit per *evaluated* loan. While the former profit variable provides a direct measure of the profitability of individual lending decisions, the latter accounts provides a measure of loan-level profit accounts for the change in lending volume under different performance incentives documented in the previous section. The first two columns review the lending volume results presented in Table 11. Columns (3) and (4) look at the effect of performance pay on profit per approved loan and columns (5) and (6) consider profit per screened loan. In line with the results of the previous section, the results confirm that high-powered incentives lead to slightly more conservative but significantly more profitable lending decisions. While the results indicate only a small decline in the overall lending volume, the selecton effec induced by high-powered incentives leads to a significant improvement in the quality of approved loan portfolios. The coefficient estimate indicates that profit per approved loan increase by approximately \$185 (or 2.5% of the median loan size) compared to the baseline. Incentives that reward origination without penalizing default analogously lead to a decline in profitability and the quality of loan portfolios. The average loan approved under high-powered incentives is approximately \$290 (or 4% of the median loan size) more profitable than the average loan originated under the *performance bonus high* treatment, which offers a high reward for lending volume, but carries no downside for approving loans that default. Notably, this pattern is unchanged when we consider profits per screened loan (columns 5 and 6). This indicates that the decline in lending volume we documented in the previous section does not offset the strong positive selection effect of high-powered incentives. The results show that this leads to the origination of significantly more profitable loans, suggesting that the introduction of high-powered incentives are an overall a profitable proposition from the bank's point of view.

6.4 When do Loan Officers Outperform a Credit Scoring Model?

Can well-incentivized loan officers outperform the predictions of a statistical credit scoring model? To explore this question, we estimate a basic credit scoring model using a standard methodology employed in credit card and consumer loan approvals (see Greene 1992) and compare the predictions of the model to the lending decisions of loan officers in the experiment.

The setup of the model is as follows. Suppose that at time $t = 0$, individual i with personal attributes $\mathbf{x}_i$ applies for a loan. These attributes may include characteristics of the applicant, such as age, gender, income, expenditures, current assets and current liabilities, credit history and characteristics of the loan for which the applicant has applied, such as ticket size, maturity, interest rate and the predicted monthly installment. Since the model is calibrated using past loan data, we observe the random variable y_i, which indicates whether an applicant has defaulted on their loan ($D_i = 1$) or not ($D_i = 0$) during the time period that has elapsed since the origination of the loan.

We are interested in predicting $P_i = Prob[D_i = 1|\mathbf{x}_i]$, that is, the probability that a loan to an applicant with characteristics $\mathbf{x}_i$ will default. Because our credit scoring model predicts default only in the sample of approved loans, rather than the universe of loan applications, we account for selection into the subsample of approved loans using a standard Heckman (1979) two-step correction. The overall probability of default is described by the Probit model

$$Prob[D = 1|\mathbf{x}_i] = \Phi[\theta'\mathbf{x}_i + u_i] \tag{6.2}$$

where $\mathbf{x}_i$ is a vector of borrower characteristics and u_i is a stochastic error term. We assume that a loan is approved if the applicant attains the minimum qualifying score in the bank's initial loan appraisal process. We observe $z_i = 1$ if the latent variable $z^* = \mathbf{z}_i'\gamma + v_i > 0$ and zero otherwise, so that the probability of selection into the sample of approved loans is

$$Prob[s = 1|\mathbf{z}_i] = \mathbf{1}\left[\gamma'\mathbf{z}_i + v_i \geq 0\right] \tag{6.3}$$

where $\mathbf{z}_i$ is a vector of borrower characteristics that explain approval and $E[u|\mathbf{x}, z] = 0$. We then estimate the baseline credit scoring model, using the sample selection corrected Probit specification

$$Prob[D = 1|\mathbf{x}, s = 1] = \Phi[\theta'\mathbf{x}_i + \rho\lambda(\gamma'\mathbf{z}_i) + w_i] \tag{6.4}$$

where ρ is the correlation $E(u, v)$, λ is the inverse Mills ratio and w_i is a stochastic error term.
In many standard applications, a loan is predicted to default if $\hat{p}_i$ is greater than a threshold value of $p = 0.5$, implying that a loan is more likely to default than to perform. However, this decision rule turns out to be a poor guide for the application at hand for two reasons. First, given that at 10% default is a rare event, the rule may fail to outperform the naive rule of always (or never) predicting $Prob[D_i = 1|\mathbf{x}_i, s = 1] = 1$. Second, the decision rule does not account for the asymmetry between the cost of type I and type II errors. That is, the fact that the bank's cost of approving a non-performing loan, typically implying a loss in excess of the principal amount, is significantly greater than the profit from approving a performing loan. In order to address these limitations, we derive the bank's profit maximizing default and approval probability from a loss function, which describes the tradeoff between the probability weighted benefit from approving a performing loan and the probability weighted cost of originating a loan that later becomes delinquent. Let π_i denote the profit from approving loan i, we choose the profit-maximizing default probability p^* based on the condition

$$E[\pi] = (1 - p)\left[(1 + r)f - c\right] - p(-f) \tag{6.5}$$

where f is the face value of the loan, r is the interest rate and c is an estimate of the lender's cost of capital. Figure 8 plots this function for estimated default probabilities between $p = 0$ and $p = 0.25$ and shows that, within the sample of loans used in the experiment, the profit-maximizing default probability occurs between 10% and 12%.

We estimate a credit scoring model based on equation (6.4) using data on all loans evaluated in the experiment. In the preferred specification of the model, the vector $\mathbf{x}$ includes variables measuring the ticket size, term and monthly installment as well as the client's overall debt burden, monthly income and monthly debt service. These correlates of default are a subset of the vector $\mathbf{z}$, which additionally includes client characteristics such as credit history, years of business experience, and the presence of a credit bureau report, which are predictive of the approval decision but do not affect repayment once we condition on borrower financials Table 13 summarizes the preferred specification of the credit scoring model and reports the corresponding coefficient weights. In this specification, our credit scoring model correctly identifies 82% of all loans out of sample. As is the case with loan officer evaluations, the model performs significantly better in identifying performing loans than identifying loans that were approved by the Lender but ultimately defaulted. This, once again, underscores the difficulty of using incentives to affect the predictability non-idiosyncratic default.

In order to compare loan officer performance to the predictions of our simple credit scoring model, we define the variable $\textit{perform}_{ik} \in [-1, 1]$ for each lending decision i and loan officer k. This variable takes on a value of 0 when the prediction of the credit scoring model and the decision of the loan officer are in agreement, irrespective of whether the decision is profitable or not. The variable takes on a value of 1 if the loan officer outperforms the credit scoring model in the sense that she correctly approves a performing loan or declines a non-performing loan when the credit scoring model would have suggested otherwise. Similarly, $\textit{perform}_{ik}$ takes a value of -1 whenever a loan officer approves a bad loan or declines a good loan when the credit scoring model would have correctly suggested otherwise.

In Table 14 we use this comparative measure of loan officer performance as the outcome of interest to examine to what extent well-incentivized loan officers can outperform the recommendations of a simple credit scoring model. In Panel A, we present the results for the basic set of treatments, and in Panel B results for the subset of treatments in which loan officers were provided with an endowment of information credits and charged for acquiring additional client information. We repeat the comparison between model and loan officer performance for model approval thresholds of 0.08, 0.10 and 0.12 and all comparisons are based on *out of sample* predictions of the credit scoring model. The results in Panel B indicate that, when information is costly, loan officers who face high-powered incentives are significantly more likely to outperform the predictions of a the credit scoring model. Specifically, a loan officer's assessment of a credit file is more accurate than the prediction of the model in approximately 5-10% of all cases. The coefficient estimate is similar in magnitude throughout, but attains statistical significance in only two of the specifications, due to the smaller sample size of the dataset for which out-of-sample predictions are available.

6.5 Deferred Compensation

Similar in spirit to much recent regulation around the world, the European Parliament recently approved a regulation requiring 70% of bonus payments to be deferred, paid only in case the banks performance does not suffer. We test the effect of interventions affecting the time horizon of compensation in the following manner. Because we are interested in understanding whether deferred compensation weakens incentives for effort, we include the 'costly effort' treatment, whereby loan officers must pay Rs 3 for each set of information in the loan application file. We compare immediate payment under low-powered, high-powered and origination incentives to deferred compensation, in which the loan officer may collect payment 3 months after the experiment is completed.

Table 15 present results. Note that, unlike in the previous tables, the omitted category and relevant basis for comparison here is the low-powered treatment with information credits. The results show that deferred compensation affects both loan approvals but (more strongly) all three measures of screening effort. Both effects are strongest for high powered incentives: while high-powered incentives with immediate compensation lead to an economically and statistically significant decline in loan approvals, this effect is attenuated when incentive payments are deferred. Dividing loans into performing and non-performing/rejected loans in columns (2) and (3), we see that this difference is driven mainly by the higher approval of 'bad' loans.

