

REWARDING CALCULATED RISK-TAKING: EVIDENCE FROM A SERIES OF EXPERIMENTS WITH COMMERCIAL BANK LOAN OFFICERS

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July 2010*

Preliminary and Incomplete

Abstract: We analyze the underwriting process of small-business loans to entrepreneurs in an emerging market, using data obtained from a large commercial lender in India. Using a series of randomized experiments involving loan officers from several banks, this paper provides the first rigorous test of theories of incentives for lending. We compare four commonly implemented incentive schemes: low-powered scheme 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. Preliminary results show strong and economically significant effects of performance-based incentive schemes on screening behavior and risk taking. Incentives that penalize officers for bad decisions cause loan officers to sanction 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. 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, with the objective of improving the financial access of previously unbanked entrepreneurs.

*scole@hbs.edu, kanz@fas.harvard.edu, and lklapper@worldbank.org. We thank the Financial Institution for providing us with the data on historical loan applications used in this paper, the numerous loan officers who participated in the study, Philippe Aghion, Quy-Toan Do, Raj Iyer, Michael Kremer, Andrei Shleifer, Antoinette Schoar, Erik Stafford, Jeremy Stein, and seminar participants at the World Bank-Kauffman Foundation conference on Entrepreneurship and Growth and the 2010 Emerging Markets Finance Conference for helpful comments and suggestions. Atul Agrawal and Samantha Bastian provided excellent research assistance. Financial assistance from the Kauffman Foundation, the International Growth Center, the World Bank Development Research Group, and the Harvard Business School Division of Faculty Support and Research, is gratefully acknowledged. The opinions expressed do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent.

Introduction

“An evaluation of some 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 [...]. 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 after the transactions were completed. 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 may share the blame. Providing incentives for loan officers and other front-line employees within the financial firm 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; and may be more risk-averse and have a shorter time horizon than the bank’s shareholders.²

This paper presents the first experimental evidence on the relationship between performance incentives and loan officer behavior. We study lending decisions in the market for small enterprise retail loans in India, using active loan officers with an average of more than fifteen 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 front-line employees. We pay loan officers to review and assess actual loan applications, comparing four commonly implemented incentive schemes: a flat wage; a bonus for origination; a bonus for originating only loans that perform; and a high-powered scheme which involves a penalty for approving loans that become delinquent as well as a bonus for originating loans that perform.

We find a strong effect of performance incentives on screening effort, risk ratings, and the quality of lending decisions: Loan officers who are rewarded for lending volume rather than the quality of their lending portfolio sanction a significantly higher share of the loans they evaluate. Moreover, we find that compensation schemes that penalize bad decisions lead to a strikingly

¹ In a speech entitled “Incentive Compensation, Risk Management, and Safety and Soundness,” at the University of Maryland’s Robert H. Smith School of Business Roundtable: Executive Compensation: Practices and Reforms, Washington, D.C., November 2, 2009.

²For a detailed review of compensation practices in wholesale and investment banking see “Compensation in Financial Services: Industry Progress and the Agenda for Change” (IIF, 2009).

more conservative lending. The difference is statistically significant and economically meaningful: Loan officers who received a performance bonus with a penalty for bad decisions sanctioned 10 percentage points fewer loans than loan officers who faced an origination bonus. We further document a strong effect of performance based compensation on subjective risk-assessment. Loan officers who facing incentive schemes that provide large bonuses for sanctioning performing loans inflate their risk assessment. Finally, we test the effect of delayed compensation on the exertion of costly effort. Any performance-based incentive scheme must, by definition, involve deferred compensation, as the outcome of a loan is not immediately known. We demonstrate that deferring bonus payments by three months reduces our measure of costly effort by *fifty percent*.

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 three studies that link loan officer incentives to actual lending behavior. Hertzberg, Liberti, and Paravisini (2009) 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. Finally, 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. Furthermore, loan officers who are offered quantity-based 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 necessary for efficient capital allocation and firm growth (Levine, 1997), and that cross-sectional differences in the ability of markets to finance the most promising entrepreneurs may lead to differences in productivity growth across countries (Greenwood and Jovanovic 1990, Guiso et al. 2004). Moreover, entrepreneurial firms with a limited financial history 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). We contribute to this strand of the literature by shedding light on the mechanism through which

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 soft information in a challenging informational environment. If performance incentives can affect the quality of project choice, this occurs either through the collection of additional borrower details or improvements in the analysis of existing information, each lending to a greater depth of the lending relationship). Studies measuring credit availability and collateral requirements 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 and Gambera, 2001, Santikian 2009). More generally, marginally creditworthy borrowers may have improved financial access when loan officers have access to greater soft information (Sharpe 1990, Rajan, 1992). We examine how the structure of compensation affects the nature of lending relationships and show that performance incentives have a strong effect on screening effort and the type of borrower information loan officers focus on when asked to assess 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, 2000a, 2000b). 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 nontrivial importance to a firm (Lazear and Rosen, 1981; Gibbons, 1998). A more recent strand of the empirical 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 both effort and selection effects (Bandiera, Barankay and Rasul, 2007, Bandiera, Barankay and Rasul 2009).³ 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 a way that balances the competing goals of risk-management and revenue generation. Empirically, the design of our experiment has the important advantage that it allows us to test a wide range of exogenously assigned incentive schemes and compare their effect on a variety of effort and performance measurements.

This paper proceeds as follows. In the next section, we describe how the standard incentive problems within the bank are likely exacerbated in emerging market contexts, and provide a brief

³ Bandiera, Barankay and Rasul (2007) show that the introduction of performance incentives at the managerial level affects both monitoring and worker selection. For a discussion of performance based compensation as a sorting mechanism see also Lazear (2000b).

theoretical framework for our experiments. Section III develops a simple theoretical model to motivate the experiment. Section IV describes the experimental design. Section V describes the empirical strategy and experimental results, and section VI concludes.

2. Incentive Schemes within the Bank

The literature on incentives within organizations has identified a range of important constraints to the optimal employment of firm resources. (see Gibbons (1998) for a review). Much of the literature in banking has focused on the problems inherent in delegated monitoring (e.g., Diamond, 1984), rather than on how to incentivize loan officers to make efficient initial *screening* decisions. Our experiments compare the impact of a variety of incentive schemes on lending decisions in order to promote safer lending, but without preventing creditworthy entrepreneurs from accessing new loans. In this section we discuss the importance of loan officer information collection and incentive designs.

2.1 Information Costs

Emerging credit markets, such as the one we study, are often characterized by severe information asymmetries between borrowers and banks, which can severely hamper new lending. While developing countries have experienced substantial liberalization over the last two decades, leading to a surge in entrepreneurship,⁴ the development of credit markets has often not kept pace with this development (see e.g. Banerjee, and Duflo, 2008; Berger, Klapper, Martinez Peria and Zaide, 2008). Especially the predominance and conservative lending practices of public sector banks have often been identified as a limiting factor for the rapid growth of new enterprises (La Porta et al. 2002, Banerjee, Cole and Duflo, 2009).

