

Incentivizing Calculated Risk-Taking

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

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Abstract

This paper analyzes the underwriting process of small-business loans to entrepreneurs in an emerging market using a series of randomized experiments with commercial bank loan officers. We test the impact of performance pay on risk-assessment and lending by comparing three commonly implemented classes of incentive schemes: incentives that reward origination, low-powered 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 screening behavior and risk-taking. Incentives that penalize bad lending decisions cause loan officers to exert significantly greater screening effort and to make 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 in emerging markets that seek 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 some of the first experimental evidence on the relationship between performance incentives and loan officer behavior. We study lending decisions in the Indian market for small-enterprise loans, using active loan officers with an average of more than ten years of experience. We focus on new applications for uncollateralized loans to small entrepreneurs with very limited credit histories –precisely the type of loans for which an accurate assessment of credit risk depends most crucially on the judgment and 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

¹In 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.

²For 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 et al. \(2011\)](#) 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 leading 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.

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

2 Incentive Schemes within the Bank

The literature on performance incentives within organizations has identified a range of important 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. In this section we first discuss the importance of loan officer information collection for the allocation of credit, and then turn to the challenges involved in the design of optimal incentive contracts in commercial lending.

2.1 Incentives and Information Costs

Emerging credit markets, such as the one we study, are often characterized by severe information asymmetries between borrowers and lenders, which can severely hamper new lending. While emerging markets have experienced substantial economic liberalization over the past decade, the development of credit markets has often not kept pace with this development (see [Banerjee and Duflo 2008](#); [Berger et al. 2008](#)). Many emerging markets lack comprehensive credit information systems, such as credit bureaus and audited financial disclosures,⁴ which places significant limitations on the use of predictive credit scoring models and similar loan approval technology. Moreover, since the costs of collecting additional borrower information are roughly invariant to loan size, commercial bank lending emerging markets tends to be heavily skewed in favor of large corporate loans for which credit information is more readily available and less costly to verify.⁵ In this lending environment, any intervention – including modifications to the structure of performance incentives – that can reduce information costs and improve screening performance holds the promise of significantly extending the financial access of marginal borrowers, such as small entrepreneurial firms.

The importance of incorporating ‘soft’ and relationship-specific credit information in emerging markets also represents an important constraint to the risk-management strategies of commercial banks. First, as levels of post-secondary education are low, the availability of highly skilled individuals able

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

⁵This is particularly true for loans to new and young firms, where it is especially difficult to verify a borrower’s true financial position from standard documents. Lenders operating in the Indian market for small-enterprise loans, for example, routinely supplement standard documentation with additional information, such as site visits to the home and office of a prospective applicant and references from employers or trade representatives. Empirical evidence shows that small- and medium enterprises greatly benefit from relationship-lending in terms of credit availability, interest rates and collateral requirements ([Petersen and Rajan 1994, 1995](#), [Berger and Udell 1995](#), [Elsas and Krahnen 1998](#), [Harhoff and Korting 1998](#)). Stylized evidence from the recent downturn suggests that financial intermediaries with a relationship-based lending model suffered smaller losses due to (i) a more carefully vetted client portfolio and (ii) an improved ability to detect repayment risks and offer customized solutions, such as a flexible rescheduling of installments.

to make credit judgments may be particularly limited. Second, the importance of private information gathered through relationship-lending makes the bank more reliant on the risk-assessment and expertise of its front-line employees. This introduces a significant scope for moral hazard in the relationship between the bank and its employees. [Hertzberg, Liberti, and Paravisini \(2010\)](#), for example, use internal data from an Argentinean bank to show that, unless faced with the imminent threat of an audit, credit officers have a significant incentive to inflate the risk-assessment of their lending portfolio. Such evidence of moral hazard within lending institutions 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 a variety of effort and performance measurements.

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](#) and [Fuentes 1996](#)). 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](#), [Hertzberg, Liberti, and Paravisini 2010](#)). 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 portfolio. 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, ([Diamond 1984](#), [Fuentes, 1996](#)). In contrast to this line of research, we focus on incentive contracts for loan officers, 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 ([Rajan 1992](#), [Margiotta and Miller 2002](#)). 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. [Kashyap, Rajan, and Stein \(2008\)](#) argue that, in the lead-up to the crisis, the increasing amounts of problematic assets acquired by banks were the result of a breakdown of incentive and risk-control systems at both a management and the sales level, exemplary of these sources of moral hazard. 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.
- **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, $\pi p r + (1 - \pi p)(-1)$. We generally assume that this amount is negative, so that it is not profitable to lend to all applicants.

The loan officer has the ability to 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

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

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

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

We assume that 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,

$$\pi[pr + (1 - p)(-1)] + (1 - \pi)[\gamma \cdot 0 + (1 - \gamma)(-1)] - e \geq 0 \quad (3.2)$$

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 $\Omega(w_P, w_D, \bar{w})$, which specifies a fixed payment for declining a loan application \bar{w} , and contingent payments for approving a loan that subsequently performs w_P , and approving a loan that subsequently becomes delinquent w_D . To simplify the exposition, we assume the bank is risk-neutral. Because the objective function and constraints are all linear, the loan officer's decision problem is simply to choose whether to screen or not, and whether or not to originate the loan.⁶

The loan officer thus chooses the return to three possible actions: declining the loan application without screening, accepting the application without screening, or screening the application, and accepting it only if no bad signal is observed. The payoff to rejecting a loan without screening is simply $u_R = \bar{w}$. The loan officer's expected utility from approving the loan without screening it is

$$u_{NS} = \pi p w_P + (1 - \pi p) w_D \quad (3.3)$$

Whereas the expected utility of screening a loan is

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

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

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

This is, however, not the only constraint that must bind to ensure the loan officer screens. It must

⁶We rule out perverse incentive schemes that pay a higher amount for defaults than for loans that perform. This means, since $e > 0$, if the loan officer screens, then she will not lend to firms for which she draws a bad signal. If a loan officer were willing to lend to a bad firm ex-ante, she would make the loan without incurring the screening cost e .

also be more advantageous to screen than to simply reject loans, That is, $u_S > u_R$

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

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 fraction 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 effort, 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 officer, if $e > 0$, there exists parameters such that the loan officer cannot be induced to screen. The basic problem here is that if effort is costly, and default sufficiently rare, then loan officers will prefer to lend to all applicants. While (3.5) can be made slack for any cost of effort e , by increasing \bar{w} , increasing \bar{w} has the opposite effect of making (3.6) less likely to be satisfied.*

Prediction 3a: *High-powered incentives, including penalties for failure, can induce screening effort. 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 officer will screen, as long as condition (3.2) is satisfied.*

Prediction 3b: *High-powered incentives result in more conservative lending. A corollary of (3.6) is that when loan officers exert greater screening effort, they are more likely to discover that a firm 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:

$$e_{s,t+\Delta}^* = \pi \delta [p w_P + (1 - p) w_D] + (1 - \pi) [\gamma \bar{w} + (1 - \gamma) \delta w_D] \quad (3.7)$$

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

$$e_{s,t+\Delta}^* - e_{s,t}^* = \pi(\delta - 1) [p w_P + (1 - p) w_D] + (1 - \pi) [(1 - \gamma)(\delta - 1) w_D] \quad (3.8)$$

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 , deferring incentive 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 officers have a positive discount rate, any performance based incentive scheme will induce less effort 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 effect of deferred compensation is greater for loan officers with a higher discount factor, since $\frac{\partial(e_{s,t+\Delta}^* - e_{s,t}^*)}{\partial\delta} < 0, \forall \delta > 0$.*

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:

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

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.⁷ Table ?? 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

⁷We discuss the calibration of monetary incentives in greater detail in section 3.5 below.

