NBER WORKING PAPER SERIES

# INCENTIVIZING CALCULATED RISK-TAKING: EVIDENCE FROM AN EXPERIMENT WITH COMMERCIAL BANK LOAN OFFICERS

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Working Paper 19472
http://www.nber.org/papers/w19472

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2013

We thank the cooperating financial institution for providing us with the data on loan applications used in this paper. For helpful comments and suggestions, we thank Philippe Aghion, Andreas Fuster, Victoria Ivashina, Raj Iyer, Michael Kremer, Rohini Pande, Jose Liberti, Daniel Paravisini, Enrichetta Ravina, Andrei Shleifer, Antoinette Schoar, Erik Stafford, Jeremy Stein, and numerous seminar and conference participants. Samantha Bastian, Doug Randall, and Wentao Xiong provided excellent research assistance. Data from loan files, used in this experiment, were obtained under a Non-Disclosure Agreement from a financial institution. Financial assistance from the Kauffman Foundation, the International Growth Center, and the Harvard Business School Division of Faculty Support and Research, is gratefully acknowledged. None of the authors has a potentially relevant outside financial relationship. The opinions expressed do not necessarily represent the views of the World Bank, its Executive Directors, the countries they represent, or the National Bureau of Economic Research.

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NBER Working Paper No. 19472
September 2013
JEL No. D03,G21,J33

**ABSTRACT**

We use an experiment with commercial bank loan officers to test how performance based compensation affects risk-assessment and lending. High-powered incentives lead to greater screening effort and more profitable lending decisions. This effect, however, is muted by deferred compensation and limited liability, two standard features of loan officer incentive contracts. We find that career concerns and personality traits affect screening behavior, but show that the response to monetary incentives does not vary with traits such as risk-aversion, optimism or overconfidence. Finally, we present evidence that incentive contracts distort the assessment of credit risk, even among trained professionals with many years of experience. Loans evaluated under permissive incentives are rated significantly less risky than the same loans evaluated under pay-for-performance.

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# 1 Introduction

The effect of performance-based compensation on risk-taking is of fundamental importance in finance.[1] However, the precise mechanism through which financial incentives affect risk-assessment and decision making remains poorly understood. Existing research has established that bank lending is responsive to the external economic environment (see, for example, Dell'Ariccia and Marquez [2006] or Keys et al. [2010])[2] and, more recently, that agency problems within a bank may affect credit allocation (Liberti and Mian [2009], and Hertzberg et al. [2010]). By contrast, there is little evidence on individual responses to performance-based compensation, a key instrument banks may use to influence the decisions of loan officers tasked with making actual lending decisions.[3]

Linking compensation practices to lending decisions is difficult, for at least two important reasons. First, incentive structures are endogenously determined by financial institutions, yielding standard identification problems. Second, even setting identification challenges aside, the data typically available in observational studies, such as lending, interest income, and write-offs, are often insufficient to distinguish between competing hypotheses.

To surmount these challenges, this paper uses a high-stakes field experiment with commercial bank loan officers in India, that enables us to present direct evidence on the effect of performance-based compensation on risk-assessment and lending decisions. In the experiment, loan officers were paid to review and assess actual loan applications, making 14,675

[1]The impact of incentives on risk-taking has been cited as an key factor in several financial crises preceded by a lending boom. See Bebchuk et al. [2010], Fahlenbrach and Stulz [2012], Acharya et al. [2013] for a discussion of incentives and risk-taking in the run-up to the recent global financial crisis. Devlin [1989] and Gourinchas et al. [2001] highlight the role of employee incentives and supply side factors in the Latin American debt crisis. For a general discussion of incentives and risk-taking at banks, see also *"Crazy compensation and the crisis"*. Alan Blinder, The Wall Street Journal. May 28, 2009.

[2]For evidence on credit booms and screening incentives see also Dell'Ariccia et al. [2012]. Theoretical approaches have modeled variation in screening standards as a result of herding, business cycle factors [Kiyotaki and Moore, 1997], or limited screening capacity of banks [Berger and Udell, 2004].

[3]See Freixas and Rochet [2008] for a discussion of incentive problems specific to lending. For reviews of the literature on incentive compensation in firms see Baker et al. [1988] and Prendergast [1999].

lending decisions under exogenously assigned incentives. We pinpoint the relationship between compensation and lending decisions by exogenously varying the incentive contracts faced by loan officers and evaluate three classes of incentive schemes [i.] volume incentives that reward origination, [ii.] low-powered incentives that reward origination conditional on performance and [iii.] high-powered incentives that reward performance and penalize default.