The importance of soft information represents a particularly important constraint in emerging markets for two reasons: First, as levels of post-secondary education are low, the relative price of highly skilled individuals able to make credit judgments may be particularly limited. Second, the costs of soft-information collection are roughly invariant to loan size,⁵ making it particularly uneconomical to collect extensive soft information for small loans. Therefore, while the reliance on non-traditional information has allowed financial intermediaries with a more decentralized lending model to mitigate default risk, the advantage offered by an increased reliance on soft information usually comes at a significant cost. It is not a coincidence that traditional lenders in emerging markets still shy away from small enterprise loans and the retail segment, for the precise reason that effective risk management in this segment requires a very relationship-

⁴ In India the number of annually newly registered corporations increased by over 60% between 2001 and 2008 (see Klapper, et al, 2009).

⁵ Indeed, small opaque borrowers may take *more* time to evaluate than larger firms, which have audited accounts and longer histories.

intensive lending model. This comes with very high costs of collection and verification of client information beyond; for this segment, audited financial disclosures either do not exist, or are not credible. As a result, the business of retail banks in emerging markets is still heavily skewed away from small enterprise lending and in favor of large, corporate loans where standard hard information is more reliable and screening costs are lower.

The ability of financial intermediaries to meet rising demand depends critically on their ability to screen and monitor borrowers. However, many emerging markets lack comprehensive credit information or verifiable credit ratings for the majority of new enterprises, which limits the use of predictive credit scoring and other loan approval technology (Djankov et al., 2007). For example, only 10% of Indian adults are included in a credit bureau, in comparison to 60% of adults in OECD countries (Doing Business, 2010). In countries with weak institutions and poor informational environments, the loan officer and risk-management team play an especially critical role in screening decisions of the loan officer in the field. The difficulty of lending to small businesses in emerging markets has long been recognized, with many small businesses reporting access to finance as their primary constraint to growth (Beck, Demirguc-Kunt, and Maksimovic, 2008).⁶

In the absence of reliable credit information, financial intermediaries in emerging markets rely heavily on soft information gathered through relationship lending. This 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. Financial intermediaries operating in the Indian retail lending market, for example, routinely supplement the documentation required by the country's central bank with additional information determined by personal observations of the loan officer, such as site visits to the home and office of a prospective applicant, interviews with business partners and references from employers or trade representatives in the area. Empirical evidence suggests that SMEs greatly benefit from relationship-lending in terms of credit availability, interest rates and collateral requirements (Petersen and Rajan, 1994, 1995; Petersen, 2004; Berger and Udell, 1995; Cole, 1998, Elsas and Krahn, 1998, Harhoff and Korting, 1998a).⁷ Moreover, stylized evidence from the recent downturn suggests that financial intermediaries with a relationship-based lending model that places greater emphasis on the use of soft information 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 more flexible rescheduling of installments that takes account of the client's true financial position (Kashyap, Rajan, Stein, 2008).

⁶ See World Bank (2009) for a review of the literature related to barriers to finance for SME's.

⁷ Theory and evidence also show a relationship between the organizational form of a bank and the use of soft information: larger, more hierarchical banks are found to collect less soft information and lend less to informationally opaque and small firms.

2.2 Incentives and Lending

The design of optimal incentives is a central lending issue that has been addressed by both theoretical and empirical studies. Diamond (1984) and Fuentes (1996) examine the optimal design of delegated monitoring contracts.

The potential for unbalanced incentive schemes to induce privately beneficial but socially costly behavior, often in the form of excessive risk-taking, has long been documented (Holstrom, 1991; Rajan, 1995; Kashyap, Rajan, and Stein, 2008; Erkens, Hung, and Matos, 2009). This is of particular concern to commercial banks that aim to walk a fine line between increasing lending capacity while maintaining sustainable risk levels. Much of the previous work in this area focuses on delegated monitoring contracts which, when optimally designed, enable financial intermediaries to reduce their risk through diversification, while extending their loan portfolio (Diamond, 1984; Fuentes, 1996). However, bank managers may want to focus their energies more explicitly on the loan officers and devise optimal incentive schemes to boost loan origination without incurring unmanageable risk. Beyond the form of the incentive scheme, a firm must also consider the strength of the incentive program so as to avoid motivating employees to emphasize the rewarded aspects of their performance in non-profit-maximizing ways (Holmström, 1991; Baker, 2002).

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, 1995; Margiotta, 2000). Kashyap, Rajan, and Stein (2008) argue that, in the lead-up to the crisis, the increasing amounts of dubious assets acquired by banks were the result of a breakdown of incentives and risk control systems at both a management and trader level. However, apart from the three studies mentioned in the introduction, there is relatively little evidence on the efficacy of various potential incentive schemes.

2.3 Barriers to Efficient Incentive Schemes

If the bank were owned by a single individual, who investigated borrowers and made lending decisions, there would be no incentive problem within the bank.⁸ Similarly, one might imagine simply giving the loan officer an "equity stake" in the loan, in the limit selling her the use of the banks facilities, but having her trade on her own account. That we do not observe this contract in practice suggests that a range of frictions prevents writing contracts that obtain 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:

⁸ A banker with a government deposit guarantee might still be tempted to take socially inefficient gambles; we abstract from these considerations.

- 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 the banker cannot. 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 equity holders.
- Differential discount rates. Loan officers, especially in developing countries, may be less patient 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 standard production tasks, banks do *not* want to maximize their output (loan volume), but instead seek to lend only to clients with a sufficiently high probability of repayment.

Rather than solve a (necessarily incomplete) model of optimal loan officer incentives, we instead focus on a range of incentive schemes that are used by lending institutions around the world.

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. Firms are either good type with probability of success p , or bad type, with probability of success 0, where naturally $p > 0$. 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, e.g., 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 (binary) decision requires effort, which comes at private cost e to the loan officer. If a loan officer engages in screening, she gets a signal the firm is bad, σ_B with probability:

$$P(\sigma_B) = \begin{cases} \psi & \text{if borrower is type } \theta^B \\ 0 & \text{if borrower is type } \theta^G \end{cases}$$

Thus, the posterior probability that a firm is good, given a good signal, is:

$$\hat{\sigma}_G = \frac{1\pi}{\pi + (1 - \pi)(1 - \psi)}$$

The bad signal is fully informative, so the posterior probability 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 taking screening costs into consideration:

$$\pi pr + \pi(1 - p)(-1) + (1 - \pi)\psi * 0 + (1 - \pi)(1 - \psi)(-1) - e > 0 \quad (3.1)$$

The incentive problem for the bank is how to motivate the loan officer to exert costly effort e , and to lend only when they do not observe the bad signal.