Turning to the impact of deferred compensation on effort, the results again indicate that deferred compensation leads to a significant attenuation of the effect of high-powered incentives on loan officer behavior. While screening effort, as measured by number of loan file sections and information credits spent, is significantly greater than in the baseline under immediate high-powered incentives, none of the three effort measures differs significantly from the baseline when high-powered incentives are deferred. This finding is confermed by the t-tests for equality of the immediate versus deferred treatment coefficients, reported at the foot of the table. These results suggest a nontrivial impact of deferred compensation on loan approval volume and effort, and significant differential impacts of deferred compensation among our treatments.

6.6 Shared Liability

In the wake of the financial crisis, much attention was paid to the structure of incentives in the financial sector, particularly the prevalence of moral hazard due to the systematic absence of shared liability for a large subset of decision-makers. To test the impact of shared liability on loan officer behavior, we added an endowment component to the high-powered incentive whereby the loan officer received Rs 200 at the beginning of each session, essentially a bonus from which his/her penalties would be deducted. Table 16 presents our results. As in the previous subsection, we again find the strongest results of this intervention in its effect on screening effort. In line with theoretical predictions, we find that introducing a degree of shared liability that increases loan officers' 'skin in the game' leads to a significant increase in screening effort, as measured by (log) evaluation time, the number of credit file sections reviewed *and* the number of information credits spent (columns 7 to 12). These results are again confirmed by tests for the equality of basic and shared liability coefficients, reported at the foot of Table 16, and suggest that incentive designs that relax the limited liability constraint of the loan officers can be an effective tool to encourage attentiveness in the evaluation of borrower information.

6.7 Heterogeneity in Treatment Effects

Finally, we examine the heterogeneous effect of alternative incentive schemes. Does the response of credit officers vary with individual characteristics, such as age or experience? To answer this question, we first, in Table 10, report treatment interactions between each of the basic incentive schemes and the age of participating loan officers. In order to facilitate the interpretation, we interact each treatment dummy with a variable indicating the quartile rank of a loan officers age. The estimates in column (1) show that, overall, older loan officers spend more time reviewing borrower information a one quartile step in loan officer age is associated with a 10% in increase in screening effort. Turning to the interaction effects, we see that older loan officers respond much more strongly to high-powered incentives where, again a one quartile step in a loan officers age is associated with an additional 10% increase in (log) screening effort under high-powered incentives. The interaction effect is significant the 1% level. Interestingly, the results also reveal a positive and significant interaction effect between loan officer age and the origination bonus treatment. This suggests that older loan officers may be more immune to incentives that reward lending volume at the expense of credit quality.

Table 11, presents interaction effects between each of the basic incentive treatments and loan officer experience measured as the years of experience in a branch manager or comparable senior management position. Again, the estimates suggest that more experienced loan officers exert greater effort under both high- and low-powered incentives. A one-quartile step in loan officer experience increases the time spent evaluating credit files by 7% (column 1) and makes a loan officer approximately 40% more likely to review an additional section of the credit file relative to the mean. We see a particularly strong effect of management experience on screening effort in the number of information credits used under medium and high performance incentives, two incentive schemes that we would expect to induce relatively careless lending decisions since (in contrast to high-powered incentives) there is no penalty for originating bad loans (column 3). In the non-interacted baseline treatment, we see that loan officers are indeed significantly less likely to exert costly screening effort. However, this effect is more than compensated among loan officers with greater experience as indicated by the interaction effects that are positive and significant at the 1% level for both performance bonus interactions. In summary, we thus find evidence that both age and experience moderate the negative effect of incentive schemes that would otherwise tempt credit officers to originate a large number of poorly screened loans.

7 Discussion and Conclusion

In this paper, we analyze the underwriting process of small-business loans in an emerging market, using data obtained in cooperation with a large commercial lender in India. These loan applications include only new loans –entrepreneurs applying for their first commercial loan– which require extensive screening and are therefore particularly sensitive to loan officer judgment.

Our experiments provide the first rigorous test of theories of loan officer decision-making, through a series of randomized experiments. We compare four commonly implemented incentive schemes: low-powered incentives, providing modest rewards for making correct decisions, a bonus for origination, a bonus for originating only loans that perform, and a high-powered scheme which involves both a performance bonus and a penalty for approving loans that default. The results show strong and economically significant effects of performance based incentives on screening behavior and risk-taking. Incentives that penalize bad lending decisions cause loan officers to approve significantly fewer loans. In a second experiment, we measure the effect of deferred compensation, finding that delaying incentive payments by three months significantly reduces costly effort. We further provide evidence on the heterogeneous effects of loan officer age and experience on the impact of performance incentives and find that more experienced loan officers exert higher effort, regardless of the incentive scheme in place. The results from these experiments can provide practical guidance for lenders in emerging markets that seek to develop staff incentives which reduce bias and default-risk in lending environments characterized by high idiosyncratic risk. Furthermore, our results speak to the shifting paradigm in bank compensation following the Dodd-Frank Act in the United States and recent regulation that has sought to regulate the structure and time horizon of bank compensation. This paper provides some of the first empirical evidence on the implications of such regulation on portfolio growth and risk-taking at the loan officer level.

The experiments in this paper represent the first step of an ambitious agenda to fully understand the loan underwriting process. With a view towards lending in emerging markets, an important next step on this research agenda is to better understand the interplay between performance pay and incentives to incorporate various types of borrower information into the lending decision. In future work, we plan to vary the information environment faced by loan officers to explore the interaction between monetary incentives and the use of information in lending.

In future work, we aim to understand the role of individual characteristics in lending decisions, and how these characteristics interact with incentive schemes. On the first point, lenders have increasingly relied on credit scoring models rather than human judgment. But it is unclear whether credit scoring models can outperform human judgment, particularly in informationally opaque credit markets. Nor is it obvious what individual characteristics are associated with screening ability and to what extent they help or hinder the use of performance incentives as a tool to manage credit-risk in commercial lending. The results in this paper provide a first step in answering these questions, exploring them in greater depth is a promising avenue for future research.

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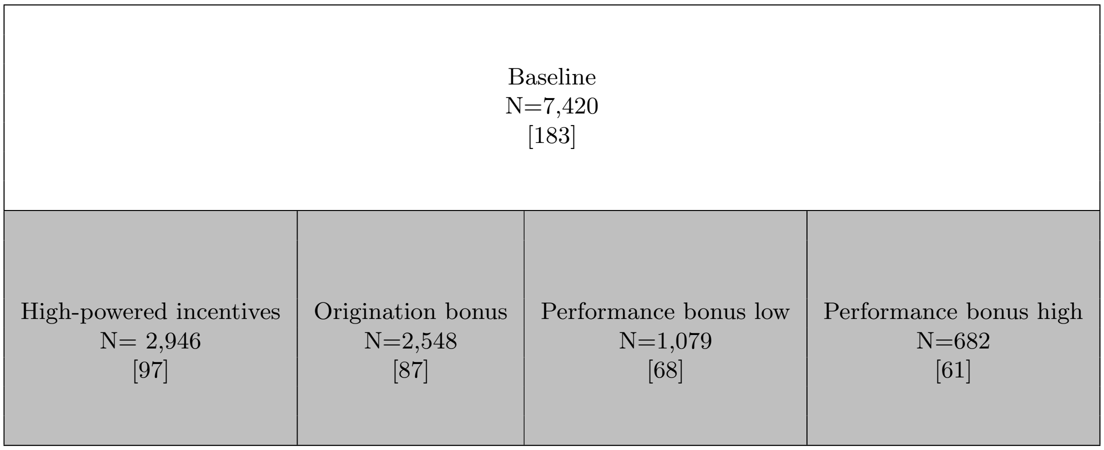
Figure 1: Treatment Design



Notes: This chart summarizes the experimental design. Randomization was carried out at the loan officer level for each session of the experiment. Loan officers were assigned to the *Baseline* treatment (low-powered incentives) or one of four alternative incentive treatments. N refers to the number of loan evaluations carried out under each incentive treatment. Figures in brackets indicate the number of loan officers assigned to each incentive treatment. Within each treatment, a subset of observations was implemented with additional features, such as costly information, deferred compensation or shared liability. Treatment features were phased in sequentially and experimental sessions were carried out at two separate locations. We therefore control for treatment and sub-treatment dummies as as well as week and location fixed effects throughout the analysis. In total, 206 loan officers participated in the experiment and completed 14,675 loan evaluations.

Table 1: Loan Officer Summary Statistics

This table reports demographic summary statistics for the pool of participants. *Age* is the loan officer's age in years, *Male* is a dummy variable taking a value of 1 if the participant is male. *Rank* is the loan officer's level of seniority level in the bank. *Experience* is the total number of years the participant has been employed with the bank. *Branch Manager* is a dummy variable indicating whether the participant has ever served as a branch manager or in a comparable management role. *Business Experience* is a dummy variable taking on a value of 1 if a loan officer reports having any previous business experience outside banking.