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 <i>High-powered</i> incentive rewards participants with Rs 50 for approving a loan that performs, but a significant Rs 100 penalty if they approve a loan that becomes 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 <i>Origination Bonus</i> scheme provides loan officers with a reward for originating a loan, irrespective of performance.
D Performance Bonus, Low ^a	50, 0, 0	The <i>Performance Bonus (low)</i> 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 <i>Performance Bonus (high)</i> 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.

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 indiscriminately 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 officer's discount rate is greater than zero, the amount of effort induced by incentives *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.⁸

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.⁹ 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.

⁸Since the treatments are randomly assigned, the co-existence of career concerns and monetary incentives will not bias our results. Rather, it will mimic an important feature of a real lending environment, in which monetary incentives coexist with career concerns or intrinsic motivation.

⁹Since 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.

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 met 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 officers 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.

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 *financial 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. In addition, all participants completed an exit survey, which collected demographic details and included questions relating to 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:

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

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 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 193 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 piece rate*, 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.4.

To test our hypotheses, we consider three groups of outcome variables: measures of screening effort, subjective risk-assessment, 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 for each of the 15 credit rating questions (assessed on a scale from 1-5) and calculate the average for each sub-category. 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 bank’s proprietary data. We code a lending decision as ‘correct’, if a loan officer declined a loan that subsequently became delinquent or approved a loan that subsequently performed.

6.1 Incentivizing Screening Effort

We first analyze the effect of incentives on screening effort. Performance-based compensation can affect the quality of lending decisions if it induces a loan officer to choose higher screening effort, which translates either into the collection of borrower information that was not previously available or an improvement in the assessment of borrower risk based on a more thorough scrutiny of available information. The setting of our experiment provides us with several straightforward measures of screening effort. First, our software records the amount of time the loan officer spends on the entire credit file. Second, we record how many of the ten sections of the credit file the loan officer chooses

to review. Third, in a separate set of treatments loan officers were given an endowment of Rs 18 at the beginning of each experimental session, which they could either take home with them, or purchase access to information tabs in the credit files they review. Under this treatment, three ‘basic’ information documents were ‘free’, but loan officers had to pay to review each additional information tab. This design is meant to capture the idea that effort is costly (site visits and reference checks take time and require travel; even evaluating the financial statement requires transcription of often haphazard records into a standard format.) Since screening effort is not observable to the bank, we do not tie bonus payments to effort.

Table 5 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 low-powered treatment, we see that the time spent evaluating each credit file declines by 5-14% under performance incentives that reward origination but have no downside risk for the loan officer. By contrast, under the high-powered incentive scheme which offers a reward for profitable lending decisions and a steep penalty for originating 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 spend .77 additional information credits. Both effects are statistically significant at the 1% level. In line with the predictions of the theoretical framework set out above: (i) loan officers exert less effort per loan file when the incentive is placed on lending volume, and (ii) exert greater screening effort under incentives that penalize bad lending decisions. 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

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 Indian commercial banks (a higher number is always better). We emphasized that, in contrast to what is common practice for larger loans, the ratings are not binding for the officers decision. That is, an applicant did not have to attain a minimum score to be considered for a loan.

Table 6 reports risk ratings for each incentive scheme. The estimates suggest that relative to

low-powered incentives, performance bonuses that reward loans only if the loan performs causes loan officers to inflate their risk ratings. Additionally, the degree of risk-rating inflation is proportional to the magnitude of the performance bonus. The low performance bonus is half the size of the high performance bonus, and the coefficient on the low performance bonus is also half of the coefficient on the high performance bonus. 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, loan officers inflate their risk ratings only for non-performing loans.

In the next step, we disaggregate ratings and explore the effect of performance incentives on risk perception along four sub-categories of credit risk: personal risk, business risk, management risk, and financial risk. Our prior is that loan officers seeking to distort ratings will adjust the criteria that do not have ‘objective’ benchmarks (e.g., management skill is subjective, while all applicants must demonstrate a sufficiently high verifiable current ratio). The results are presented in Table 6, columns (4) to (7). Again, we see significant effects only for the performance bonus treatments. Under the *performance bonus low* treatment, loan officers, on average, inflate the management and financial risk subratings whereas under the *performance bonus high* treatment, loan officers inflate risk rating scores across the board.

6.3 Lending Decisions and Performance

We next analyze how the provision of monetary incentives affects lending volume and the profitability from the perspective of the bank. In Table 7, we report 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 origination piece rate baseline. We present results for the entire sample of loans, as well as three subsamples: performing loans, non-performing loans, and loans that were originally declined by our partner bank. The results show an economically and statistically significant effect of performance pay on loan approvals. In Table 7, columns (1) and (2), we see that the switch from the baseline incentive to high-powered incentives leads to slightly more conservative lending decisions and a decline in loan approvals by up to 4%. 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. Taken together, the 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.

How do these changes in lending volume affect the quality of approved loan portfolios? We turn to the quality of decisions in Table 8 and consider three measures of performance: the share of correct lending decisions (performing loans accepted, non-performing and rejected loans not accepted), profit to the bank per *approved loan* and profit to the bank per *evaluated loan*. Table 3 presents descriptive statistics on the performance of loan officers in the experiment. We first note that the fraction of correct decisions under the baseline treatment is 65%, suggesting that the lending decision is quite difficult. Unconditionally, loan officers make the correct decision for good files 80% of the time; 30% of the time for bad loans; and 45% of the time for loan applications that were turned down by the Lender. This likely reflects the fact that many loans that were originally approved looked good, but default for reasons unrelated to their financial position at the time the loan was approved. The fact that apparently ‘good’ loans may default for idiosyncratic reasons that are not predictable from ex-ante client characteristics is a feature of many actual lending environments and illustrates an important limitation in the use of performance pay as a tool to manage default risk.