The bank offers the loan officer a loan contract $\{w_0, w_N, w_P, w_D\}$, which specifies a fixed payment w_0 plus contingent payments in case the loan officer rejects the loan w_N , accepts a loan which subsequently performs w_P , or accepts a loan which is subsequently delinquent w_D . 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 make the loan. We 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.⁹

The loan officer thus chooses the return to three possible actions: rejecting the loan without screening it, accepting the loan without screening it, or screening the loan, and accepting it only if there is no bad signal. The payoff to rejecting the loan is $u^R = w_0 + w_D$. The loan officer's payoff

⁹If she is willing to lend to a bad firm, then she should simply make the loan without screening, saving herself the screening cost.

to accepting the loan without screening it is:

$$u^{NS} = w_0 + \pi p w_p + (1 - \pi p) w_D$$

Finally, the payoff to screening is:

$$u^S = w_0 + \pi(p w_p + (1 - p) w_D) + (1 - \pi) \psi w_R + (1 - \pi)(1 - \psi) w_D - e$$

We begin by remarking the efficient outcome can be obtained if the loan officer is risk-neutral, by setting $w_N=0$, $w_R=0$, $w_p=r$ and $w_D = -1$. The loan officer's incentives are then perfectly aligned with the bank. However, this contract is expensive for the bank, in the sense that it gives the entire expected net interest margin to the loan officer, and risky for the loan officer, who may be obliged to reimburse the bank the entire cost of the failed loan. Any contract that induces effort must satisfy two incentive constraints: $u^S \geq u^{NS}$ and $u^S \geq u^R$. The requirement $u^S > u^{NS}$ simplifies to the condition:

$$e < \psi((1 - \pi)(w_R - w_D)) \quad (3.2)$$

which generates the following several intuitive predictions: It is easier for the bank to induce effort if a.) the cost of effort is lower, b.) the signal is more informative, c.) the fraction of bad firms is greater, d.) the probability that a good firm repays increases, e.) the reward for rejecting a loan increases or f.) the penalty for default increases. This is, however, not the only constraint that must bind to ensure the loan officer screens. It must also be more advantageous to screen than to simply reject loans, i.e. $u^S < u^R$ which simplifies to:

$$e < (\pi p) w_p + (\pi \psi - \pi p - \psi) w_D - (1 - \psi) w_R \quad (3.3)$$

Since both constraints are upper bounds for the cost of effort, only one will bind. If (3.3) binds, the following comparative statics hold: It is easier to induce effort when: a) the cost of effort is lower, b) the fraction of good firms in the pool increases, c) the reward for a loan that performs increases, d) the payment for a loan that fails becomes greater (or less negative) and e) the probability a good firm repays increases.

In separate work, we formalize the optimal contracts under a range of parameters and conditions. While the above comparative statics generate several testable predictions, for the purposes of the present paper, we focus on the following five results:

RESULT 1: A origination bonus scheme $w=w_P=w_D>0$, as often employed in banks, leads to indiscriminate lending, low effort, and high defaults.

RESULT 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 sufficiently costly, and default sufficiently rare, then loan officers will prefer to lend to all applications. While (3.2) can be made slack for any cost of effort e , by increasing w_R , increasing w_R has the opposite effect of making (3.3) less likely to be satisfied.

RESULT 3: 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 principle of the loan), and $w_P=r$, the loan officer will screen, as long as condition (3.1) is satisfied.

RESULT 4: High-powered incentives can result in more conservative lending. A corollary of (3.3) is that when loan officers screen, they are more likely to discover a firm is bad, and thus less likely to make a loan.

RESULT 5: If loan officers have a positive discount rate for financial compensation, an incentive scheme that induces effort may induce less effort if payment is deferred.

3.1 Experimental Incentive Schemes

We operationalize this setting by testing the following four incentive schemes. Loan officers faced with a loan file make a decision of whether to accept or reject the application. The bank in turn may compensate them for three possible outcomes: the loan is rejected, the loan is accepted but defaults, or the loan is accepted and performs. Throughout the paper and in the tables, we remind the reader of the structure of the scheme by listing the payment made in case of [Accept loan that ultimately performs, Accept loan that defaults, Reject]. The amounts indicated are Indian Rupees—the economic magnitude of these payments is significant, and discussed in greater detail in section 3.

- **A:** Low-Powered Incentive Scheme [20, 0, 10]. This scheme rewards loan officers for processing a loan, regardless of whether it is rejected or approved.

- **B:** High-Powered Incentive Scheme [50, -100, 0]. This scheme provides loan officers with a large reward if they approve the loan, but a significant penalty if they sanction a loan that ultimately does not perform. It should be noted that loan officers enjoy limited liability, and if their total incentive payment for a particular session is negative, no penalty is collected from them.
- **C:** Origination Bonus [20, 20, 0]. This scheme provides loan officers with a reward if they approve the loan, regardless of whether it is paid or not
- **D:** Medium Performance Bonus [50, 0, 0]. This scheme provides a bonus of Rs. 50 in case a sanctioned loan performs, and no payment otherwise.
- **E:** Large performance Bonus [100, 0, 0]. This scheme provides a bonus of Rs. 100 in case a sanctioned loan performs, and no payment otherwise
- **F:** Deferred compensation of origination bonus. In this treatment, a bonus of [20/20/0] per loan evaluated is paid three months after the evaluation, rather than on the same day. This treatment also includes costly effort, described below.
- **G:** Deferred compensation of low-powered incentives. In this treatment, a bonus of [20, 20, 0] per loan evaluated is paid three months after the evaluation, rather than on the same day. This treatment also includes costly effort, described below.

An obvious feature of schemes C - F is that they provide very little incentive for a loan officer to exert effort in making the right decision. Indeed, under these schemes, accepting every loan application that comes their way is a (weakly) dominant strategy for the loan officer. Yet, such schemes have often been observed in consumer lending, and for that reason we include them among the first set of incentive schemes we test.

One possibility is that career concerns cause loan officers to invest in making the right decision, even without explicit monetary rewards. While we do not address this explicitly in the present draft, future versions will include a treatment in which a loan officer's performance in the experiment is shared with her direct supervisor. A second possibility is that loan officers enjoy some intrinsic utility from properly allocating capital—we will be able to say something about this by analyzing data from a follow-up survey about motivation.

If we assume that loan-officers care exclusively about minimizing effort and maximizing financial reward, we can make the following specific predictions.

- 1) Bonuses awarded for origination will lead to excessive risk-taking
Loan officers will approve all applications under scheme C, D, and E.
- 2) High-powered incentives will increase effort
The amount of effort exerted under various treatment can be ranked $B > A > C, D, E$
- 3) High-powered incentives will induce conservative lending behavior
The probability amount of effort exerted under various treatment can be ranked $B > A > C, D, E$.
- 4) If a loan officer's discount rate is greater than zero, the amount of effort induced by G will be less than the amount of effort induced by A.

If in fact loan officers are intrinsically motivated, or erroneously believe that their performance on this task may affect their career concerns, they may in fact invest in scrutinizing loan applications even when such scrutiny will not yield additional remuneration. However, since the treatments are randomly assigned, this will not bias our results. Rather, it will mimic the real world, in which monetary incentives are combined with career concerns or intrinsic motivation.