	Demographics									
	N	Mean	Median	StDev	Min	Max	10%	25%	75%	90%
Male	206	0.89	1.00	0.31	0.00	1.00	0.00	1.00	1.00	1.00
Age	206	38.62	36	10.88	23	64	25	30	48	54
Education [Master's Degree]	186	0.34	0.00	0.47	0.00	1.00	0.00	0.00	1.00	1.00
Experience [Years]	206	13.77	11	11.44	0.00	40	1.00	3.00	25	31
Rank [1 Low - 5 High]	206	1.97	2.00	1.00	1.00	5.00	1.00	1.00	3.00	3.00
Branch Manager Experience	206	0.36	0.00	0.48	0.00	1.00	0.00	0.00	1.00	1.00
Business Experience	206	0.47	0.00	0.50	0.00	1.00	0.00	0.00	1.00	1.00

Table 2: Loan File Summary Statistics

This table reports summary statistics for the database of loans used in the experiment. Columns (1) to (3) show summary statistics for the entire sample of loans used in the experiment. Columns (4) to (6) report summary statistics for the sub-sample of performing loans and columns (7) to (9) show summary statistics for the sub-sample of non-performing loans and loans that were declined by the Lender. In columns (10) and (11) we show differences in means between the two groups and corresponding standard errors. The variable *Monthly Installment* refers to the estimated monthly installment of the present loan, assuming the median interest rate of 14%. *Total Income* measures a client's monthly revenue, including all business and household production. *Personal Expenses* measure a client's monthly personal expenses and *Business Expenses* measure a client's total monthly business expenses, including all inputs to production. *Gross Profit* is the applicant's annual operating profit before interest and taxes. The variable *Total Debt Burden* measures a client's total outstanding debt and *Monthly Debt Service* is the sum of all monthly installments on the applicant's outstanding loans. *Credit Report, Amount* is the amount of outstanding loans and *Credit Report, Accounts Overdue* is the number of accounts reported to be overdue on a client's credit report for the subset of loan applicants with a documented credit history. *EBIT* refers to earnings before interest and taxes. All variables are denominated in US$.* $p<0.10$ ** $p<0.05$ *** $p<0.01$.

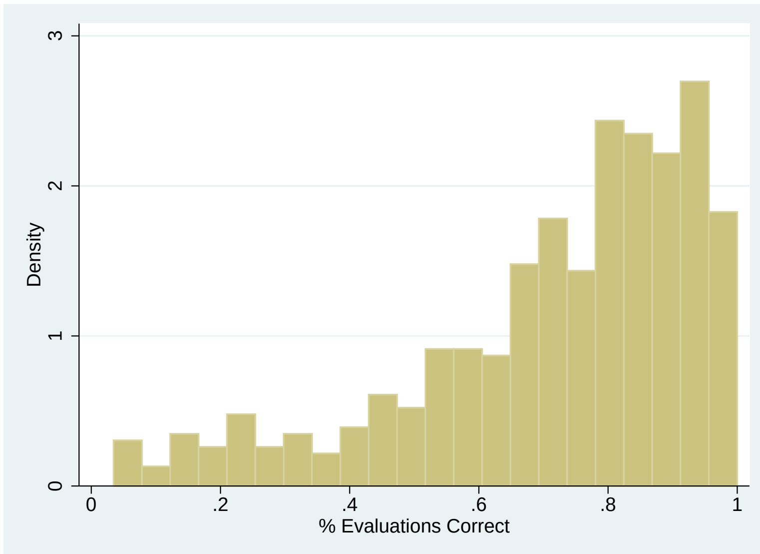
	Panel A All Loans			Panel B Performing Loans			Panel C Non-Performing and Declined Loans			Difference in means B - C	
	Mean	Median	StdDev	Mean	Median	StdDev	Mean	Median	StdDev	Diff	$p > \|t\|$
Loan Amount	6,009	6,383	2,627	5,987	6,383	2,613	6,147	6,383	2,722	-160	[0.58]
Monthly Installment	420	208	855	413	208	878	476	205	620	-63	[0.58]
Loan Tenure	32.64	36.00	9.04	31.80	36.00	7.57	37.90	36.00	14.35	-6.10***	[0.00]
Years in Business	11.27	9.00	7.99	11.64	9.00	8.35	9.50	8.00	5.80	2.14**	[0.02]
Total Income	11,680	6,383	18,621	12,126	6,383	19,257	7,850	5,309	11,224	4,276*	[0.07]
Personal Expenses	283	223	304	285	223	317	270	231	209	15	[0.66]
Business Expenses	9,818	5,191	17,438	10,529	5,559	18,354	5,368	3,514	8,771	5,161***	[0.01]
Gross Profit	13,365	6,926	37,257	11,111	6,910	14,010	23,979	7,967	83,569	-12,868**	[0.03]
Total Debt Burden	6,776	0	31,572	6,820	0	33,425	6,504	955	15,887	316	[0.93]
Total Monthly Debt Services	227	0	733	226	0	777	234	112	358	-8.00	[0.92]
Credit Report, Amount	2.94	1.00	5.46	2.97	1.00	5.66	2.80	1.00	4.30	0.17	[0.79]
Credit Report, Accts Overdue	0.20	0.00	0.40	0.18	0.00	0.38	0.32	0.00	0.47	-0.14**	[0.04]
EBIT	1,844	1,007	6,523	1,904	991	7,002	1,467	1,074	1,388	437	[0.55]
Total Liabilites/Net Income	0.02	0.01	0.04	0.02	0.01	0.04	0.03	0.01	0.09	-0.01*	[0.05]
Total Debt/Net Income	0.37	0.00	1.50	0.34	0.00	1.41	0.66	0.00	2.12	-0.32	[0.10]
Total Liabilities/Total Sales	0.04	0.02	0.05	0.03	0.02	0.05	0.06	0.03	0.07	-0.03***	[0.00]

Table 3: Loan Evaluation Summary Statistics

This table reports descriptive statistics on loan evaluations by incentive scheme and loan type. In Panel A, we report summary statistics on loan approvals, Panel B presents summary statistics on loan officer performance as measured by the percentage of correct lending decisions. Here, a 'correct' lending decision is defined as approving a performing loan or declining a non-performing loan. Panel C provides descriptives of the internal risk-ratings assigned to each loan by loan officers participating in the experiment and Panel D reports summary statistics on the profitability of lending decisions, measured as the net profit per approved loan, denominated in units of US$ '000. Standard errors in parentheses are clustered at the loan officer and session level.

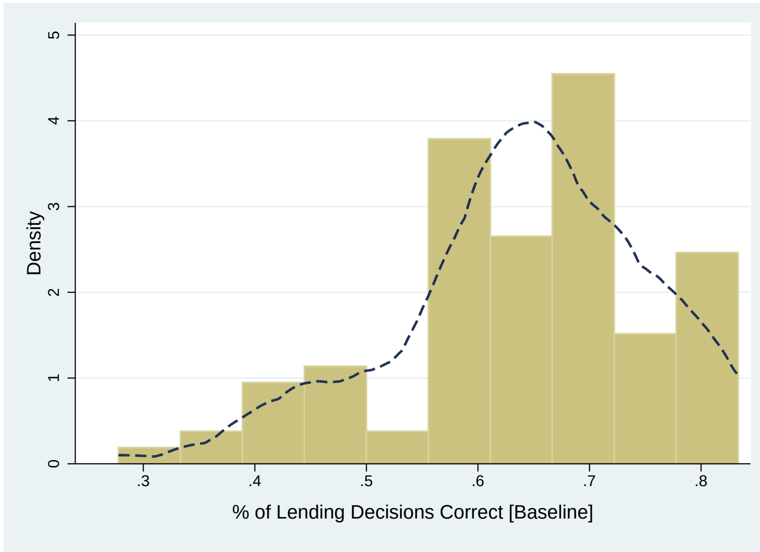
	Loan Type			Sample
Panel A: Loans Approved	Performing	Non-Performing	Declined by Bank	Average
Baseline	*.770*	*.698*	*.484*	*.711*
	(.032)	*(.031)*	*(.025)*	(.007)
High-Powered	.735	.598	.509	.674
	(.068)	(.096)	(.058)	(.017)
Origination	.847	.741	.672	.801
	(.052)	(.060)	(.057)	(.015)
Performance bonus high	.851	.828	.587	.792
	(.070)	(.072)	(.060)	(.021)
Performance bonus low	.900	.855	.597	.838
	(.069)	(.069)	(.066)	(.023)
Sample average	.797	.738	.546	.746
	(.004)	(.008)	(.010)	(.004)
Panel B: % Evaluations Correct				
Baseline	*.770*	*.302*	*.516*	*.642*
	(.032)	*(.031)*	*(.025)*	(.008)
High-Powered	.735	.402	.491	.636
	(.068)	(.096)	(.058)	(.019)
Origination	.847	.259	.328	.659
	(.052)	(.060)	(.057)	(.013)
Performance bonus low	.851	.172	.413	.659
	(.070)	(.072)	(.060)	(.019)
Performance bonus high	.900	.145	.403	.665
	(.069)	(.069)	(.066)	(.016)
Sample average	.797	.262	.454	.640
	(.004)	(.008)	(.010)	(.004)
Panel C: Profit per Approved Loan				
Baseline				*.275*
				(.036)
High-Powered				.328
				(.090)
Origination				.158
				(.078)
Performance bonus low				.163
				(.110)
Performance bonus high				.238
				(.018)
Sample average				.238
				(.018)

Figure 2: % Evaluations Correct by Loan File
[Difficulty of the Lending Decision]



Notes: This figure explores the difficulty of lending decisions by plotting the percentage of times a loan file was evaluated correctly for each loan application evaluated in the experiment. Here, a correct lending decision is defined as an experimental subject approving a loan that performed or declining a loan application that later became delinquent. The sample is restricted to loan applications that received at least ten independent evaluations.