Table 8 presents treatment effects of monetary incentives on performance and profitability. The first two columns review the lending volume results presented in Table 7. Columns (3) and (4) look at the effect of performance pay on correct decisions and in columns (5) to (8) we turn to our two measures of profitability. 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 and the share of correct decisions, these effects are important enough to lead to a significant improvement in the quality of approved loan portfolios and the profitability of approved loans. The coefficient estimate indicates that profit per approved loan increase by approximately \$180 (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 \$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.

6.4 When do Loan Officers Outperform a Credit Scoring Model?

To what extent is it possible for a well-incentivized loan officer to outperform 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 $P_i = \text{Prob}[D_i = 1|\mathbf{x}_i]$, 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

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

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

$$\text{Prob}[s = 1|\mathbf{z}_i] = \mathbf{1}[\gamma'\mathbf{z}_i + v_i \geq 0] \quad (6.3)$$

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

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

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

$$E[\pi] = (1 - p)[(1 + r)f - c] - p[-f] \quad (6.5)$$

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 3 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 9 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 $perform_{ik} \in [-1, 1]$ 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, $perform_{ik}$ 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 10 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 11 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 confirmed 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 12 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 12, 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% 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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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.

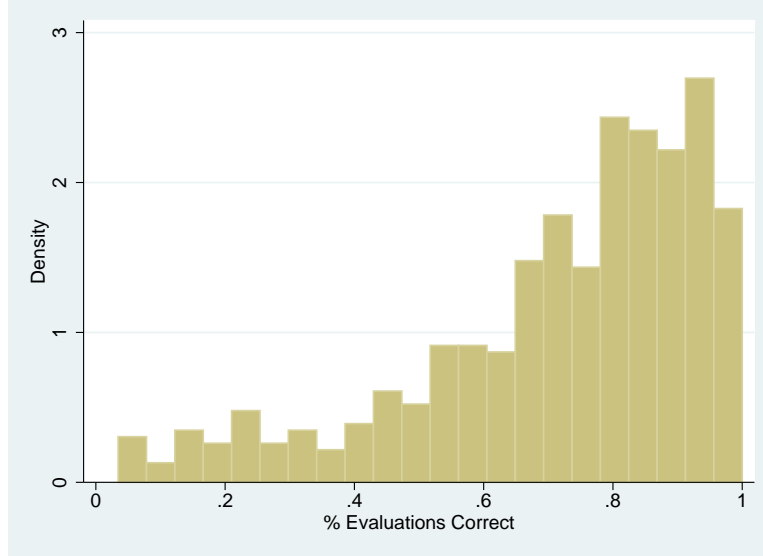
	DEMOGRAPHICS									
	N	Mean	Median	StDev	Min	Max	10%	25%	75%	90%
Male	193	0.89	1.00	0.31	0.00	1.00	0.00	1.00	1.00	1.00
Age	193	38.62	36	10.88	23	64	25	30	48	54
Education [Master's Degree]	189	0.34	0.00	0.47	0.00	1.00	0.00	0.00	1.00	1.00
Experience [Years]	193	13.77	11	11.44	0.00	40	1.00	3.00	25	31
Rank [1 Low - 5 High]	193	1.97	2.00	1.00	1.00	5.00	1.00	1.00	3.00	3.00
Branch Manager Experience	193	0.36	0.00	0.48	0.00	1.00	0.00	0.00	1.00	1.00
Business Experience	193	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 <i>B - C</i>	
	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 Liabilities/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]

Figure 1: DIFFICULTY OF THE LENDING DECISION

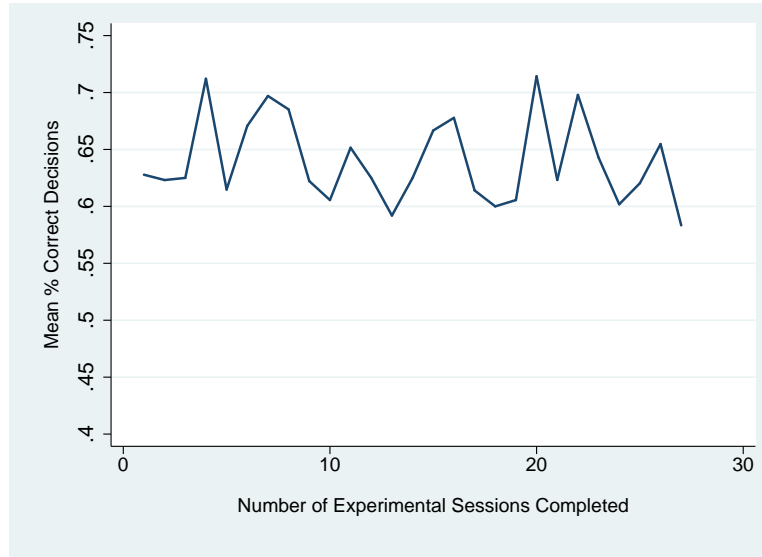


Notes: This figure explores the difficulty of lending decisions by plotting the percentage of times a loan file was evaluated correctly for each loan application used in the experiment. Here, a correct lending decision is defined as an experimental subject approving a loan that performed or declining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

Table 3: SUMAMRY STATISTICS, PERFORMANCE

	% Evaluated Correctly		
	Incentive		
	Baseline	High-Powered	Origination
Performing	0.80	0.74	0.85
Non-Performing	0.30	0.40	0.26
Declined by Bank	0.45	0.49	0.33

Figure 2: LEARNING DURING THE EXPERIMENT



Notes This figure examine 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 correct lending decision is defined as a loan officer correctly approving a performing loan or correctly declining a loan that subsequently became delinquent.

Table 4: TEST FOR LEARNING EFFECTS

	Lending Decision Correct, OLS (1)	Profit per Approved Loan, OLS (2)
Number of sessions completed	0.0011 (0.00)	-0.0091*** (0.00)
Loan officer fixed effects	Yes	Yes
Loan fixed effects	Yes	Yes
Lab fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Observations	14,675	13,084
R^2	0.275	0.124

Table 5: 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 5th to 95th 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, the number of times a loan officer has completed the exercise under the incentive scheme in place and the difficulty of the loan file under evaluation as measured by the total percentage of evaluations in which the loan file was classified correctly. Regressions without loan officer fixed effects additionally control for loan officer age, seniority, education and business experience. 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	-0.04	-0.04	0.39*	0.41***	0.93**	0.77***
[50, -100, 0]	(0.04)	(0.03)	(0.23)	(0.14)	(0.43)	(0.25)
Origination bonus	-0.06*	-0.05	-0.15	0.02	-0.35	-0.17
[20, 20, 0]	(0.03)	(0.03)	(0.22)	(0.15)	(0.41)	(0.20)
Performance bonus low	-0.14**	-0.10*	0.06	-0.13	-0.08	-0.08
[50, 0, 0]	(0.06)	(0.05)	(0.29)	(0.21)	(0.25)	(0.16)
Performance bonus high	-0.08	-0.09*	-0.06	0.02	0.06	0.10
[100, 0, 0]	(0.08)	(0.05)	(0.44)	(0.24)	(0.32)	(0.23)
Total Sessions	-0.01***	-0.01***	-0.00	-0.01*	-0.02	-0.04**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Loan officer fixed effects		Yes		Yes		Yes
Loan fixed effects		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	0.455	0.535	0.512	0.698	0.324	0.695
Dependent variable mean	5.20	5.20	6.43	6.43	5.22	5.22