While much of the literature on performance-based compensation in banking and finance has focused on incentives for risk-taking provided to top management,[4] this paper explores the hypothesis, often advanced in the aftermath of the global financial crisis, that non-equity incentives for loan originators, such as commissions, can play an important role in determining the fate of a bank's lending operation.[5] Indeed, providing appropriate incentives to employees at the lower tiers of a commercial bank's corporate hierarchy is a difficult problem: their very responsibility is to collect information that the bank cannot otherwise observe, making monitoring difficult. They enjoy limited liability, and may have different risk and time preferences than the bank's shareholders.

The design of our experiment closely matches the loan approval process of low- documentation loans in an emerging credit market, and has several features that are particularly well-suited for studying the question at hand. First, while still novel in finance, the use of randomized experiments has grown rapidly in other areas of economics, in large part because they allow clear tests of causal relationships. Our unique experimental approach, which brings professional loan officers with many years of experience in credit assessment into a controlled laboratory environment, allows us to track aspects of loan officer behavior that would normally be unobservable to a bank or econometrician and allows for the causal identification of the impact of monetary incentives on loan officer behavior.

[4]See Jensen and Murphy [1990] and Murphy [1999] for an overview of this literature.

[5]Acharya et al. [2013] note that the literature on executive compensation disagrees about the effect of performance pay on risk-taking and argues that these conflicting results could be due to an omitted factor, such as the impact of non-executive compensation on risk-taking.

Second, by design, our experiment focuses on the lending decision and allows us to isolate the impact of performance pay on the quality of initial screening from other channels that may affect lending, such as the collection of soft information or the degree of ex-post monitoring.[6] Finally, participants completed a set of standard psychological tests, similar to those used in the literature on managerial characteristics and decision-making (Malmendier and Tate [2005], Graham et al. [2013]). We use this information to shed light on the mechanism through which incentives affect loan officer decisions, and to benchmark the size of the effects. In particular, we examine whether monetary incentives affect lending decisions directly or through their interaction with personality traits, such as overconfidence, conscientiousness or risk-aversion.

We present three main results. Our first set of results documents the efficacy and limitations of performance incentives in lending. We provide evidence that the structure of performance incentives strongly affects screening effort, risk-assessment, and the profitability of originated loans. Loan officers who are incentivized based on lending volume rather than the quality of their loan portfolio originate more loans of lower average quality. By contrast, high-powered incentives that reward loan performance and penalize bad lending decisions cause loan officers to exert greater screening effort, reduce exposure to loans with higher perceived ex-ante credit risk, and induce significantly more profitable lending decisions while leading only to a small reduction in lending volume. Relative to a baseline treatment with low-powered incentives, high-powered incentives increase the probability that a bad loan is detected and increase profits per originated loan by up to 3.5% of the median loan size; in contrast, origination incentives lead to a substantial decline in the quality of originated loans and reduce profits per loan by up to 5% of the median loan size.

Building on these results, we explore a number of constraints, inherent to any incentive

[6]The distinction between screening, information production and ex-post monitoring is also a feature of the real lending environment that is being replicated by our experiment, where these tasks are carried out by separate employees, each facing their own wage schedule.

contract in lending, that may limit the efficacy of pay for performance. Consistent with the predictions of a simple model of loan officer decision-making, we find that deferred compensation attenuates the effectiveness of high-powered incentives. When incentive payments are awarded with a three month delay, our measures of costly screening effort decline by between 5% and 14%, and we document a corresponding but less pronounced decline in the quality of originated loans. Notably, we find that deferred compensation also moderates the negative effect of incentive schemes that emphasize loan origination over the quality of originated loans. Relaxing loan officers' limited liability constraint (similar in spirit to giving a loan officer equity in the loan) induces greater screening effort and leads to more conservative lending decisions, but has only a moderate effect on the profitability of originated loans.