In this paper, we report on preliminary results from these incentive schemes; however, the experiments are still on-going, and we plan to test a range of alternative incentive schemes.

4. Experimental Design

To study loan officer decision making, we use a framed field experiment in which loan officers process a set of loan applications, drawn randomly from a database of real historical loans. While the decisions 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 incentive schemes that depend both on the loan officer's decision and the eventual outcome of the loan.

The loan database used in the experiment was constructed in collaboration with a large financial firm in Mumbai, India. With the assistance of our partner firm's risk analytics team, we constructed a database of 500 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 150,000 (US\$ 3,300) and 500,000 (US\$ 11,000) Rupees. We consider only term loans to borrowers new to our financial firm, many of whom are borrowing from the formal sector for the first time. None of the loans in our sample are collateralized and, as a result, they are priced at an annual interest rate of between 15 and 30 per cent. The mean loan in our database has a tenure of 36.14 months and a monthly installment of 14,320 Rupees.

To ensure consistency in asset quality and screening criteria applied to the original loan, we restricted our sample to loans from two vintages, 2008 Q1 and 2008 Q2. Within this set of loans, we considered files from three geographical areas, where the client profile, sectoral composition and average ticket size of our partner firm's lending portfolio are broadly comparable.¹⁰ Based on our partner firm's internal data on the repayment history of each loan, we then classified the loans 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 non-delinquent otherwise.

To achieve as representative sample as possible, we include loan applications that filed, but ultimately rejected, by the lending institution. The mix of loans presented to a loan officer in each six-file session was as follows: four "good" loans that were accepted and ultimately performed; one "bad" loan that was originally accepted by the lender, but eventually defaulted; and one "rejected" loan, which not accepted. Loan officers were told the mix of files they would process.

To implement the experiment, we use a simple software exercise in which loan officers are presented with the pre-sanction information of a sequence of applications drawn randomly from the database of historical loans. The software allows the loan officer to review all applicant information available to the bank at the time the loan was originated, with each tab corresponding to a particular section of the loan application, such as business description, balance sheet, trade reference verification, site visit report, document verification and credit bureau report for the few businesses that have a formal sector borrowing track record. While reviewing this information, the loan officer is asked to provide a subjective assessment of the application's merit along a set of 15 rating criteria adapted from the internal assessment formats of Indian public sector banks and grouped under the categories personal risk, business risk, management risk, financial risk and strength of general asset position.

The experiments were conducted in two offices in the West Indian city of Ahmedabad, Gujarat. Participants were recruited from the staff of three of India's three largest commercial banks; some elected to sign up for 15 sessions, while others attended fewer sessions. In every session, each loan officer was assigned a set of six randomly drawn applications and asked to rate them under an incentive scheme which was exogenously varied for each experimental session, ensuring a sequence of treatments orthogonal to officer characteristics, composition of the session members and type of incentive scheme. Experimental subjects received a fixed

¹⁰ Files are selected from the Indian states of Gujarat, Karnataka and Maharashtra. In robustness checks, we control for the geographical origin of the loan. For the state of Maharashtra, we distinguish between locations within and outside the Greater Mumbai area.

compensation of 100 Rupees to cover time and travel costs. In addition, each incentive scheme offered participants the opportunity to win an additional reward, which varied according to the treatment in place and the participant's performance. The validity and real-world implications of our results require that experimental subjects perceive conditional payoffs as both salient and sufficient to motivate behavior. To ensure that this is the case, we set the expected payoff of our basic 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 240,000 Rupees (US\$ 5,400) and an approximate hourly wage of 125 Rupees.

Experimental sessions were conducted according to the following procedure. 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. On the day of the session, an incentive scheme was then randomly assigned to each session. Before beginning the session, participants received a standardized presentation introducing the day's incentive scheme as well as instruction cards summarizing the conditions of the experiment and payoffs for each of the three possible decisions (reject, sanction a performing loan or sanction a delinquent loan). Loan officers then rated the files they had been assigned, without restrictions on the time they could take to review each file. When a participant completed the exercise, her decision to sanction or reject a file was compared to the true historical performance of the file and she received an incentive payment according to her performance and the incentive scheme in place.

The software design offered us the unique opportunity to collect data both on outcomes as well as on the behavior of loan officers during the exercise. In addition to the performance measures required to test our basic hypotheses (sanction/reject), we collected data on a set of subjective risk assessment rankings (personal risk, business risk, etc.) as well as indicators of behavior during the exercise, such as total viewing time for each file and viewing time for each sub-category, which we use as a measure of screening effort. Once a participant has completed their course of sessions, we administer a detailed exit survey in which we ask questions relating to risk-aversion, time-preference, trust, altruism and self-control. Taken together with the loan officer's observed behavior under alternative incentive schemes, these variables will allow us to take a much closer look at how individual characteristics interact with the structure of monetary incentives to alter loan officer decisions.

5. Empirical Strategy and Results

To present formal evidence on the effect of incentive schemes on observed loan officer behavior, we estimate regressions in which we compare screening effort, risk perception and screening performance under each incentive scheme to the baseline treatment. The baseline incentive we use across all specifications is an origination piece rate in which the loan officer receives no reward for rejected applications and a piece rate for accepted applications. This incentive scheme

is in a sense a natural benchmark and corresponds to the case in which the loan officer is incentivized only on lending volume, irrespective of the quality of sanctioned loans. To examine the relationship between incentives, loan officer behavior and outcomes more formally, we estimate the following empirical model:

$$y_{ij} = a + \phi_1 \mathbf{T}_{1ij} + \phi_2 \mathbf{T}_{2ij} + \phi_3 \mathbf{T}_{3ij} + \phi_4 \mathbf{T}_{4ij} + \gamma_i + \eta_j + \varepsilon_{ij} \quad (5.1)$$

where y_{ij} is an outcome for loan officer i and file j , \mathbf{T}_{kji} is a treatment vector, taking on a value of one for loan officer-file combinations rated under the incentive scheme that is being compared to the baseline and zero for loan officer-file combinations rated under the baseline, γ_i is a loan officer fixed effect, η_j is a loan file fixed effect and ε_{ij} is a stochastic error term. The baseline is the omitted treatment vector \mathbf{T}_{0ij} , which throughout the paper is low-powered incentives [20, 0, 10], paid immediately. We are interested in estimating the coefficients ϕ . We also include fixed-effects for the calendar week of the treatment, as the probability of assignment to treatments sometimes varied across weeks.

We estimate equation (5.1) using data on a total of 3,899 evaluations, representing 109 unique subjects across five treatments. Treatments were randomly assigned at the “session” level. Each session consisted of a loan officer visiting and evaluating six files, which she or he could do whenever the lab was open. Each set of six files included four accepted loans and two rejected loans. On every lab visit by a particular loan officer the treatment status was randomly assigned. All experiments reported in this paper were conducted between March and July of 2010.

Table 1 presents summary statistics, describing characteristics of loan officers. Randomization checks confirm that the observable characteristics of participating loan officers are not significantly different across treatments.