Table 6: TREATMENT EFFECTS, RISK-ASSESSMENT

This table explores the treatment effect of performance pay on loan officers' subjective risk-assessment. 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) to (3) is the internal risk-rating assigned to each loan and measured on a scale from 0 (High Risk) - 100 (Low Risk). The dependent variable in columns (4) to (7) are the four sub-components of the overall risk-rating *Personal Risk*, *Business Risk*, *Management Risk* and *Financial Risk*. Reported coefficient estimates are based on regressions that use the full sample and include dummy variables for all treatments. Estimates for the full specification are reported in Appendix A, Table A.2. 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. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

	<i>Panel A: Overall Risk-Rating</i>			<i>Panel B: Risk-Rating Sub-Categories</i>			
	All Loans (1)	Performing Loans (2)	Non-Performing Declined Loans (3)	Personal Risk (4)	Business Risk (5)	Mgmt Risk (6)	Financial Risk (7)
Low-powered [20, 0, 10]							
High-powered [50, -100, 0]	0.00 (0.04)	-0.02 (0.04)	0.04 (0.06)	-0.02 (0.04)	0.03 (0.04)	0.01 (0.04)	0.01 (0.04)
Origination bonus [20, 20, 0]	0.02 (0.04)	-0.01 (0.04)	0.05 (0.06)	-0.02 (0.04)	0.01 (0.04)	0.01 (0.04)	0.04 (0.04)
Performance bonus low [50, 0, 0]	0.16** (0.06)	0.07 (0.07)	0.29** (0.08)	0.12 (0.07)	0.11 (0.06)	0.15** (0.06)	0.13* (0.06)
Performance bonus high [100, 0, 0]	0.30** (0.05)	0.23** (0.06)	0.45** (0.09)	0.29** (0.07)	0.21** (0.06)	0.28** (0.06)	0.29** (0.06)
Loan officer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	13,661	8,875	4,786	13,661	13,661	13,661	13,661
R^2	0.650	0.687	0.619	0.597	0.596	0.630	0.613
Dependent variable mean	69.9	69.9	69.9	73.2	70.0	71.4	66.6

Table 7: TREATMENT EFFECTS, LENDING DECISIONS

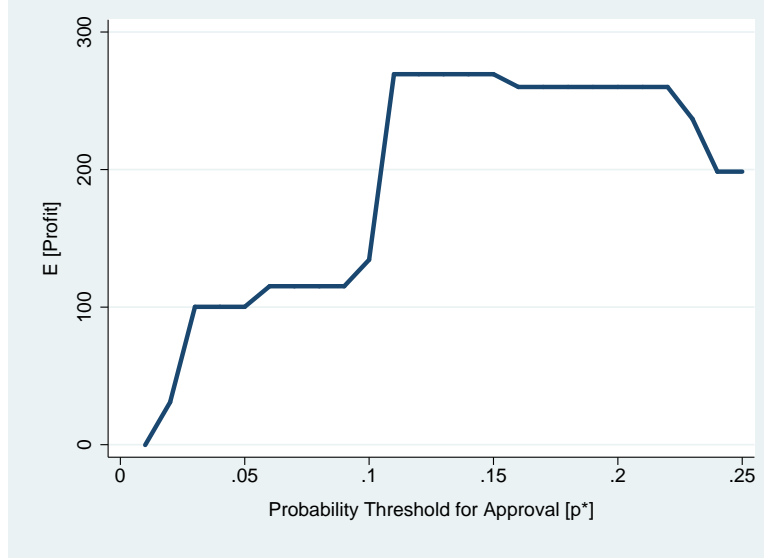
This table reports treatment effect estimates of performance pay on loan approvals. The omitted category in each regression is the low-powered baseline treatment. The dependent variable in all regressions is a dummy equal to one for loans approved by an experimental participant and zero otherwise. The 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. The reported coefficient estimates are based on regressions controlling for all $k - 1$ treatment dummies. We report estimates for the full specification are reported in Appendix A, Table A.3. 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 5. 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 [50, −100, 0]	-0.04* (0.02)	-0.01 (0.02)	-0.02 (0.02)	0.00 (0.03)	-0.07 (0.06)	-0.04 (0.05)	-0.01 (0.06)	-0.02 (0.06)	-0.04 (0.04)	-0.02 (0.04)
Origination bonus [20, 20, 0]	0.08*** (0.02)	0.08*** (0.02)	0.06*** (0.02)	0.07*** (0.02)	0.04 (0.05)	0.07 (0.05)	0.09 (0.06)	0.10* (0.05)	0.07* (0.04)	0.09** (0.04)
Performance bonus low [50, 0, 0]	0.10*** (0.03)	0.14*** (0.03)	0.07* (0.04)	0.10*** (0.04)	0.09 (0.09)	0.15* (0.08)	0.25*** (0.09)	0.21** (0.09)	0.15** (0.06)	0.17*** (0.05)
Performance bonus high [100, 0, 0]	0.13*** (0.04)	0.16*** (0.03)	0.13*** (0.04)	0.13*** (0.04)	0.06 (0.09)	0.12* (0.07)	0.26*** (0.10)	0.24** (0.10)	0.16** (0.07)	0.20*** (0.05)
Total Sessions	0.00 (0.00)	-0.00*** (0.00)	-0.00 (0.00)	-0.00*** (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
Loan officer fixed effects		Yes		Yes		Yes		Yes		Yes
Loan fixed effects		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	0.051	0.157	0.115	0.122	0.050	0.141	0.131	0.195	0.094	0.184
Dependent variable mean	0.71	0.71	0.77	0.77	0.70	0.70	0.48	0.48	0.60	0.60

Table 8: 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 (2) and (3) is a dummy variable equal to one if a performing loan was approved or a non-performing loan was declined. The dependent variable in columns (5) and (6) is the net profit of *approved* loans from the perspective of the bank, denominated in units of US\$ '000. The dependent variable in columns (7) and (8) is the profit per *screened* loan, where non-approved loans have a profit of zero and profit is again denominated in units of US\$ '000. Estimates are obtained from regressions based on the full sample and controlling for all $k - 1$ treatment dummies. Estimates for the full specification are reported in Appendix A, Table A.3. 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 5. Standard errors in parentheses are clustered at the individual and session level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