Second, we demonstrate that performance incentives have important effects on loan officers' subjective perception of credit risk. We find that loan officers evaluating applications under performance contracts that provide strong incentives for approval systematically inflate internal ratings they assign to the loans they process. While internal ratings are strongly predictive of default under all incentive schemes, loan officers facing volume incentives inflate risk ratings by as much as .3 standard deviations, irrespective of the underlying asset quality. Since incentives affect both risk ratings and approvals, the loan book approved under a permissive incentive scheme may therefore be of poorer quality but, based on internal ratings alone, may in fact look less risky than a set of comparable loans approved under a more conservative incentive contract.

Third, we provide evidence on the interaction between loan officer characteristics and the response to performance incentives, using data from psychometric tests administered to a subset of the participants in our experiment. We show that loan officer characteristics have a strong effect on loan officers' baseline level of screening effort. In particular, we find evidence that career concerns are a key non-monetary determinant of loan officer behavior. However, personality traits show only a weak interaction with monetary incentives. This indicates that personality traits can be useful in identifying conscientious screeners, but are unlikely to affect individual performance differentially under alternative incentive schemes.

This paper contributes to several literatures. A growing body of research highlights the importance of incentives for the transmission and use of information in lending (Hertzberg, Liberti and Paravisini [2010], Qian, Strahan and Yang [2011], Berg, Puri and Rocholl [2012]). Most closely related to our study, Agarwal and Ben-David [2012] exploit a change in the compensation structure of a U.S. bank and show that volume incentives lead to greater risk-taking and a deterioration in loan performance.

Second, we contribute to the literature on incentive compensation and risk-taking. Existing research in this area has focused almost exclusively on risk-taking among CEOs and senior management (see Bebchuk and Spamann [2010], Bolton, Mehran and Shapiro [2010], Edmans and Liu [2011] and Fahlenbrach and Stulz [2012]). Mechanisms similar in their effect to equity compensation for senior executives have been proposed to align the incentives of employees at lower levels of a bank's corporate hierarchy with those of the bank.

Finally, our findings add to the literature on lending in informationally opaque credit markets. We examine the role of loan officer effort and risk-assessment in an environment of high idiosyncratic risk (see Petersen and Rajan [1994], Berger, Klapper and Udell [2001]). This is related to, but distinct from, the special role played by loan officers in collecting soft information, and monitoring borrowers following the disbursal of a loan.

While we feel that our setting offers important advantages –for example we are able to study lending decisions amounting to the allocation of approximately US$ 88 million in credit– there are also two limitations worth mentioning. First, this paper studies one specific lending model, often used in practice, where the loan officer's primary function is to screen loans, rather than to prospect for new clients, cross-sell other products, or gather soft information.[7] This allows us to devise a clean test for the impact of incentives that can

[7]The organizational form of the lending process is a distinct topic that is being explored in concurrent

rule out multitasking concerns, but naturally confines the scope of our analysis to the loan officer's traditional screening role (Freixas and Rochet [2008]). Second, while the information environment and lending process in our experiment match what's done in practice, one might be concerned that studying lending decisions in a lab may lead us to underestimate the role of career concerns and other longer term motivations that may influence behavior in a real lending environment. As we shall see, we do find evidence of career concerns and other reputational motivations. These should, however, be interpreted as lower bound estimates.

The remainder of the paper proceeds as follows. In Section 2 we discuss the basic incentive problem in lending. Section 3 describes the experimental design. Section 4 reviews the empirical strategy and presents our results. Section 5 examines the interaction between performance compensation and loan officer characteristics and Section 6 concludes.

# 2 Performance Incentives in Lending

The potential for excessive[8] and socially inefficient risk-taking in response to poorly designed incentive schemes has long been recognized. However, in many real world settings, first-best contracts may be difficult to implement, as they require easily quantifiable criteria against which to measure and reward performance. The basic incentive problem in lending arises from the fact that loan officers are tasked with allocating the bank's capital based on private information and risk-assessments that are not independently verifiable by the bank [Stein, 2002]. This generates significant scope for agency conflict within the lending institution and creates a strong rationale for the use of performance pay to align the risk and time preferences of the bank's employees with those of the institution.

work. See for example Paravisini and Schoar [2012].

[8]The literature does not provide a universally accepted definition of what constitutes "excessive" risk-taking. In the context of our experiment, we define excessive risk-taking with reference to the hypothetical first-best contract in which a loan officer would be made a fully liable residual claimant of the loans she originates. Excessive risk-taking denotes the case in which a loan officer with rational beliefs takes higher risk at a weakly lower rate of return than she would under the hypothetical first-best contract.