To test our hypotheses, we consider three groups of outcome variables: measures of decision and decision quality, measures of subjective risk assessment and measures of screening effort. To measure loan officer decisions and performance under alternative incentive schemes, we match the loan officer’s decision to the loan’s historical delinquency status, obtained from the bank’s internal data. We code a decision as correct, if a delinquent file was rejected, or a performing file was accepted. Similarly, we calculate the fraction of correctly sanctioned loans as the fraction of loans that ultimately performed that the loan officer sanctioned, and the fraction of correctly rejected files as the fraction of applications that were ultimately delinquent that were in fact rejected. To measure the loan officer’s subjective assessment of credit risk, we record the 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. Finally, to measure effort, we measure the number of pages of the file that the subject accessed.¹¹

5.1 Decisions and Performance

We first analyze how the provision of monetary incentives affects lending volume, defined as the share of loans accepted under each incentive scheme. The baseline incentive across all of our treatments corresponds to low-powered incentives. Figure 1 provides some simple stylized evidence regarding the predictions described in Section 3.

In Table 3, we report coefficients from regressions of the number of accepted files on each incentive scheme. The coefficient estimates measure the percentage decline in sanctioned applications relative to the origination piece rate baseline. We present results for each regression without any controls, with loan officer fixed-effects only, with loan file fixed-effects only, and with both loan-officer and loan-file fixed-effects. Results are generally invariant to the inclusion of either loan officer or loan file fixed effects. The results show that the structure of incentives has a strong economically and statistically significant effect on the number of loans made. Table 3, column (1) shows that high powered incentives yield roughly the same share of loans made. The switch from a low-powered incentive to an origination bonus increases the number of sanctioned files by about 10 percentage points. The share of loans accepted in the baseline treatment [20, 0, 10] is 70 percent, meaning an origination bonus increases loan approvals by approximately 14 percent.

We next turn to the quality of decisions under each alternative incentive scheme. Specifically, we consider four outcome measures: the share of correct decisions (performing loans accepted, delinquent and rejected loans not accepted¹²), the share of good files that were correctly accepted, the share of bad files that were not accepted, and the share of original rejected files that were rejected in the experiment. Table 4 summarizes our results.

We first note that the fraction of correct decisions in our sample is 67%, suggesting that the lending decision is quite difficult. Unconditionally, loan officers make the correct decision for good files 84% of the time; 18% of the time for bad loans; and 46% of the time for originally rejected files. This likely reflects the fact that many loans that were originally sanctioned looked good. The fact that apparently good loans may often default of course makes it more difficult to provide performance-based incentives.

¹¹ Going forward, we will also use the amount of time spent with a given file as a measure of effort. However, we recently discovered the software program was not correctly recording time, and hence do not use it in this version.

¹² Recall that a “rejected” loan is one that the lending institution found sufficiently bad that they declined to lend to the applicant.

The first three columns compare each incentive scheme to a benchmark. We first focus on column (1), which includes all loans. Relative to the low-powered incentive scheme, loans sanctioned under the high-powered incentive scheme are ten percentage points more likely to be correct, which is economically a very meaningful amount. However, the point estimate is not statistically significant. The origination bonus (in column (1)) has a positive and statistically significant effect, which at first may seem puzzling, since it would seem to generate overly lax lending.

Columns (2)-(4) clear up this mystery. In particular, the incentive schemes that reward lending without penalizing defaults lead to more “correct” decisions when loans are good, suggesting that for good loans, loan officers are too conservative under the low-powered incentive scheme. However, for bad and rejected loans, schemes that reward lending lead to fewer correct decisions. While statistically significant for bad loans with the [50, 0, 0] scheme, the point estimates are negative in columns (3) and (4) for all schemes that do not punish default. In contrast, only the high-powered scheme increases the share of good decisions for both good, bad, and rejected loans, although again these estimates are not statistically significant.

5.2 Screening Effort

We now turn to 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 two straightforward measures of screening effort. First, we record the fraction of the loan file the loan officer examines (our software records the amount of time each loan officer spends on each information tab.). Second, in a separate set of treatments described in greater detail below, loan officers are endowed with Rs. 108 at the beginning of the experiment, which they can either take home with them, or use to purchase pieces of the credit files they review. 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 this effort is generally unobservable in the real world, we do not tie bonus payments to the amount of effort spent.

Table 5 reports our estimates of the effect of incentives on screening effort, proxied by the fraction of each loan application reviewed. We find no statistically significant effects of incentive schemes on effort.¹³

5.3 Risk Assessment

Before participants made a decision to sanction or reject a loan, 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 officer's decision. That is, an applicant did not have to attain a minimum score to be considered for a loan. Using the resulting data, we can investigate how well the loan officer's subjective assessment of credit risk lines up with actual lending decisions under each incentive. This is interesting for at least three reasons: First, the loan officers' subjective risk-assessment can tell us whether incentives affect decisions directly or by altering the loan officer's subjective perception of credit risk. Second, if a loan officer is strongly incentivized on asset quality and stands to gain from a more discriminating analysis, the ratings tell us which indicators of expected credit risk are perceived as more salient for arriving at a correct decision. Finally, we can test for various types of strategic behavior induced by monetary incentives that may induce a discrepancy between loan officer's private assessment and the actual lending decision. In a set of separate treatments (not reported here), we impose a minimum required rating for a loan to be sanctioned and examine to what extent quantity incentives, such as an origination piece rate, cause loan officers to bias their reported credit ratings in response.

Table 6A reports risk ratings for each incentive scheme, with and without loan- and loan officer fixed-effects. The estimates suggest that relative to low-powered incentives, high-powered incentives cause loan officers to rate files much more conservatively. In contrast, incentive schemes that reward loans only if they perform, [50, 0, 0] and [100, 0, 0], lead to significantly higher risk ratings, on average.

In the next step, we disaggregate ratings and explore the effect of performance incentives on risk perception along five sub-categories of credit risk: personal risk, business risk, management risk, financial risk and and security risk. Our prior is that loan officers seeking to distort ratings will adjust the 'soft' criteria that have less objective benchmarks. For instance, "Business risk" is based on softer information, such as ratings (1-5) for: "intensity of competition"; "reputation in market" and "diversification of customer base". In comparison, "Financial risk", depends more on hard information, such as total debt burden, interest coverage ratio, and current ratio. The results are presented in Table 6B, columns (2) to (7). High-powered incentive schemes cause loan officers to shade down the more subjective business risk and management risk ratings; perhaps relative to our base model that rewards loan officers even for loans that don't perform, loan officers rating loans more cautiously are less likely to inflate subjective ratings. However, when officers seek to inflate the lending rating for performance bonuses, they appear to inflate scores across the board.

5.4 Deferred Compensation

The European Parliament recently approved a regulation limiting the amount of up-front cash bonus payments at banks to 30% of total performance compensation. We test the effect of the spirit of this regulation 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 both origination and low-powered incentives to deferred compensation, in which the loan officer may collect payment 3 months after the experiment is completed.¹⁴

We randomly assign loan officers to one of five treatments.