	Approved		Lending Decision Correct		Profit per Approved Loan		Profit per Screened Loan	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-powered [20, 0, 10]								
High-powered [50, -100, 0]	-0.04* (0.02)	-0.01 (0.02)	-0.00 (0.02)	0.02 (0.02)	0.10* (0.05)	0.18** (0.08)	0.09* (0.05)	0.12** (0.05)
Origination bonus [20, 20, 0]	0.08*** (0.02)	0.08*** (0.02)	0.02 (0.02)	0.02 (0.02)	-0.05 (0.05)	-0.05 (0.07)	-0.06 (0.05)	-0.01 (0.05)
Performance bonus low [50, 0, 0]	0.10*** (0.03)	0.14*** (0.03)	-0.01 (0.03)	-0.00 (0.03)	-0.17 (0.11)	-0.05 (0.10)	-0.13 (0.08)	-0.01 (0.07)
Performance bonus high [100, 0, 0]	0.13*** (0.04)	0.16*** (0.03)	0.02 (0.03)	0.01 (0.03)	-0.30** (0.13)	-0.27** (0.11)	-0.21** (0.10)	-0.17** (0.08)
Total Sessions	0.00 (0.00)	-0.00*** (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.01*** (0.00)	-0.00* (0.00)	-0.01*** (0.00)
Loan officer fixed effects		Yes		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes		Yes
Lab fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,802	14,675	12,802	14,675	8,078	9,357	11,374	13,084
R^2	0.051	0.157	0.264	0.275	0.666	0.782	0.478	0.522
Dependent variable mean	0.71	0.71	0.64	0.64	0.27	0.27	0.19	0.19

Figure 3: 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 approving 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 9: 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 the loans evaluated in the experiment. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

	Selection Equation		Second Stage	
	γ	t	θ	t
Loan amount	-0.0146	[-3.09]***	0.0012	[0.53]
Loan tenure	0.0084	[0.30]	-0.0459	[-2.17]**
Monthly installment	0.3245	[2.22]***	-0.0615	[-1.07]
Total sales	0.0004	[0.39]	0.0003	[0.93]
Personal expenditure	-0.0219	[-1.40]	-0.0025	[-0.39]
Business expenditure	0.0034	[2.36]***	0.0003	[0.59]
Total debt	0.0010	[1.63]*	0.0096	[0.32]
Business Experience	0.0130	[0.67]		
Financial History	-0.066	[-1.26]		
N				353
Censored				0.04
Adjusted R^2				0.09

Table 10: 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 credit scoring model outlined in Table 9. 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	Threshold for predicting default					
	$p^* = 0.08$		$p^* = 0.10$		$p^* = 0.12$	
	(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 file difficulty	1.14***		1.01***		1.05***	
	(0.06)		(0.06)		(0.05)	
Loan type = performing	-0.73***		-0.76***		-0.83***	
	(0.03)		(0.03)		(0.03)	
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 11: TREATMENT EFFECTS, DEFERRED COMPENSATION

This table reports treatment effect estimates of performance pay on lending decisions and screening effort under deferred compensation. 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) to (6) is a dummy equal to one for loans approved by experimental participants and zero otherwise. Columns (2) and (3) restrict the sample to performing loans, columns (4) and (5) restrict the sample to non-performing loans and loans declined by the lender. The dependent variable in column (5) and (6) is the log evaluation time for each credit file, restricted to observations between the 5th and 95th percentile. The dependent variable in column (7) and (8) records the number of information credits spent as a proxy of costly screening effort. The dependent variable in columns (9) and (10) is the number of information credits used and the sample in both columns is restricted to the subset of treatments implemented with the ‘information credits’ feature. In addition to the variables listed, we control non-parametrically for the randomization strata from which assigned incentive schemes are drawn and the controls summarized in Table 5. Standard errors, in parentheses, are clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Approved		Approved Performing		Approved Non- Performing or Declined		Log Evaluation Time		Number of Loan File Sections Reviewed		Information Credits Used	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Low-powered, credit [20, 0, 10]												
Low-powered, deferred [20, 0, 10]	-0.01 (0.02)	0.03 (0.02)	-0.00 (0.02)	0.02 (0.02)	-0.03 (0.04)	0.03 (0.04)	-0.06 (0.04)	-0.08** (0.03)	-0.22 (0.14)	-0.15** (0.08)	-0.64* (0.36)	-0.26 (0.20)
High-powered, credit [50, -100, 0]	-0.06** (0.02)	-0.06*** (0.02)	-0.04 (0.02)	-0.04 (0.02)	-0.10** (0.04)	-0.09** (0.04)	0.04 (0.04)	-0.01 (0.04)	0.27* (0.16)	0.23** (0.10)	0.93** (0.43)	0.77*** (0.25)
High-powered, deferred [50, -100, 0]	-0.04 (0.03)	-0.02 (0.03)	-0.03 (0.03)	-0.02 (0.03)	-0.04 (0.05)	-0.03 (0.05)	-0.03 (0.06)	-0.04 (0.04)	-0.09 (0.20)	-0.00 (0.12)	-0.23 (0.51)	0.02 (0.29)
Origination bonus, credit [20, 20, 0]	0.11*** (0.02)	0.09*** (0.02)	0.09*** (0.02)	0.09*** (0.02)	0.13*** (0.04)	0.10*** (0.03)	-0.01 (0.04)	-0.03 (0.04)	-0.25* (0.15)	-0.13 (0.08)	-0.35 (0.41)	-0.17 (0.20)
Origination bonus, deferred [20, 20, 0]	0.07*** (0.02)	0.09*** (0.02)	0.04* (0.02)	0.07*** (0.02)	0.11*** (0.04)	0.12*** (0.03)	-0.06 (0.04)	-0.06* (0.03)	-0.09 (0.14)	-0.15* (0.09)	-0.29 (0.39)	-0.39* (0.23)
Loan officer fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Lab fixed effects	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
<i>Test: immediate=deferred</i>												
High-powered, p-value	0.59	0.10*	0.89	0.50	0.32	0.27	0.06*	0.37	0.10*	0.10	0.03**	0.02**
Origination bonus, p-value	0.03**	0.89	0.03**	0.33	0.57	0.51	0.94	0.59	0.29	0.86	0.89	0.29
Observations	7,572	8,688	4,748	5,624	2,824	3,064	7,572	8,688	7,572	8,688	7,572	8,688
R ²	0.052	0.154	0.097	0.118	0.098	0.189	0.512	0.635	0.367	0.693	0.324	0.695
Dependent variable mean	0.71	0.71	0.77	0.77	0.60	0.60	5.20	5.20	6.43	6.43	5.22	5.22