Figure 3: Loan Officer Performance



Notes: This figure shows the distribution of loan officer performance, measured by the average percentage of correct decisions per session under the *Baseline* treatment. The dashed line plots the Kernel density of the performance distribution. We define a correct lending decision as approving an ex-post performing loan or declining an ex-post non-performing loan.

Table 4: Loan Officer Performance

This table reports descriptive statistics of loan officer performance, measured as the percentage of correct lending decisions. We define a correct lending decision as approving an ex-post performing loan or declining an ex-post non-performing loan.

	% Evaluated Correctly				
	Min	Max	Mean	Median	StDev
Baseline	.167	1.00	.636	.667	[.149]
High-Powered	.333	1.00	.657	.667	[.183]
Origination Bonus	.333	1.00	.647	.667	[.125]
Entire Sample	.278	1.00	.642	.654	[.101]

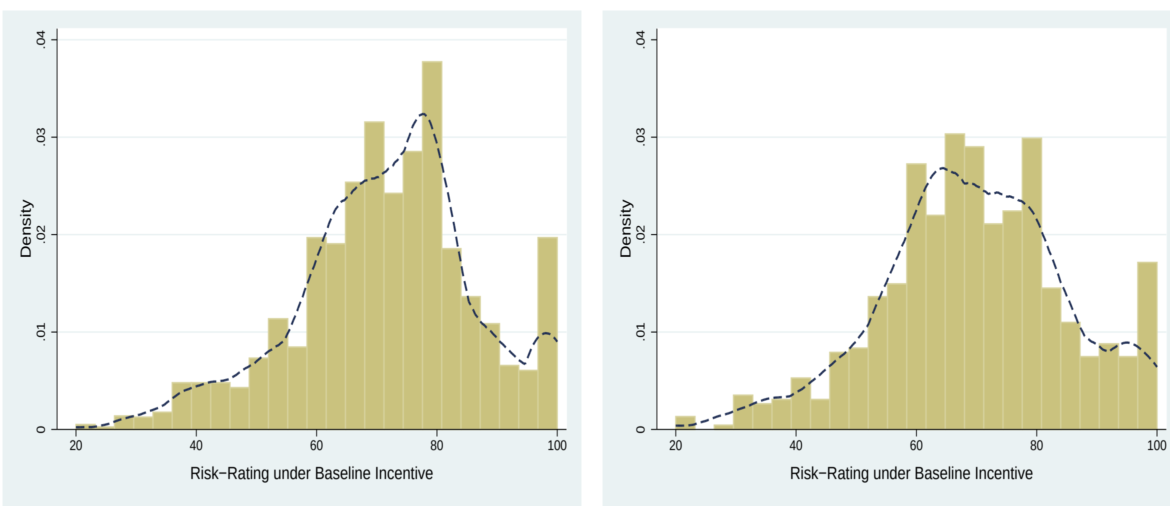
Table 5: Internal Risk-Ratings

This table presents summary statistics of overall risk-ratings by loan type. Loan officers were asked to assess the credit risk of each evaluated loan along 18 rating criteria. The rating criteria contained questions on *personal risk*, *management risk*, *business risk* and *financial risk* and were assigned on a scale from 0 (High risk) to 100 (Low risk). Standard errors are clustered at the loan officer and session level, significance levels refer to two sample t-tests for equality of means and Wicoxon tests for equality of medians against the subsample of performing loans. p<0.10 ** p<0.05 *** p<0.01.

	Performing Loans	Non-Performing Loans	Loans Declined by Bank	Sample Average
Baseline risk-rating	71.62	67.19***	62.99***	66.14
[Mean]	(1.07)	(1.02)	(.816)	(.492)
Baseline risk-rating	72.00	67.00**	63.00***	72.00
[Median]	(1.22)	(1.13)	(1.53)	(1.64)

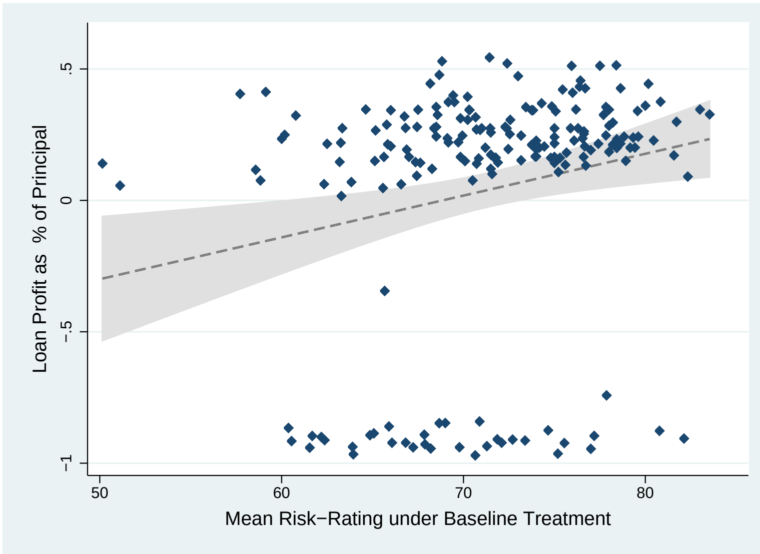
Figure 4: Distribution of Internal Risk-Ratings

(a) Performing loans **(b)** Non-performing loans



Notes This figure plots the distribution of internal risk-ratings assigned to loans evaluated in the experiment. In sub-figure (a) we plot the distribution of risk-ratings for the sample of performing loans, in panel (b) we plot the distribution for non-performing loans and loans that were declined by the Lender ex-ante.

Figure 5: Risk-Ratings and Loan Performance



Notes: This figure plots the bank's net profit per loan as a percentage of the principal against the average overall risk-rating assigned to the loan under the baseline treatment. Risk-ratings are on a scale from 0 to 100. The plot is restricted to loans with a minimum of five evaluations under the *Baseline*.

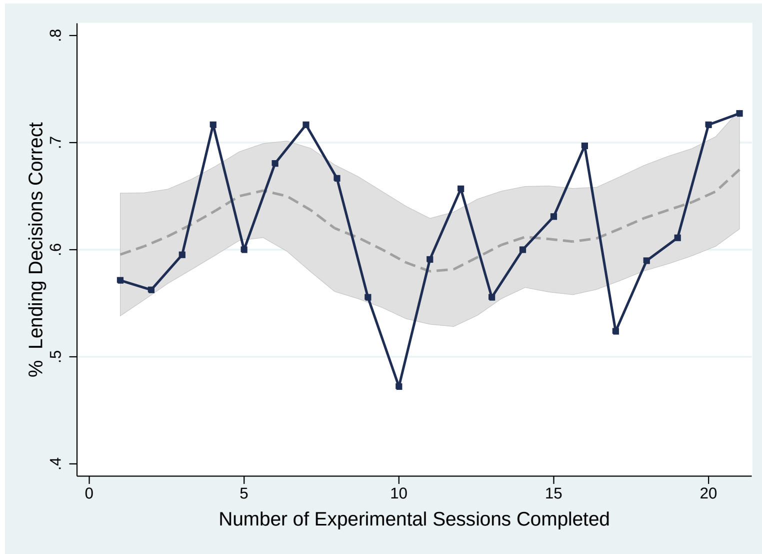
Table 6: Predictive content of Risk-Ratings

This table presents evidence on the predictive content of risk-ratings. The dependent variable in column (1) is a dummy equal to 1 if a loan was approved by the reviewing loan officer and 0 otherwise. The dependent variable in column (2) is a dummy equal to 1 if a loan performed and 0 otherwise. In column (3) the dependent variable is the profit per loan of *approved* loans, denominated in units of US$ '000. The dependent variable in column (4) is the profit per screened loan, denominated in units of US$ '000. Each regression controls for $n-1$ treatment dummies and the number of experimental sessions completed by the reviewing loan officer. * p<0.10 ** p<0.05 *** p<0.01.