Name	Collecting information is:	Payment
T1-Base case	Free	Immediate
T2-Origination, Paid Now	Costly (Rs. 3 / panel)	Immediate
T3-Origination, Deferred	Costly (Rs. 3 / panel)	In 3 months time
T4-Low-powered, Paid Now	Costly (Rs. 3 / panel)	Immediate
T5-Low-powered, Deferred	Costly (Rs. 3 / panel)	In 3 months time

Panels A and B present results.

First, we note that columns (1) and (2) confirm the results from the previous experiments: relative to low-powered incentives, origination bonuses lead to more permissive lending, and higher ratings.

Columns (3) and (4) represent the key regressions for this treatment. First, there is a large and significant effect of making effort costly: the mean amount of time spent on an application under T4 (low-powered incentives with immediate payment) is sixty seconds less, and loan officers view 2.73 fewer information panels.

Second, by comparing the coefficient of T3 to T2, and of T5 to T4, we can estimate the effect of deferred payment on effort exerted. When payment is deferred, effort, as measured both by time spent, and number of tabs viewed, is lower. Two lines below Panel A test the hypothesis that $T3=T2$, and that $T4=T5$.

For the “origination bonus” treatment, we find that deferring compensation does not change behavior. In contrast, for the low-powered incentive schemes, we find strong evidence that

¹⁴ Deferred payment will be delivered to the loan officer to ensure she does not face any differences in transaction costs.

deferred compensation reduces the time spent evaluating files, and the amount of costly effort exerted. The size of the effect is large, representing approximately a *fifty percent* decrease in the amount of information viewed.

6. Discussion and Conclusion

In this paper, we analyze the underwriting process of new 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 sensitive to loan officer judgment. Our experimental design provides 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 scheme 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. Results show strong and economically significant effects of performance-based incentive schemes on screening behavior and risk taking. Incentives that penalize officers for bad decisions cause loan officers to sanction 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. 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, with the objective of improving the financial access of previously unbanked entrepreneurs.

The experiments in this paper represent the first step of an ambitious agenda to fully understand the loan underwriting process. To better understand incentives, the next version of this paper will include an additional range of linear and non-linear monetary incentives. We will also vary the role of career concerns by randomly informing some loan officers that their performance in the exercise will be reported to their immediate supervisor.

Second, we aim to understand the role of individual characteristics of loan officers in lending decisions, and how these characteristics interact with incentive schemes. This includes both demographic information, such as age, gender, and work experience, as well as indicators of risk preferences and career concerns collected through supplemental loan officer surveys. 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 sectors. Nor is it obvious what individual characteristics are associated with screening ability. Moreover, understanding the distribution of ability within

the banking sector, and how human capital is allocated, will aid in our understanding of the information processing production function.

Third, we hope to understand how individual characteristics interact with incentive schemes. The current policy debate tends to suggest banks should find a single “optimal incentive scheme,” which may overlook the fact that individuals with different discount rates or risk preferences may respond very differently to any given incentive scheme. By allowing loan officers to select their incentive scheme from a menu of options, we can also generate some of the first empirical evidence of the usefulness of incentive schemes as screening devices.

Finally, the software allows us to implement a much richer and more realistic information environment. In particular, we plan to augment selected loan files with video interviews from the applicants, as well as photographs of residential and business property taken by the financial institution at the time of the loan application. By varying the amount of soft information present in the loan, we can measure the incremental value of soft information in facilitating correct decisions. Moreover, by endowing loan officers with a budget (real money), and allowing them to “purchase” soft information (e.g., pay Rs. 20 to watch a video of the applicant), we can understand whether loan officers themselves make the correct trade-offs in allocating effort.