Table 12: TREATMENT EFFECTS, SHARED LIABILITY

This table reports treatment effect estimates of performance pay on lending decisions and screening effort under shared liability. 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) to (6) is a dummy equal to one for loans approved by experimental participants and zero otherwise. Columns (2) and (3) restrict the sample to performing loans, columns (4) and (5) restrict the sample to non-performing loans and loans declined by the lender. The dependent variable in column (5) and (6) is the log evaluation time for each credit file, restricted to observations between the 5th and 95th percentile. The dependent variable in column (7) and (8) records the number of information credits spent as a proxy of costly screening effort. The dependent variable in columns (9) and (10) is the number of information credits used and the sample in both columns is restricted to the subset of treatments implemented with the ‘information credits’ feature. In addition to the variables listed, we control non-parametrically for the randomization strata from which assigned incentive schemes are drawn and the controls summarized in Table 5. Standard errors, in parentheses, are clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Approved		Approved Performing		Approved Non- Performing or Declined		Log Evaluation Time		Number of Loan File Sections Reviewed		Information Credits Used	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Low-powered [20, 0, 10], credit												
High-powered [50, −100, 0], credit	-0.06** (0.02)	-0.06*** (0.02)	-0.04 (0.02)	-0.04 (0.02)	-0.10** (0.04)	-0.09** (0.04)	0.04 (0.04)	0.01 (0.03)	0.27* (0.16)	0.23** (0.10)	0.93** (0.43)	0.77*** (0.25)
High-powered [50, −100, 0], credit+endow	-0.07*** (0.02)	-0.07*** (0.02)	-0.04 (0.03)	-0.06** (0.03)	-0.08** (0.04)	-0.11*** (0.04)	0.15*** (0.04)	0.10*** (0.03)	0.64*** (0.15)	0.36*** (0.08)	2.24*** (0.41)	1.23*** (0.22)
Loan officer fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Loan fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
Lab fixed effects	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
Test: <i>individual=shared</i>												
High-powered, p-value	0.73	0.61	0.89	0.58	0.71	0.67	0.03**	0.04**	0.07*	0.34	0.02**	0.17
Observations	7,572	8,688	4,748	5,624	2,824	3,064	6,839	7,834	7,572	8,688	7,572	8,688
R ²	0.052	0.154	0.097	0.118	0.098	0.189	0.443	0.553	0.367	0.693	0.324	0.695
Dependent variable mean	0.71	0.71	0.77	0.77	0.60	0.60	5.20	5.20	6.43	6.43	5.22	5.22

Table 13: 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 5. 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 (1)	Sections Reviewed (2)	Information Credits Used (3)	Approved (4)	Correct (5)	Profit per loan (6)
Age \times High-powered	0.01*** (0.00)	0.03** (0.01)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.02 (0.02)
Age \times Origination bonus	0.00* (0.00)	0.01 (0.01)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.02)
Age \times Performance bonus low	0.00 (0.00)	-0.00 (0.02)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.04 (0.04)
Age \times Performance bonus high	0.00 (0.00)	-0.01 (0.02)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.10* (0.06)
High-powered	-0.32*** (0.10)	-0.59 (0.44)	0.02 (0.07)	-0.04 (0.07)	-0.12 (0.13)	1.53* (0.80)
Origination bonus	-0.19** (0.09)	-0.50 (0.49)	0.14** (0.06)	0.04 (0.06)	-0.00 (0.12)	-0.15 (0.65)
Performance bonus low	-0.19 (0.22)	0.05 (0.95)	0.30*** (0.10)	-0.17 (0.13)	0.06 (0.20)	-1.22 (1.17)
Performance bonus high	-0.23 (0.21)	0.39 (0.80)	0.24** (0.11)	0.10 (0.11)	-0.15 (0.19)	-2.89* (1.60)
Loan officer fixed effects						
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	13,121	14,675	14,675	14,675	13,084	8,688
R^2	0.537	0.699	0.157	0.275	0.753	0.695
Dependent variable mean	5.20	6.43	5.22	0.71	0.65	0.27

Table 14: 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 5. 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 (1)	Sections Reviewed (2)	Information Credits Used (3)	Approved (4)	Correct (5)	Profit per loan (6)
Experience \times High-powered	0.06*** (0.02)	0.24*** (0.07)	-0.01 (0.01)	0.01 (0.01)	0.02 (0.02)	-0.04 (0.06)
Experience \times Origination bonus	0.02*** (0.01)	0.12** (0.05)	-0.01** (0.01)	-0.00 (0.01)	0.02 (0.01)	-0.05 (0.06)
Experience \times Perform bonus low	0.00 (0.01)	-0.03 (0.06)	0.01 (0.01)	0.00 (0.01)	-0.01 (0.02)	0.14 (0.10)
Experience \times Perform bonus high	0.04** (0.02)	0.11* (0.06)	0.03* (0.01)	0.02 (0.01)	0.01 (0.01)	0.56** (0.23)
High-powered	-0.09*** (0.03)	0.14 (0.15)	0.00 (0.02)	0.01 (0.03)	-0.01 (0.05)	0.79*** (0.27)
Origination bonus	-0.08** (0.03)	-0.18 (0.16)	0.09*** (0.02)	0.02 (0.02)	-0.06 (0.04)	-0.09 (0.23)
Performance bonus low	-0.10* (0.06)	-0.07 (0.26)	0.11*** (0.03)	-0.01 (0.04)	-0.04 (0.06)	-0.12 (0.17)
Performance bonus high	-0.15** (0.06)	-0.12 (0.28)	0.13*** (0.04)	-0.01 (0.03)	-0.06 (0.06)	-0.05 (0.24)
Loan officer fixed effects						
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	13,121	14,675	14,675	14,675	13,084	8,688
R^2	0.537	0.702	0.157	0.275	0.753	0.696
Dependent variable mean	5.20	6.43	5.22	0.71	0.65	0.27

A Appendix Tables

Table A.1: TREATMENT EFFECTS, INCENTIVIZING EFFORT [FULL SPECIFICATION]