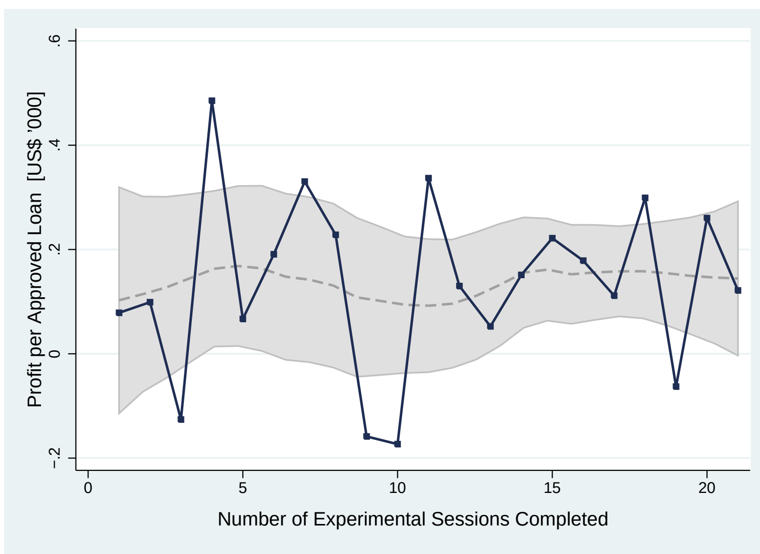
	Approved (1)	Perform (2)	Profit per approved loan (3)	Profit per screened loan (4)
Risk-rating	.374***	.112***	.199***	.151***
	(.009)	(.006)	(.043)	(.013)
Loan officer fixed effects	Yes	Yes	Yes	Yes
Loan fixed effects	Yes	Yes	Yes	Yes
Lab fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Observations	14,675	14,675	9,357	13,084
R^2	.440	.008	.008	.008

Figure 6: Learning During the Experiment

(a) Lending Decisions



(b) Profit per Approved Loan



Notes This figure examines the presence of learning effects over the course of the experiment by plotting the percentage of correct decisions by the total number of experimental sessions completed (a) and the profit per approved loan by the total number of experimental sesssions completed (b). A correct lending decision is defined as a loan officer correctly approving a performing loan or correctly declining a loan that dubsequently became delinquent. The dashed lines and accompanying shaded areas are Kernel-weighted local polynomial regressions with corresponding 95% confidence intervals.

Table 7: Test for Learning Effects

This table presents a formal test for the presence of learning effects during the experiment. The dependent variable in column (1) is a dummy variable taking on a value of one for a correct lending decision, defined as approving a performing loan or declining a non-performing loan. The dependent variable in column (2) is the profit per loan for the sample of *approved* loans, denominated in US$ '000, The dependent variable in column (3) is the profit per loans for the total sample of screened loans in units of US$ '000. * p<0.10 ** p<0.05 *** p<0.01.

	Lending Decision Correct (1)	Profit per Approved Loan (2)	Profit per Screened Loan (3)
Number of experimental sessions completed	−.002**	.002	−.002
	(.00)	(.00)	(.00)
Loan officer fixed effects	Yes	Yes	Yes
Loan fixed effects			
Lab fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
Observations	13,875	8,789	12,318
R^2	.273	.659	.471

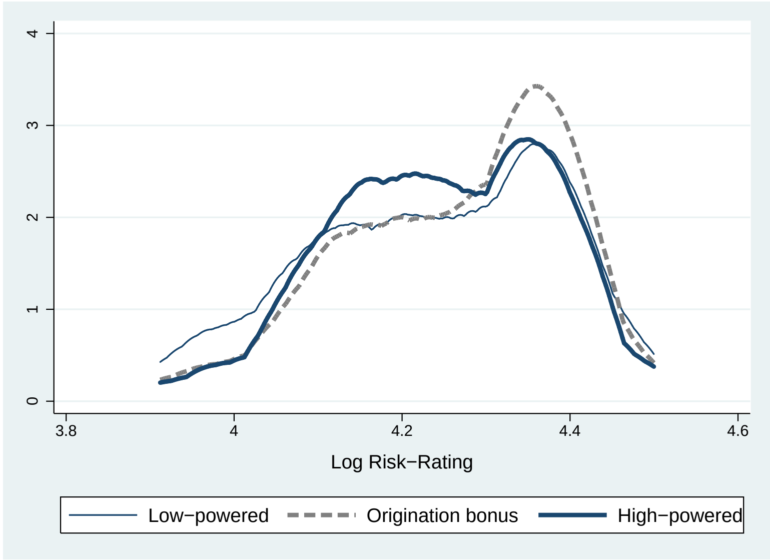
Table 8: Treatment Effects, Incentivizing Effort

This table reports treatment effects of performance pay on measures of screening effort. The omitted category in each regression is the low-powered baseline treatment. The dependent variable in columns (1) and (2) is the total log evaluation time per loan file, excluding observations outside the 5^{th} to 95^{th} percentile. The dependent variable in columns (3) and (4) is the number of credit file sections reviewed. In column (4) and (5) we use the number of information credits used as the dependent variable and a proxy for costly screening effort. The sample used to estimate these two regressions is restricted to the subset of observations implemented with the 'information credits' feature. In addition to the variables listed, we control for the randomization strata from which individually assigned incentive schemes are drawn, the total number of experimental sessions completed. Loan officer controls include age, seniority, education, business experience and mean response time under the baseline. Standard errors reported in parentheses are clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Log Evaluation Time		Number of Loan File Sections Reviewed		Information Credits Used	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-powered $[20, 0, 10]$						
High-powered $[50, -100, 0]$	–.042 (.036)	–.042 (.033)	.385* (.230)	.408*** (.144)	.933** (.425)	.767*** (.252)
Origination bonus $[20, 20, 0]$	–.059* (.029)	–.047 (.029)	–.153 (.216)	.017 (.153)	–.346 (.408)	–.166 (.205)
Performance bonus low $[50, 0, 0]$	–.142** (.064)	–.097* (.051)	.058 (.286)	–.134 (.212)	–.076 (.247)	–.077 (.165)
Performance bonus high $[100, 0, 0]$	–.079 (.081)	–.091* (.051)	–.059 (.438)	.019 (.243)	.060 (.322)	.099 (.228)
Loan officer fixed effects		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,492	13,121	12,802	14,675	7,572	8,688
R^2	.455	.535	.512	.698	.324	.695
Dependent variable mean	5.20	5.20	6.43	6.43	5.22	5.22

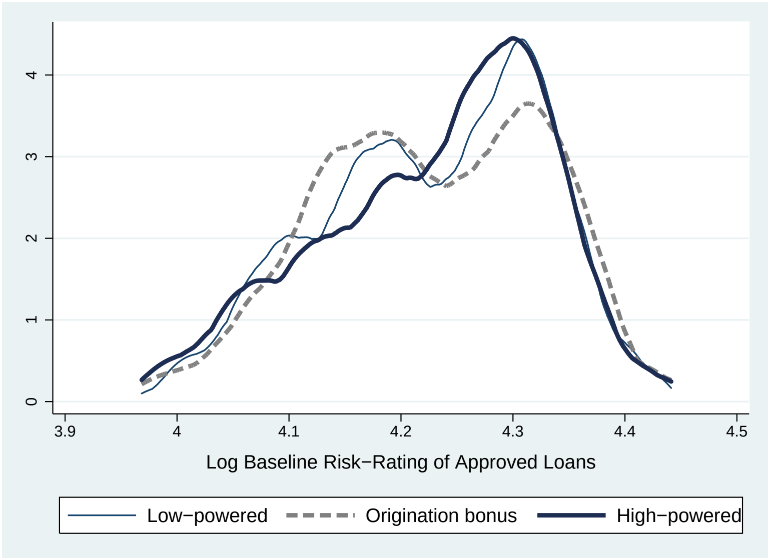
Figure 7: Risk-Assessment and Risk-Taking

(a) Risk Assessment



Notes: This figure plots the Kernel density of risk-ratings for each evaluated loan under the *Baseline*, *Origination bonus* and *High-powered* incentive treatments. A Kolmogorov-Smirnov test rejects the equality of distributions at 1% for the comparison of the *Baseline* against *High-powered* treatments (p=.0002), 1% for *Baseline* against *Origination bonus* (p=.0000) and 10% for the comparison of *Origination* against *High-powered* incentives (p=.0623).

(b) Risk-Taking



Notes: This figure plots the Kernel density of our measure of perceived credit risk, the mean risk-rating assigned to each loan under the *Baseline* incentive treatment. Kolmogorov-Smirnov tests reject the equality of distributions at 1% for the comparison of the *Baseline* against *High-powered* incentives (p=.0052), at 5% for the comparison of *Origination bonus* against *High-powered* incentives (p=.0174), but fails to reject the equality of distributions for the comparison of *Baseline* against the *Origination bonus* incentive treatment (p=.4952).