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FIGURES AND TABLES

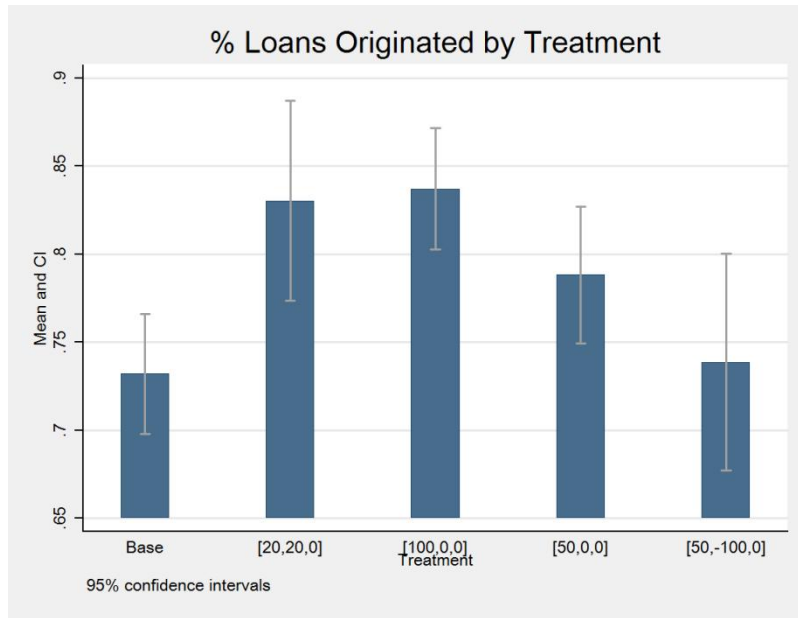


Figure 1: Loans Originated

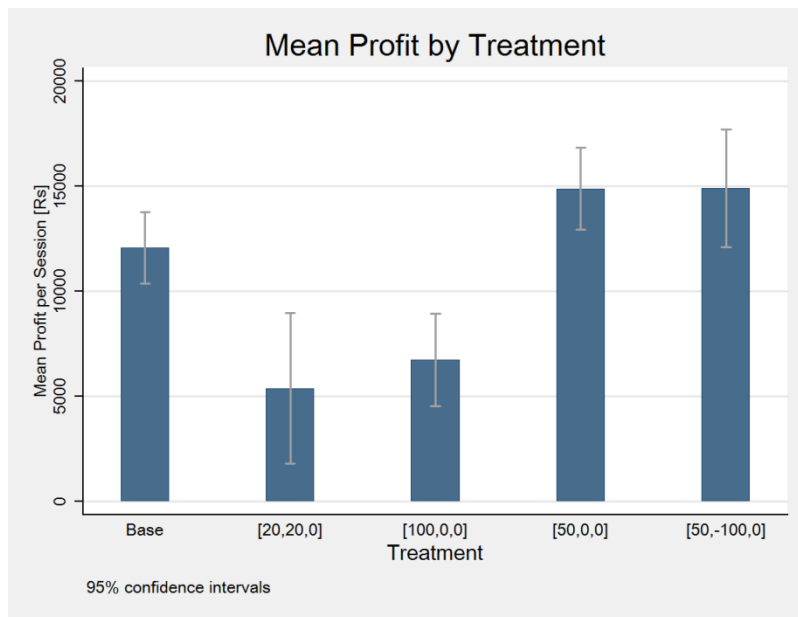


Figure 2: Profit of Lending Decisions

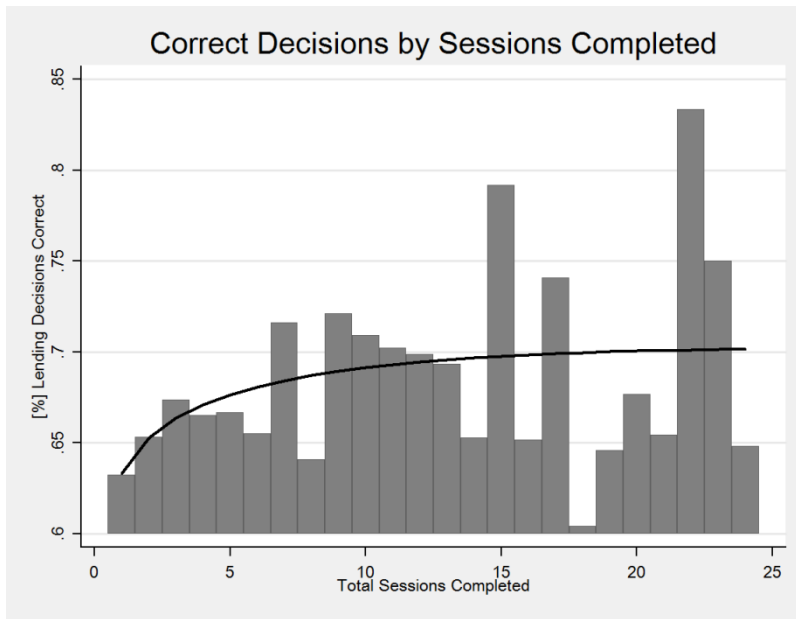


Figure 3: Learning – Correct Decisions

Table 1: Loan Officer Summary Statistics

	Mean	Median	StDev	Min	Max	10%	25%	75%	90%	N
Age	40.64	40	10.54	14	64	25	33	49	54	109
Male	0.87	1	0.34	0	1	0	1	1	1	109
Rank [1 Low - 4 High]	1.88	2	0.85	1	4	1	1	2	3	109
Tenure in Bank [Years]	16.66	13	11.07	0	38	1	10	26	31	109
Loan Officer Experience [Years]	7.39	5	7.30	1	27	1	2	10	20	83
Branch Manager Experience [Y/N]	0.47	0	0.50	0	1	0	0	1	1	83
Branch Manager Experience [Years]	4.10	3	3.42	1	15	1	1	5	9	62
Other Business Experience [Y/N]	0.53	1	0.50	0	1	0	0	1	1	109
Other Business Experience [Years]	3.78	1	6.67	0	35	0	0	5	10	109
Time Preference [Discount Factor]	0.58	0.71	0.30	0.00	0.83	0.00	0.56	0.83	0.83	57
Overconfidence Score	3.34	4	2.78	0	9	0	0	6	7	109
Altruism Score	4.49	4	1.76	1	7	2	3	6	7	55
Career Concerns	0.71	1	0.46	0	1	0	0	1	1	55

Table 2: Loan, Client, and Loan Rating Summar Statistics

Panel A: Loan and Client Characteristics

	Full Sample					Type = Perform					Type = Default				
	Mean	Median	StDev	Min	Max	Mean	Median	StDev	Min	Max	Mean	Median	StDev	Min	Max
Loan Amount (Rs '000)	188.33	150.00	85.12	100.00	500.00	192.32	150.00	87.59	100.00	500.00	171.43	141.13	71.39	102.27	400.00
Loan Tenure	34.2	36.0	8.8	10.0	48.0	33.1	36.0	8.5	10.0	48.0	38.9	36.0	8.4	15.0	48.0
EMI	8.846	7.536	4.512	2.626	29.750	9.342	7.917	4.471	3.300	29.750	6.745	6.198	4.063	2.626	24.260
Total income (Rs '000)	506.90	295.50	709.66	33.80	6512.50	528.04	300.00	730.04	35.00	6512.50	344.47	200.00	506.43	33.80	3000.00
Personal expenses (Rs '000)	14.19	11.00	18.64	2.00	289.43	14.17	11.00	19.44	2.00	289.43	14.30	10.70	10.88	4.30	52.00
Business expenses (Rs '000)	425.60	238.80	634.96	8.50	6081.00	446.03	251.50	651.78	8.50	6081.00	268.53	133.20	464.38	9.00	2740.00
Gross Profit (Rs '000)	707.05	317.48	2368.97	14.45	27474.80	466.58	302.45	450.17	14.45	2561.28	374.37	313.13	213.14	70.50	870.00
Total Debt Burden (Rs '000)	611.14	18.39	2086.75	0.00	23018.40	638.38	5.73	2247.02	0.00	23018.40	676.58	183.00	1179.62	0.00	5504.24
Total Monthly Debt Service (Rs '000)	16.53	3.51	46.68	0.00	500.92	16.89	2.90	50.16	0.00	500.92	19.07	6.87	27.12	0.00	110.35
Total Liabilities/Income (Rs '000)	0.04	0.02	0.10	0.00	1.43	0.04	0.02	0.10	0.00	1.43	0.06	0.04	0.07	0.00	0.28
Total Debt/Net Annual Income	0.72	0.00	2.03	0.00	19.18	0.69	0.00	1.91	0.00	19.18	1.02	0.27	2.93	0.00	15.29
Monthly Debt Service/Total Sales	0.04	0.01	0.08	0.00	1.00	0.04	0.01	0.08	0.00	1.00	0.07	0.05	0.08	0.00	0.28

Panel B: Loan Ratings

	Full Sample					Type = Perform					Type = Default				
	Mean	Median	StDev	Min	Max	Mean	Median	StDev	Min	Max	Mean	Median	StDev	Min	Max
Total Risk Rating [0 low - 5 high]	65.38	67.00	14.65	0	100	66.78	69.00	14.35	0	100	66.22	67.00	13.20	28	100
Risk Rating: Personal Risk [0 low - 5 high]	3.45	3.67	0.79	1	5	3.50	3.67	0.78	1	5	3.47	3.67	0.73	1	5
Risk Rating: Business Risk [0 low - 5 high]	3.31	3.40	0.75	1	5	3.39	3.40	0.71	1	5	3.36	3.40	0.68	1	5
Risk Rating: Management Risk [0 low - 5 high]	3.34	3.50	0.80	1	5	3.41	3.50	0.77	1	5	3.40	3.50	0.74	1	5
Risk Rating: Asset Position [0 low - 5 high]	3.20	3.00	0.92	1	5	3.28	3.00	0.91	1	5	3.21	3.00	0.87	1	5
Acceptances	0.79	1.00	0.41	0	1	0.84	1.00	0.36	0	1	0.82	1.00	0.39	0	1
Correct Decisions	0.67	1.00	0.47	0	1	0.83	1.00	0.37	0	1	0.18	0.00	0.38	0	1

Table 3: Share of Applications that Are Accepted

	Accepted (1)	Accepted (2)	Accepted (3)	Accepted (4)
Low-Powered Incentives (20 0 10)				
High Powered Scheme (50 -100 0)	-0.02 (0.07)	-0.04 (0.06)	0.03 (0.08)	0.00 (0.06)
Origination Bonus (20 20 0)	0.10 ** (0.05)	0.08 ** (0.04)	0.07 (0.07)	0.06 (0.05)
Performance Bonus (50 0 0)	0.09 *** (0.03)	0.10 *** (0.03)	0.12 *** (0.03)	0.13 *** (0.03)
Performance Bonus (100 0 0)	0.11 *** (0.03)	0.13 *** (0.03)	0.13 *** (0.04)	0.16 *** (0.03)
N	1566	1566	1566	1566
Loan Officer FE	No	Yes	No	Yes
Loan File FE	No	No	Yes	Yes

Table 4: Do Incentives Improve the Quality of Sanctioning Decisions?