This table reports treatment effect estimates of performance pay on screening effort. 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 the total log evaluation time per loan file, excluding observations outside the 5th to 95th percentile. The dependent variable in columns (2) and (3) is the number of credit file sections reviewed. In columns (3) and (4), we use the number of information credits used by loan officers as the dependent variable and a proxy for costly screening effort. In addition to the variables listed, we control non-parametrically for the randomization strata from which incentive schemes are drawn and the full set of controls as previously defined. Standard errors are reported in parentheses and 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]	-0.04 (0.04)	-0.04 (0.03)	0.39* (0.23)	0.41*** (0.14)		
Origination bonus [20, 20, 0]	-0.06* (0.03)	-0.05 (0.03)	-0.15 (0.22)	0.02 (0.15)		
Performance bonus low [50, 0, 0]	-0.14** (0.06)	-0.10* (0.05)	0.06 (0.29)	-0.13 (0.21)		
Performance bonus high [100, 0, 0]	-0.08 (0.08)	-0.09* (0.05)	-0.06 (0.44)	0.02 (0.24)		
Low-powered [20, 0, 10], credit	-0.14*** (0.02)	-0.14*** (0.02)	-2.16*** (0.10)	-2.17*** (0.07)		
High-powered [50, -100, 0], credit	-0.10*** (0.03)	-0.12*** (0.03)	-1.97*** (0.17)	-1.94*** (0.12)	0.93** (0.43)	0.77*** (0.25)
Origination bonus [20, 20, 0], credit	-0.14*** (0.03)	-0.15*** (0.03)	-2.45*** (0.16)	-2.29*** (0.11)	-0.35 (0.41)	-0.17 (0.20)
Performance bonus low [50, 0, 0], credit	-0.19*** (0.04)	-0.19*** (0.03)	-2.24*** (0.15)	-2.21*** (0.12)	-0.08 (0.25)	-0.08 (0.16)
Performance bonus high [100, 0, 0], credit	-0.11** (0.05)	-0.13*** (0.05)	-2.08*** (0.17)	-2.02*** (0.14)	0.06 (0.32)	0.10 (0.23)
Low-powered [20, 0, 10], credit def	-0.16*** (0.03)	-0.19*** (0.03)	-2.43*** (0.15)	-2.46*** (0.11)	-0.64* (0.36)	-0.26 (0.20)
High-powered, [50, -100, 0], credit def	-0.18*** (0.04)	-0.17*** (0.04)	-2.31*** (0.20)	-2.28*** (0.14)	-0.23 (0.51)	0.02 (0.29)
Origination bonus [20, 20, 0], credit def	-0.13*** (0.03)	-0.16*** (0.03)	-2.27*** (0.15)	-2.38*** (0.11)	-0.29 (0.39)	-0.39* (0.23)
High-powered credit, shared liability	-0.01 (0.03)	-0.01 (0.03)	-1.50*** (0.15)	-1.64*** (0.11)	2.24*** (0.41)	1.23*** (0.22)
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	11,492	13,121	12,802	14,675	7,572	8,688
R ²	0.455	0.535	0.512	0.698	0.324	0.695
Dependent variable mean	5.20	5.20	6.43	6.43	5.22	5.22

Table A.2: TREATMENT EFFECTS, RISK-ASSESSMENT [FULL SPECIFICATION]

This table presents treatment effect estimates of performance pay on loan officers' subjective risk-assessment. 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) to (3) is the internal risk-rating assigned to each loan and measured on a scale from 0 (High Risk) - 100 (Low Risk). The dependent variable in columns (4) to (7) are the four sub-components of the overall risk-rating *Personal Risk*, *Business Risk*, *Management Risk* and *Financial Risk*. 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 additional controls as previously defined. Standard errors are reported in parentheses and clustered at the individual and session level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

	<i>Panel A: Overall Risk Rating</i>			<i>Panel B: Risk Rating Sub-Categories</i>			
	All Loans (1)	Performing Loans (2)	Non-Performing and Declined (3)	Personal Risk (4)	Business Risk (5)	Mgmt Risk (6)	Financial Risk (7)
Low-powered [20, 0, 10]							
High-powered [50, -100, 0]	0.00 (0.04)	-0.02 (0.04)	0.04 (0.06)	-0.02 (0.04)	0.03 (0.04)	0.01 (0.04)	0.01 (0.04)
Origination bonus [20, 20, 0]	0.02 (0.04)	-0.01 (0.04)	0.05 (0.06)	-0.02 (0.04)	0.01 (0.04)	0.01 (0.04)	0.04 (0.04)
Performance bonus low [50, 0, 0]	0.16*** (0.06)	0.07 (0.07)	0.29*** (0.08)	0.12 (0.07)	0.11* (0.06)	0.15*** (0.06)	0.13** (0.06)
Performance bonus high [100, 0, 0]	0.30*** (0.05)	0.23*** (0.06)	0.45*** (0.09)	0.29*** (0.07)	0.21*** (0.06)	0.28*** (0.06)	0.29*** (0.06)
Low-powered [20, 0, 10], credit	-0.02 (0.03)	-0.05* (0.03)	0.02 (0.04)	-0.04 (0.03)	-0.03 (0.03)	-0.03 (0.03)	-0.01 (0.03)
High-powered [50, -100, 0], credit	-0.00 (0.04)	-0.04 (0.04)	0.07 (0.06)	-0.01 (0.04)	-0.00 (0.04)	-0.02 (0.04)	-0.02 (0.04)
Origination bonus [20, 20, 0], credit	0.05 (0.04)	-0.00 (0.05)	0.12** (0.06)	0.05 (0.05)	0.03 (0.04)	0.03 (0.04)	0.06 (0.04)
Performance bonus low [50, 0, 0], credit	0.15*** (0.05)	0.13*** (0.05)	0.17* (0.09)	0.11** (0.05)	0.09* (0.05)	0.12** (0.05)	0.14*** (0.05)
Performance bonus high [100, 0, 0], credit	0.07 (0.06)	-0.01 (0.07)	0.19** (0.09)	0.06 (0.06)	0.04 (0.07)	0.03 (0.06)	0.09 (0.06)
Low-powered, credit [20, 0, 10], deferred	0.01 (0.03)	-0.03 (0.04)	0.06 (0.05)	-0.03 (0.04)	0.01 (0.04)	-0.03 (0.04)	0.03 (0.04)
High-powered, credit [50, -100, 0], deferred	-0.04 (0.05)	-0.08 (0.05)	0.01 (0.08)	-0.06 (0.05)	-0.04 (0.05)	-0.03 (0.05)	-0.04 (0.05)
Origination bonus, credit [20, 20, 0], deferred	0.02 (0.04)	-0.06 (0.04)	0.13** (0.05)	-0.03 (0.04)	-0.02 (0.04)	0.00 (0.04)	0.07* (0.04)
High-powered [50, -100, 0], endowment	-0.04 (0.03)	-0.05 (0.04)	-0.03 (0.04)	-0.03 (0.03)	-0.02 (0.03)	-0.04 (0.03)	-0.03 (0.03)
Loan officer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	13,661	8,875	4,786	13,661	13,661	13,661	13,661
R^2	0.650	0.687	0.619	0.597	0.596	0.630	0.613
Dependent variable mean	69.9	69.9	69.9	73.2	70.0	71.4	66.6

Table A.3: TREATMENT EFFECTS, DECISIONS AND PERFORMANCE [FULL SPECIFICATION]