There are, however, several important constraints that generally preclude a bank from offering a first-best contract that would make a loan officer a fully liable residual claimant of the loans she originates. First, loan officer effort is typically unobservable. Second, loan officers are necessarily protected by limited liability, as they take decisions on large amounts of money, which typically far exceed the amount of any penalty a bank could enforce to deter bad lending decisions. Third, the risk and time preferences of loan officers are likely to differ significantly from those of the bank's shareholders. This may make it difficult to generate effort with deferred pay conditioned on loan outcomes, rather than with an immediate bonus. Finally, in a lending environment characterized by high aggregate *and* idiosyncratic risk, it is difficult to reliably identify idiosyncratic defaults, which further complicates the use of realized outcomes for the measurement of loan officer screening effort and performance.

Where banks provide performance incentives, loan officer compensation typically consists of a fixed base salary plus a performance component. This performance component may place weight on lending volume, loan performance, or a combination of the two.[9]

The debate on bank compensation has revolved around two main features of such incentive contracts: first, the incentive power of the contract, which is a function of the reward for good and the penalty for bad decisions, and determines the perceived cost of originating a loan that might become delinquent. Second, the often short time-horizon of compensation, which may lead loan officers to prioritize short-term gains over long-term loan performance.

Theoretical work on performance incentives in lending has been relatively scarce. Heider and Inderst [2012] develop a model of relationship lending and analyze the optimal contract when loan officers, in addition to their traditional screening role [Freixas and Rochet, 2008],

[9]The U.S. Department of Labor, for example, describes the structure of loan officer compensation contracts as follows: *"The form of compensation for loan officers varies.* [...] *Some institutions pay only salaries, while others pay loan officers a salary plus a commission or bonus based on the number of loans originated."* (See http://www/bls.gov/oco/ocos018.htm, as also cited in Heider and Inderst [2012]). Examples of specific compensation schemes that reward loan officers based on lending volume or loan performance are also discussed in Berg et al. [2012] and Paravisini and Schoar [2012].

also act as "salespeople", tasked with prospecting for new loans and producing soft information through the cultivation of lending relationships. They show that in this setting, the optimal contract is a function of the bank's competitive position, as well as the degree of private information the loan officer can conceal from her employer.

In contrast to this line of research, our experiment is set in a lending environment where loan solicitation and approvals are strictly distinct, such that loan officers approve loans with little or no contact with the borrower. This enables us to rule out multitasking concerns in the response to incentives. An additional advantage of this approach is that we can rank incentive contracts offered in the experiment with reference to the hypothetical first-best in which a loan officer would be made a fully liable residual claimant of the loans she originates.

The separation of information collection and loan approvals is common for a wide range of financial products, and especially prevalent in emerging markets where the small loan sizes, relative to the high fixed cost of screening, often rule out the use of an expensive relationship lending model that relies on repeated personal interaction with the client. This places greater importance on incentives at the time of the initial screening decision, which is the focus of our analysis.

In this paper, we study the impact of performance pay in lending in the context of an experiment with commercial bank loan officers in India. The design of our experiment builds on a simple model of loan officer decision making, outlined in the Supplemental Appendix,[10] in which loan officer behavior depends on both financial incentives and non-monetary repu-

[10] We follow, in particular, Levitt and List [2007], who propose a model in which an experimental subject optimizes a utility function that is additively separable in the monetary and non-monetary arguments: "The choice of action affects the agent through two channels. The first effect is on the individual's wealth [...], the second effect is the non-pecuniary moral cost or benefit associated with [the] action. [...] More generally, we have in mind that decisions which an individual views as immoral, anti-social or at odds with her own identity (Akerlof and Kranton [2000]; 2005) may impose important costs on the decision maker)" This model is sufficiently general to encompass a range of non-monetary motivations including career concerns, the desire for social status and more general reputational motivations. See also Prendergast [1999] and Bloom and Van Reenen [2011] for evidence from the literature on personnel economics, and Bandiera et al. [2011] on non-monetary incentives in field experiments with firms using real employees as subjects.

tational concerns. Specifically, we assume that in addition to monetary rewards, loan officers care about the possibility that their actions may affect others' inference about their type. This is the standard approach suggested by a growing literature on how to model behavior in experiments with real subjects (see Harrison and List [2004] and Levitt and List [2007]).