Table 9: Treatment Effects, Risk-Assessment

This table explores the effect of performance pay on loan officers' subjective assessment of credit risk. Each column reports results from a separate regression, the omitted category in each regression is the low-powered *Baseline* treatment. The dependent variable in regressions (1) and (2) is the overall risk rating, standardized to have mean zero. The dependent variable in columns (3) and (4) is the normalized sub-rating for all categories that pertain to the personal risk of a potential applicant. In columns (5) and (6) the dependent variable is the normalized sub-rating for all rating categories that pertain to the business, management and financial risk of a loan applicant. In addition to the variables listed, we control for the randomization strata from which assigned incentive schemes are drawn and the total number of experimental sessions completed by a loan officer. Standard errors in parentheses are clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Overall Rating		Personal Risk		Business and Financial Risk	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-powered $[20, 0, 10]$						
High-powered	.036	.007	–.003	–.010	.052	.018
$[50, -100, 0]$	(.090)	(.039)	(.087)	(.041)	(.090)	(.040)
Origination bonus	.159**	.005	.129*	–.027	.170**	.011
$[20, 20, 0]$	(.077)	(.040)	(.074)	(.042)	(.078)	(.040)
Performance bonus low	.042	.157***	.009	.116	.048	.141**
$[50, 0, 0]$	(.104)	(.059)	(.115)	(.071)	(.102)	(.056)
Performance bonus high	.244**	.297***	.271**	.284***	.230**	.270***
$[100, 0, 0]$	(.109)	(.055)	(.120)	(.067)	(.107)	(.054)
Loan officer fixed effects		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,675	14,675	14,675	14,675	14,675	14,675
R^2	.132	.615	.101	.559	.140	.618

Table 10: Treatment Effects, Risk-Taking

This table explores the treatment effect of performance pay on risk-taking. We focus on the sample of *approved* loans and each column reports results from a separate regression, the omitted category in each regression is the low-powered baseline treatment. We measure the degree of uncertainty about the quality of an applicant loan as the coefficient of variation of all risk-ratings assigned to the loan under the *Baseline* treatment $cv_l = \frac{\sigma_l}{|\mu_l|}$. The dependent variable in regressions (1) and (2) is the log of the coefficient of variation across all risk-rating categories. In columns (3) and (4) the dependent variable is the log of the coefficient of variation for all risk-rating questions that pertain to an applicant's personal risk. In coluns (5) and (6) the dependent variable is the log of the coefficient of variation for all risk-rating questions that pertain to the business, management and financial risk of the loan application. In addition to the variables listed, we control for the randomization strata from which assigned incentive schemes are drawn and the total number of experimental sessions completed by a loan officer. Standard errors are reported in parentheses and clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Overall Rating		Personal Risk		Business and Financial Risk	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-powered $[20, 0, 10]$						
High-powered $[50, -100, 0]$	–.153*** (.039)	–.151*** (.039)	–.042 (.030)	–.042 (.029)	–.161*** (.040)	–.155*** (.040)
Origination bonus $[20, 20, 0]$	–.044* (.026)	–.030 (.026)	.001 (.024)	.009 (.24)	–.047* (.025)	–.030 (.026)
Performance bonus low $[50, 0, 0]$	–.053 (.046)	-.035 (.050)	–.037 (.039)	–.028 (.042)	–.052 (.041)	–.042 (.047)
Performance bonus high $[100, 0, 0]$	–.040 (.049)	.005 (.055)	–.019 (.042)	.020 (.048)	–.064 (.044)	–.043 (.049)
Loan officer fixed effects		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,547	9,547	9,402	9,402	9,552	9,552
R^2	.005	.010	.006	.010	.005	.009

Table 11: Treatment Effects, Lending Decisions

This table reports treatment effect estimates of performance pay on loan approvals. The omitted category in each regression is the low-powered baseline treatment. The dependent variable in all regressions is a dummy equal to one for loans approved by an experimental participant and zero otherwise. The estimates in columns (1) and (2) are based on the full sample. Estimates in columns (3) and (4) are based on the sample of performing loans, estimates in columns (5) and (6) are based on the sample of non-performing loans, estimates in columns (7) and (8) are based on the sample of loans that were initially declined by the lender and columns (9) and (10) are based on the sample of declined and non-performing loans. In addition to the variables listed, we control non-parametrically for the randomization strata from which assigned incentive schemes are drawn and the set of controls listed in Table 8. Standard errors are reported in parentheses and clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

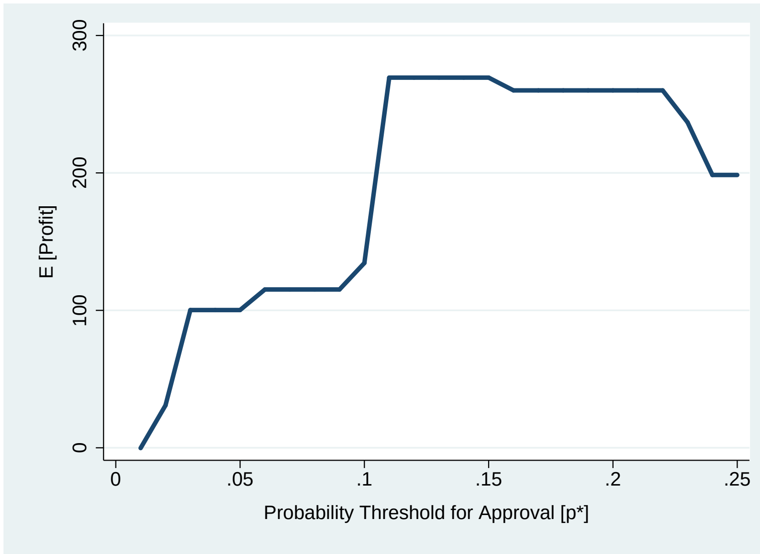
	Approved		Approved Performing		Approved Non-Performing		Approved Declined by Bank		Approved Non-Performing or Declined	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low-powered $[20, 0, 10]$										
High-powered	–.038*	–.007	–.019	.003	–.068	–.040	–.009	–.015	–.036	–.024
$[50, -100, 0]$	(.022)	(.021)	(.025)	(.027)	(.055)	(.055)	(.061)	(.059)	(.039)	(.038)
Origination bonus	.077***	.075***	.065***	.069***	.035	.069	.087	.099*	.073*	.086**
$[20, 20, 0]$	(.021)	(.020)	(.022)	(.022)	(.047)	(.048)	(.055)	(.054)	(.037)	(.036)
Performance bonus low	.095***	.137***	.070*	.104***	.087	.154*	.247***	.208**	.148**	.175***
$[50, 0, 0]$	(.034)	(.027)	(.039)	(.038)	(.088)	(.079)	(.090)	(.085)	(.062)	(.048)
Performance bonus high	.128***	.156***	.130***	.132***	.062	.124*	.264***	.240**	.156**	.201***
$[100, 0, 0]$	(.040)	(.033)	(.042)	(.042)	(.086)	(.073)	(.099)	(.096)	(.065)	(.055)
Loan officer fixed effects		Yes		Yes		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,802	14,675	8,076	9,537	2,599	2,816	2,127	2,322	4,726	5,138
R^2	.051	.157	.115	.122	.050	.141	.131	.195	.094	.184
Dependent variable mean	.71	.71	.77	.77	.70	.70	.48	.48	.60	.60

Table 12: Treatment Effects, Performance

This table reports treatment effect estimates on lending decisions and performance. Each column reports results from a separate regression, the omitted category in each regression is the low-powered baseline treatment. The dependent variable in columns (1) and (2) is a dummy variable that takes on a value of one for loans approved by an experimental participant and zero otherwise. The dependent variable in columns (3) and (4) is the net profit of *approved* loans from the perspective of the bank, denominated in units of US$ '000. The dependent variable in columns (5) and (6) is the profit per *screened* loan, where non-approved loans are recorded to have a profit of zero and profit is again denominated in units of US$ '000. In addition to the variables listed, we control for the randomization strata from which assigned incentive schemes are drawn and the controls listed in Table 8. Standard errors in parentheses are clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Approved		Profit per Approved Loan		Profit per Screened Loan	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-powered						
$[20, 0, 10]$						
High-powered	–.038*	–.007	.102*	.185**	.095*	.117**
$[50, -100, 0]$	(.022)	(.021)	(.055)	(.079)	(.055)	(.052)
Origination bonus	.077***	.075***	–.054	-0.054	–.059	–.010
$[20, 20, 0]$	(.020)	(.018)	(.052)	(.070)	(.050)	(.050)
Performance bonus low	.095***	.137***	–.169	-.052	–.127	-.012
$[50, 0, 0]$	(.032)	(.032)	(.111)	(.098)	(.079)	(.070)
Performance bonus high	.128***	.156***	–.299**	–.266**	–.210**	–.173**
$[100, 0, 0]$	(.040)	(.033)	(.132)	(.107)	(.099)	(.080)
Loan officer fixed effects		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,802	14,675	8,078	9,357	11,374	13,084
R^2	.051	.157	.667	.782	.478	.522
Dependent variable mean	.71	.71	.27	.27	.19	.19

Figure 8: Credit Scoring Model, Expected Profit



Notes This figure plots expected profit as defined in equation [6.5] as a function of the predicted probability threshold for approvig a loan p^*. We approximate the lender's cost of capital as the average 3-month rate on Indian commercial paper for the period between Q1 2008 and Q1 2010, and assume an interest rate of 12% APR and a recovery rate of 10% for loans that become delinquent.