This table reports treatment effect estimates of performance pay on loan approvals 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 equal to one for loans approved by an experimental participant and zero otherwise. The dependent variable in columns (3) and (4) is a dummy variable equal to one if a non-performing loan was declined or a performing loan was approved and zero otherwise. The dependent variable in columns (5) and (6) is the profit per approved loan, net of the bank's cost of capital, where the profit for non-approved loans is set to zero. 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 previously defined. Standard errors are reported in parentheses and clustered at the individual and session level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

	Approved		Lending Decisions Correct		Profit per Approved Loan	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-powered [20, 0, 10]						
High-powered [50, -100, 0]	-0.04* (0.02)	-0.01 (0.02)	-0.00 (0.02)	0.02 (0.02)	0.10* (0.05)	0.18** (0.08)
Origination bonus [20, 20, 0]	0.08*** (0.02)	0.08*** (0.02)	0.02 (0.02)	0.02 (0.02)	-0.05 (0.05)	-0.05 (0.07)
Performance bonus low [50, 0, 0]	0.10*** (0.03)	0.14*** (0.03)	-0.01 (0.03)	-0.00 (0.03)	-0.17 (0.11)	-0.05 (0.10)
Performance bonus high [100, 0, 0]	0.13*** (0.04)	0.16*** (0.03)	0.02 (0.03)	0.01 (0.03)	-0.30** (0.13)	-0.27** (0.11)
Low-powered, credit [20, 0, 10]	0.01 (0.01)	0.02* (0.01)	-0.01 (0.01)	0.00 (0.01)	0.01 (0.03)	-0.03 (0.04)
High-powered, credit [50, -100, 0]	-0.04* (0.02)	-0.02 (0.02)	0.02 (0.02)	0.03* (0.02)	0.11** (0.05)	0.20*** (0.07)
Origination bonus, credit [20, 20, 0]	0.13*** (0.02)	0.13*** (0.02)	0.01 (0.02)	0.02 (0.02)	-0.02 (0.06)	-0.03 (0.06)
Performance bonus low, credit [50, 0, 0]	0.10*** (0.02)	0.11*** (0.02)	-0.00 (0.02)	0.00 (0.02)	0.05 (0.06)	-0.03 (0.07)
Performance bonus high, credit [100, 0, 0]	0.10*** (0.03)	0.12*** (0.03)	-0.06** (0.03)	-0.04 (0.02)	-0.20** (0.09)	-0.32*** (0.11)
Low-powered, credit, def. [20, 0, 10]	0.00 (0.02)	0.04** (0.02)	0.01 (0.02)	0.00 (0.02)	-0.04 (0.05)	-0.08 (0.07)
High-powered, credit, def. [50, -100, 0]	-0.02 (0.03)	0.00 (0.02)	-0.01 (0.03)	0.00 (0.03)	0.05 (0.07)	0.00 (0.09)
Origination bonus, credit, def. [20, 20, 0]	0.09*** (0.02)	0.11*** (0.02)	-0.02 (0.02)	-0.01 (0.02)	0.21*** (0.06)	0.07 (0.06)
High-powered, credit, endow. [50, -100, 0]	-0.06*** (0.02)	-0.04** (0.02)	-0.01 (0.02)	-0.00 (0.02)	-0.00 (0.06)	-0.03 (0.07)
Loan officer 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	12,802	14,675	12,802	14,675	8,078	9,357
R^2	0.051	0.157	0.264	0.275	0.666	0.124
Dependent variable mean	0.71	0.71	0.65	0.65	0.27	0.27

Table A.4: RANDOMIZATION CHECKS

This table presents a test of random assignment by regressing treatment dummies on loan officer characteristics with the baseline treatment (low-powered) as the excluded category in each regression. Panel A summarizes the basic treatments, panel B summarizes the subset of treatments in which participants received an initial endowment of information credits, which were deducted for viewing credit file sections beyond the basic applicant information. Standard errors are reported in parentheses and clustered at the individual and session level. * p<0.10 ** p<0.05 *** p<0.01.

	Low-powered Incentives	High-powered Incentives	Origination Bonus	Performance Bonus, Medium	Performance Bonus, High	Low-powered Incentives [Deferred]	High-powered Incentives [Deferred]	Origination Bonus [Deferred]	High-powered Incentives [Shared Liability]
A: BASIC TREATMENTS									
Male	—	0.005 (0.037)	0.018 (0.036)	0.038 (0.028)	0.032 (0.024)	—	—	—	—
Age	—	-0.000 (0.002)	0.001 (0.002)	-0.001 (0.001)	-0.003** (0.001)	—	—	—	—
Education	—	-0.000 (0.021)	0.021 (0.022)	0.016 (0.020)	0.021 (0.018)	—	—	—	—
Experience	—	0.001 (0.002)	-0.001 (0.002)	0.000 (0.001)	0.002 (0.001)	—	—	—	—
Rank [1 Low - 5 High]	—	0.003 (0.011)	-0.008 (0.011)	0.011* (0.007)	0.011* (0.006)	—	—	—	—
Branch Manager	—	-0.002 (0.025)	0.010 (0.027)	0.000 (0.025)	0.014 (0.023)	—	—	—	—
Observations		4,052	4,148	3,835	3,726				
B: INFORMATION CREDITS									
Male	-0.005 (0.052)	0.016 (0.039)	-0.026 (0.038)	0.050* (0.027)	0.028 (0.021)	-0.016 (0.038)	-0.006 (0.034)	-0.019 (0.036)	-0.000 (0.049)
Age	0.004 (0.003)	-0.001 (0.003)	-0.002 (0.003)	0.001 (0.002)	0.001 (0.001)	-0.001 (0.003)	-0.003 (0.002)	-0.004* (0.003)	0.005* (0.003)
Education	0.048 (0.033)	-0.002 (0.026)	0.035 (0.025)	0.013 (0.015)	0.012 (0.014)	0.031 (0.026)	0.018 (0.021)	0.035 (0.025)	0.032 (0.032)
Experience	0.000 (0.003)	0.002 (0.002)	0.002 (0.002)	-0.001 (0.001)	-0.002 (0.001)	0.001 (0.002)	0.003 (0.002)	0.003 (0.002)	-0.003 (0.003)
Rank [1 Low - 5 High]	-0.016 (0.015)	-0.019 (0.012)	-0.005 (0.012)	0.006 (0.008)	0.007 (0.007)	-0.016 (0.012)	-0.014 (0.009)	-0.013 (0.011)	-0.023* (0.014)
Branch Manager	0.016 (0.041)	0.006 (0.033)	-0.003 (0.029)	-0.016 (0.011)	-0.004 (0.012)	0.033 (0.031)	0.006 (0.023)	0.016 (0.029)	-0.005 (0.040)
Observations	5,884	4,262	4,250	3,732	3,562	4244	3,848	4,302	4,376

Table A.5: 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.

	Experimental Participants (N=193)			Bank Employee Dataset (N=311)		
	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]