	Correct Decision (1)	Correct Good (2)	Correct Bad (3)	Correct Rejected (4)
Low-Powered Incentives (20 0 10)				
High Powered Scheme (50 -100 0)	0.10 (0.07)	0.05 (0.08)	0.15 (0.23)	0.13 (0.13)
Origination Bonus (20 20 0)	0.08 * (0.04)	0.15 *** (0.04)	-0.15 (0.11)	0.04 (0.13)
Performance Bonus (50 0 0)	0.02 (0.03)	0.09 *** (0.03)	-0.07 (0.06)	-0.18 ** (0.08)
Performance Bonus (100 0 0)	0.05 (0.03)	0.14 (0.03)	-0.08 (0.07)	-0.16 (0.08)
N	1566	1041	231	294
Loan Officer FE	No	No	No	No
Loan File FE	No	No	No	No

Table 5: Do Incentives Affect Effort (Information Processed)

	Effort (1)	Effort Good Loan (2)	Effort Bad Loan (3)	Effort Rejected Loan (4)
Low-Powered Incentives (20 0 10)				
High Powered Scheme (50 -100 0)	-0.36 (1.08)	-0.27 (1.19)	0.34 (1.35)	-0.93 (1.87)
Origination Bonus (20 20 0)	0.00 (0.67)	0.08 (0.68)	0.94 (0.89)	-0.93 (1.79)
Performance Bonus (50 0 0)	0.22 (0.58)	0.34 (0.58)	0.16 (0.94)	-0.19 (0.71)
Performance Bonus (100 0 0)	0.37 (0.65)	0.59 (0.66)	0.29 (0.93)	-0.40 (0.82)
	1566	1041	231	294
Loan Officer FE	No	No	No	No
Loan File FE	No	No	No	No

Table 6: Do Incentives Distort Risk Ratings?

	Overall Rating (1)	Overall Rating (2)	Overall Rating (3)	Overall Rating (4)
Low-Powered Incentives (20 0 10)				
High Powered Scheme (50 -100 0)	-5.53 ** (2.41)	-3.08 (1.98)	-4.86 * (2.53)	-1.61 (1.95)
Origination Bonus (20 20 0)	-0.54 (1.96)	0.00 (1.56)	-0.63 (2.28)	0.56 (1.80)
Performance Bonus (50 0 0)	-0.03 (1.49)	1.78 ** (0.87)	0.65 (1.48)	2.58 *** (0.80)
Performance Bonus (100 0 0)	2.12 (1.97)	2.85 * (1.50)	2.12 (1.98)	3.51 ** (1.54)
	1566	1566	1566	1566
Loan Officer FE	No	Yes	No	Yes
Loan File FE	No	No	Yes	Yes

Table 6, Panel B: Do Incentives Distort Risk Ratings?

	Overall Rating	Personal Risk	Business Risk	Management Risk	Financial Risk	Security Risk
Low-Powered Incentives						
(20 0 10)						
High Powered Scheme	-1.61	-0.08	-0.16 *	-0.19 *	0.11	-0.16
(50 -100 0)	(1.95)	(0.06)	(0.08)	(0.11)	(0.09)	(0.11)
Origination Bonus	0.56	0.02	-0.03	-0.08	0.11	0.02
(20 20 0)	(1.80)	(0.07)	(0.08)	(0.11)	(0.09)	(0.09)
Performance Bonus	2.58 ***	0.11 **	0.16 ***	0.11 ***	0.15 ***	0.15 ***
(50 0 0)	(0.80)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Performance Bonus	3.51 **	0.24 ***	0.23 ***	0.20 ***	0.28 ***	0.29 ***
(100 0 0)	(1.54)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
	1566	1566	1566	1566	1566	1566
Loan File FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Effect of Delayed Bonuses on Decisions and Effort

	Accept (1)	Rating (2)	Time (3)	Tabs Viewed (4)	
Panel A					
T1-Base Case (200 10)					
T2-Origination, Paid Now (20 200)	0.14 *** (0.03)	3.86 *** (1.25)	-56.64 *** (12.24)	-2.69 *** (0.13)	-0.90 0.04
T3-Origination, Deferred (20 200)	0.10 *** (0.03)	5.99 *** (1.20)	-62.54 *** (11.74)	-2.72 *** (0.12)	-0.91 0.04
T4-Low-powered, Paid Now (200 10)	0.04 (0.04)	0.77 (1.43)	-55.39 *** (14.04)	-2.73 *** (0.15)	-0.91 0.05
T5-Low-powered, Deferred (200 10)	0.04 (0.04)	2.94 ** (1.49)	-108.10 *** (14.63)	-3.45 *** (0.15)	-1.15 0.05
	1278	1278	1278	1278	
Origination Bonus: immediate=deferred	0.27	0.09	0.64	0.80	
Low-powered: immediate=deferred	0.99	0.20	0.00	0.00	
Loan Officer Fixed Effects	No	No	No	No	
Loan File Fixed Effects	No	No	No	No	
Panel B					
	Correct (1)	Correct/Good (2)	Correct/NPA (3)	Correct/Reject (4)	
T1-Base Case (200 10)					
T2-Origination, Paid Now (20 200)	0.02 (0.04)	0.11 *** (0.03)	-0.17 ** (0.07)	-0.19 * (0.10)	
T3-Origination, Deferred (20 200)	0.02 (0.04)	0.08 *** (0.03)	-0.16 ** (0.07)	-0.07 (0.10)	
T4-Low-powered, Paid Now (200 10)	0.07 (0.04)	0.06 (0.04)	-0.02 (0.09)	0.06 (0.12)	
T5-Low-powered, Deferred (200 10)	0.03 (0.05)	0.05 (0.04)	-0.06 (0.08)	0.09 (0.12)	
	1278	868	223	187	
Origination Bonus: immediate=deferred	0.27	0.09	0.64	0.80	
Low-powered: immediate=deferred	0.99	0.20	0.00	0.00	
Loan Officer Fixed Effects	No	No	No	No	
Loan File Fixed Effects	No	No	No	No	