Table 13: Credit Scoring Model, Specification

This table reports the coefficient weights of the basic credit scoring model to which we compare the performance of loan officers in the experiment. The coefficients weights are estimated using a Heckman sample selection model of the form $y_i = \Phi[\theta' \mathbf{x}_i + \rho\lambda(\gamma' \mathbf{z}_i) + w_i$ where y_i is a dummy variable equal to one if a loan defaults and zero otherwise, Φ is the standard normal cdf and w_i is a stochastic error term. The model is estimated using a randomly selected subsample of 353 or two-thirds of theradmplein the expeme1(n)30(t.)72(*he)-35pre

Table 14: Performance of Loan Officers Relative to Credit Scoring Model

This table compares the performance of loan officers in the experiment to the predictions of the creedit scoring model outlined in Table 13. The dependent variable in all regressions is equal to 0 if the loan officer's decision coincides with the prediction of the credit scoring model. The dependent variable is equal to 1 if the loan officer's decision differs from the prediction of the model and is *correct*, the variable is equal to -1 if the loan officer's decision deviates from the prediction of the model and is *incorrect*. Standard errors in parentheses are clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Panel A: *Basic Treatments*					
Threshold for predicting default	$\mathbf{p^* = 0.08}$		$\mathbf{p^* = 0.10}$		$\mathbf{p^* = 0.12}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-powered						
$[20, 0, 10]$						
High-powered	0.02	0.01	0.02	0.01	0.04	0.01
$[50, -100, 0]$	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Origination bonus	0.09*	-0.01	0.04	-0.01	0.01	-0.01
$[20, 20, 0]$	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Performance bonus low	0.02	0.00	-0.01	0.00	-0.02	0.00
$[50, 0, 0]$	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Performance bonus high	0.08	0.03	0.05	0.03	0.09*	0.03
$[100, 0, 0]$	(0.07)	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)
	Panel B: *Costly Information*					
High-powered	0.10**	0.05	0.07	0.05	0.08*	0.05
$[50, -100, 0]$, credit	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Origination bonus	-0.04	0.00	-0.03	0.00	-0.04	0.00
$[20, 20, 0]$, credit	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Performance bonus low	0.02	-0.04	0.05	-0.04	0.06	-0.04
$[50, 0, 0]$, credit	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Performance bonus high	-0.06	-0.01	-0.05	-0.01	-0.08	-0.01
$[100, 0, 0]$, credit	(0.06)	(0.05)	(0.07)	(0.05)	(0.06)	(0.05)
Loan officer fixed effects		Yes		Yes		Yes
Loan fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,099	4,702	4,099	4,702	4,099	4,702
R^2	0.168	0.521	0.186	0.486	0.246	0.454

Table 15: Treatment Effects, Deferred Compensation

This table reports treatment effects of performance pay under deferred compensation. Each column reports results from a separate regression, the omitted category in each regression is the low-powered baseline treatment. Columns (1) to (6) report treatment effects on screening effort, columns (7) to (10) report treatment effects on risk-taking and columns (11) to (14) report treatment effects on loan approvals and profit per approved loan. The dependent variable in columns (1) and (2) is the log of the total evaluation time for each loan file. The dependent variable in columns (3) and (4) is the number of loan file sections reviewed for each evaluated loan. The dependent variable in columns (5) and (6) is the number of information credits used. In columns (7) and (8) the dependent variable is the mean risk-rating assigned to each loan l in all evaluations under the *Baseline* treatment. The dependent variable in columns (9) and (10) is the coefficient of variation of the risk-ratings assigned to each loan l under the *Baseline*. The dependent variable in columns (11) and (12) is a dummy variable equal to 1 if a loan evaluated in the experiment was approved and 0 otherwise. The dependent variable in columns (13) and (14) is the bank's net profit per approved loan, denominated in units of US$ '000. Standard errors in parentheses are clustered at the individual and session level. In addition to the variables listed, we control for loan type and the number of experimental sessions completed by each loan officer. Test statistics at the foot of the table refer to t-tests for the equality of coefficients between the *standard* and *deferred* treatment dummies for the *High-powered* and *Origination bonus* treatments, respectively. * p<0.10 ** p<0.05 *** p<0.01.

	Effort						Risk-Taking				Lending and Profit			
	Log Evaluation Time		Number of Loan File Sections Reviewed		Information Credits Used		Risk-Rating [Baseline]				Approved		Profit per Approved Loan	
							μ		cv					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$[20, 0, 10]$,*credit*														
Low-powered	−.023	−.036	−.221	−.148**	−.641*	−.275	.030***	.030***	−.057**	−.056**	−.012	.034	−.055	−.069
$[20, 0, 10]$,*deferred*	(.035)	(.030)	(.136)	(.075)	(.357)	(.193)	(.009)	(.008)	(.024)	(.023)	(.020)	(.020)	(.056)	(.053)
High-powered	.04	.006	.265*	.185*	.933**	.662***	.024***	.026***	−.062**	−.064***	−.062**	−.061**	.119**	.129**
$[50, -100, 0]$,*credit*	(.039)	(.033)	(.159)	(.097)	(.425)	(.249)	(.007)	(.007)	(.025)	(.025)	(.020)	(.020)	(.053)	(.052)
High-powered	−.049	−.037	−.092	−.048	−.227	−.093	.019*	.017*	−.078**	−.099***	−.04	−.02	.032	.027
$[50, -100, 0]$,*deferred*	(.045)	(.038)	(.202)	(.119)	(.510)	(.276)	(.010)	(.009)	(.031)	(.029)	(.030)	(.030)	(0.076)	(0.071)
Origination bonus	−0.006	−0.005	−.251*	−0.123	−0.346	−0.152	.050***	.052***	−.072***	−.072***	.11***	.09***	−.121**	−.098*
$[20, 20, 0]$,*credit*	(.035)	(.031)	(.150)	(.078)	(.408)	(.198)	(.009)	(.008)	(.024)	(.024)	(.020)	(.090)	(.055)	(.052)
Origination bonus	−.003	−.015	−.089	−.180**	−.291	−.429**	.051***	.052***	−.029	−.036	.07***	.09***	.045	.05
$[20, 20, 0]$,*deferred*	(.036)	(.031)	(.143)	(.084)	(.386)	(.214)	(.009)	(.008)	(.025)	(.024)	(.020)	(0.020)	(0.055)	(0.050)
Loan officer fixed effects		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test:														
immediate=deferred														
High-powered, p-value	.060	.281	.103	.094	.032	.021	.539	.289	.642	.251	.591	.103	.229	.143
Origination bonus, p-value	.936	.772	.287	.492	.893	.182	.929	.997	.107	.158	.032	.891	.004	.005
Observations	6,839	7,377	7,572	8,184	7,572	8,184	7,171	7,754	6,573	7,114	7,572	8,688	6,727	7,260
R^2	.443	.527	.367	.69	.324	.694	.055	.058	.079	.08	.052	.154	.476	.476

Table 16: Treatment Effects, Shared Liability

footnotesize This table reports treatment effects of performance pay under shared liability. Each column reports results from a separate regression, the omitted category in each regression is the low-powered baseline treatment. Columns (1) to (6) report treatment effects on screening effort, columns (7) to (10) report treatment effects on risk-taking and columns (11) to (14) report treatment effects on loan approvals and profit per approved loan. The dependent variable in columns (1) and (2) is the log of the total evaluation time for each loan file. The dependent variable in columns (3) and (4) is the number of loan file sections reviewed for each evaluated loan. The dependent variable in columns (5) and (6) is the number of information credits used. In columns (7) and (8) the dependent variable is the mean risk-rating assigned to each loan l in all evaluations under the *Baseline* treatment. The dependent variable in columns (9) and (10) is the coefficient of variation of the risk-ratings assigned to each loan l under the *Baseline*. The dependent variable in columns (11) and (12) is a dummy variable equal to 1 if a loan evaluated in the experiment was approved and 0 otherwise. The dependent variable in columns (13) and (14) is the bank's net profit per approved loan, denominated in units of US$ '000. Standard errors in parentheses are clustered at the individual and session level. In addition to the variables listed, we control for loan type and the number of experimental sessions completed by each loan officer. Test statistics at the foot of the table refer to t-tests for the equality of coefficients between the standard and deferred *High-powered* treatment dummies, respectively. * p<0.10 ** p<0.05 *** p<0.01.

	Effort						Risk-Taking				Lending and Profit			
	Log Evaluation Time		Number of Loan File Sections Reviewed		Information Credits Used		Risk-Rating [Baseline]				Approved		Profit per Approved Loan	
							μ		cv					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Low-powered $[20, 0, 10]$, credit														
High-powered $[50, -100, 0]$, credit	.041	.006	.265*	.185*	.933**	.662***	.024***	.026***	−.062**	−.064***	−.06**	−.06***	.119**	.129**
	(.039)	(.033)	(.159)	(.097)	(.425)	(.249)	(.007)	(.007)	(.025)	(.025)	(.021)	(.023)	(.053)	(.052)
High-powered $[50, -100, 0]$ credit+endow	.150***	.088***	.641***	.358***	2.244***	1.233***	−.023***	−.026***	.038	.043	−.073***	−.074***	.054	0.05
	(.036)	(.029)	(.149)	(.084)	(.413)	(.217)	(.006)	(.007)	(.027)	(.028)	(.023)	(.021)	(.053)	(.052)
Loan officer effects		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Loan officer controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test: *individual=shared*														
High-powered p-value	.031	.049	.071	.166	.021	.075	.000	.000	.005	.004	.732	.611	.363	.305
Observations	6,839	7,377	7,572	8,184	7,572	8,184	7,171	7,754	6,573	7,114	7,572	8,688	6,727	7,260
R^2	.443	.527	.367	.69	.324	.694	.055	.058	.079	.08	.052	.154	.476	.476

A Appendix Tables

Table A.1: Heterogeneity in Treatment Effects, Age

This table reports treatment interactions between loan officer age and each of the four basic incentive treatments. Each column reports results from a separate regression. The dependent variables in columns (1) to (3) consider the three measures of screening effort as previously defined. The dependent variable in columns (4) to (6) are approved loans, correctly approved loans and the net profit per approved loan, denominated in units of US$ '000, respectively. In addition to the variables listed, we control non-parametrically for the randomization strata from which assigned incentive schemes are drawn and the full set of controls as reported in Table 8. Standard errors reported in parentheses are clustered at the individual and session level. ** p<0.10 ** p<0.05 *** p<0.01.

	Effort			Risk-Taking		Lending and Profit	
	Log Evaluation Time	Sections Reviewed	Information Credits Used	Risk-Rating [Base] μ	cv	Approved	Profit per loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Loan officer age							
× High-powered	.008***	.029**	–.022	.000	.002	–.001	.004
	(.003)	(.012)	(.021)	(.001)	(.003)	(.002)	(.004)
× Origination bonus	.004*	.014	–.001	.000	–.002	–.002	–.001
	(.002)	(.013)	(.017)	(.000)	(.002)	(.002)	(.003)
× Perfomance bonus low	.002	–.004	.039	.000	–.000	–.004	–.003
	(.005)	(.020)	(.041)	(.001)	(.004)	(.002)	(.005)
× Performance bonus high	.004	–.010	.102*	.002**	–.005	–.002	.003
	(.005)	(.017)	(.056)	(.001)	(.004)	(.003)	(.005)
High-powered	–.323***	–.585	1.528*	–.011	–.160*	.022	–.121
	(.099)	(.445)	(.804)	(.023)	(.094)	(.069)	(.132)
Origination bonus	–.192**	–.500	–.147	.011	.029	.140**	–.005
	(.088)	(.491)	(.654)	(.019)	(.074)	(.064)	(.121)
Perfomance bonus low	–.189	.053	–1.222	–.014	–.044	.297***	.063
	(.221)	(.946)	(1.173)	(.033)	(.157)	(.105)	(.202)
Performance bonus high	–.234	.392	–2.888*	–.083**	.148	.245**	–.151
	(.208)	(.797)	(1.601)	(.037)	(.170)	(.113)	(.193)
Loan officer fixed effects							
Loan fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,121	14,675	8,688	13,979	12,865	14,675	13,084
R^2	.537	.699	.695	.030	.002	.157	.753

Table A.2: Heterogeneity in Treatment Effects, Experience

This table reports treatment interactions between loan officer experience and each of the four basic incentive treatments. Loan officer experience is measured as the number of years that a loan officer has served as a branch manager or in a comparable management role. Each column reports results from a separate regression. The dependent variables in columns (1) to (3) consider the three measures of screening effort as previously defined. The dependent variable in columns (4) to (6) are approved loans, correctly approved loans and the log profit per approved loan, respectively. In addition to the variables listed, we control non-parametrically for the randomization strata from which assigned incentive schemes are drawn and the set of controls reported in Table 8. Standard errors reported in parentheses are clustered at the individual and session level. ** p<0.10 ** p<0.05 *** p<0.01.

	Effort			Risk-Taking		Lending and Profit	
	Log Evaluation Time	Sections Reviewed	Information Credits Used	Risk-Rating [Base] μ	cv	Approved	Profit per loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Loan officer experience							
× High-powered	.059***	.242***	–.040	.002	.000	–.008	.021
	(.018)	(.067)	(.059)	(.004)	(.011)	(.013)	(.020)
× Origination bonus	.025***	.121**	–.055	.000	–.021***	–.015**	.017
	(.008)	(.050)	(.065)	(.002)	(.008)	(.007)	(.013)
× Perfomance bonus low	.001	–.026	.140	–.000	–.022	.015	–.012
	(.014)	(.064)	(.101)	(.002)	(.014)	(.011)	(.016)
× Performance bonus high	.040**	.110*	.564**	.003	–.014	.025*	.009
	(.016)	(.058)	(.232)	(.003)	(.012)	(.015)	(.015)
High-powered	–.092***	.137	.791***	.000	–.095***	.004	–.013
	(.034)	(.152)	(.273)	(.007)	(.033)	(.022)	(.049)
Origination bonus	–.079**	–.183	–.087	.021***	–.029	.093***	–.061
	(.031)	(.158)	(.226)	(.006)	(.024)	(.021)	(.044)
Perfomance bonus low	–.098*	–.065	–.118	.000	–.018	.112***	–.037
	(.058)	(.256)	(.171)	(.010)	(.045)	(.030)	(.065)
Performance bonus high	–.146**	–.115	–.052	–.005	–.021	.126***	–.062
	(.058)	(.276)	(.237)	(.012)	(.048)	(.035)	(.060)
Loan officer fixed effects							
Loan fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,121	14,675	8,688	13,979	12,865	14,675	13,084
R^2	.537	.702	.696	.029	.002	.157	.753

Table A.3: Test of Random Assignment

This table presents a test of random assignment across the four main treatments. We report conditional means for each demographic variable by treatment, controlling for randomization strata, lab and week fixed effects. *Age* is the loan officer's age in years, *Male* is a dummy variable taking a value of 1 if the participant is male. *Rank* is the loan officer's level of seniority in the bank. *Experience* is the number of years the loan officer has been employed by the bank. *Branch Manager* is a dummy variable indicating whether the participant has ever served as a branch manager. Significance levels refer to t-tests of the conditional means of each demographic variable against the *Baseline* treatment. significance levels refer to a t-test of conditional means against the mean of the corresponding demographic variable under the *Baseline*. * p<0.10 ** p<0.05 *** p<0.01.

	Incentive Treatment			
	High-powered	Origination bonus	Performance low	Performance high
	(1)	(2)	(3)	(4)
Male	.006	–.017	.009	.024
	(0.03)	(0.03)	(0.02)	(0.02)
Age	–.002	–.001	–.001	.001
	(.002)	(.002)	(.001)	(.001)
Education [Master's Degree]	–.031	.014	.011	.010
	(.019)	(.020)	(.012)	(.014)
Experience [Years]	.002	.001	.000	–.001
	(.001)	(.001)	(.001)	(.001)
Rank [1 Low - 5 High]	–.005	–.009	.010*	.005
	(.008)	(.008)	(.005)	(.006)
Branch Manager Experience	–.007	–.012	.007	–.007
	(.023)	(.024)	(.014)	(.015)
Observations	9,268	9,806	7,910	8,343
R^2	.314	.322	.347	.378

Table A.4: Representativeness of Participant Pool

This table examines the representativeness of loan officers participating in the experiment by comparing the demographic characteristics of the participant pool with the employee population of one of the five largest Indian commercial banks in the administrative region where the experiment was conducted. Summary statistics from the bank dataset refer to all of the bank's credit officers (including agricultural) serving in a credit assessment role. The branch manager experience variable is excluded because it is defined differently in the two samples. Columns (1) to (3) report descriptive statistics for the participant pool. Columns (4) to (6) report the corresponding statistics from the bank dataset.

	Experiment Participants (N=193)			Bank Employee Dataset (N=3,111)		
	Mean	Median	StdDev	Mean	Median	StdDev
Male	0.89	1.00	[0.31]	0.90	1.0	[0.30]
Age	38.6	36.0	[10.9]	37.9	35.0	[12.0]
Experience in Bank [Years]	13.8	11.0	[11.4]	13.9	11.0	[13.0]
Rank [1-5]	2.00	2.00	[1.00]	1.6	2.0	[0.75]