Our theoretical framework makes four basic predictions about the effect of performance pay on loan officer behavior: first, origination incentives, as often employed by commercial banks, lead to indiscriminate lending, low effort and high defaults. By contrast, high-powered incentives that reward profitable lending and penalize default result in greater screening effort, but more conservative lending. Second, deferred compensation reduces the power of performance-based incentives. Third, relaxing a loan officer's limited liability constraint, for example through a contract with a "claw-back" provision, unambiguously increases effort. Finally, effort under any contract is higher, and may be independent of monetary rewards, if loan officers have reputational concerns.

# 3 Experimental Context and Design

We designed a framed field experiment[11] that closely matches the underwriting process for unsecured small enterprise loans in India. In the experiment, loan officers recruited from the active staff of several commercial banks evaluate credit applications in the context of a controlled lab experiment under exogenously assigned incentives.

The files assessed in the experiment consist of real, previously processed loan applications. Each file contains all information available to the bank at the time that the loan was first evaluated. The distribution of loan files evaluated by loan officers in the experiment is matched to the distribution of good and bad loans participants would expect to see in a real lending environment. This distribution was elicited using a pilot survey of 30 loan officers

[11] We follow the classification of experimental designs proposed by Harrison and List [2004].

prior to the main experiment.

An especially attractive feature of this experimental design is that it allows us to draw on a population of highly experienced loan officers and observe their behavior and decisions to a level of detail that would be difficult to achieve outside a controlled laboratory environment. In the analysis, we use this feature of the experiment to estimate the causal impact of alternative incentive schemes, as well as the interaction of monetary incentives with measurable loan officer attitudes and personality traits. This allows us to provide causal evidence on the channel through which incentives affect loan officer behavior.

While lending decisions in the experiment were hypothetical, in the sense that all loans had been previously processed by a bank and their realized outcome had been observed, loan officers received only information that was available to the bank at the original time of application. Since we observe the performance of all evaluated loans, we were able to pay participants performance incentives, based on their lending decision and the realized outcome of the loan applications they approve. The experimental treatments vary the magnitude and the time horizon of these conditional payments to change the terms of the incentive contract faced by loan officers participating in the experiment.

One potential concern with our experimental design is that it might not appropriately account for the role of soft information in loan giving. We however note that the aim of our experiment is to isolate the impact of incentives on screening behavior and lending decisions. In order to do this, we were careful to choose a loan product whose risk profile is determined by the quality of the initial screening decision (rather than ex-post monitoring or soft information obtained through relationship lending).

We focus on lending decisions for 'mass market' loans to small businesses, as an example of a loan product for which sales and origination channels are strictly distinct. Loans of this type are sourced by sales agents in the field, who collect all necessary client information, which is then forwarded to the bank's loan officers for approval. Loan officers do not interact with the client directly, cannot conduct interviews, and have no other way of collecting soft information. By focusing on first-time borrowers, we remove the potential influence of soft information generated over time. This allows for a clean test that isolates changes in screening behavior from other channels through which incentives might affect lending. By the same token, our results should be interpreted with care when applied to an environment where loan officers and are incentivized on tasks beyond loan screening.

In order to ensure that monetary incentives in the experiment were perceived as salient, we calibrated expected payouts to the approximate hourly wage of the median participant, a public sector loan officer with ten years of experience in banking. The remainder of this section describes the database of loans used in the experiment, the population of loan officers and the experimental protocol.

## 3.1 Loan Officers

Loan officers were recruited from the staff of several leading private and public sector commercial banks in India. We report summary statistics for the population of participating loan officers in Table II, Columns [1] to [4]. The median loan officer in our sample is a public sector bank employee who is 35 years old, and has 10 years of work experience. In Table II, Columns [5] to [8] we report comparable characteristics from a sample of all loan officers from a major commercial bank in the region where our experiment takes place. The descriptive statistics indicate that our sample is quite representative of this reference population in terms of age, rank and experience. In addition to their participation in the experiment, loan officers completed a series of tests of attitudes and personality traits commonly used in the literature on psychology and behavioral economics. Summary statistics of these tests are reported in Panel B of Table II. Additional details about the measurement of loan officer attitudes and personality traits are provided in Supplemental Appendix A.

## 3.2 Database of Loans

As a basis for the experiment, we requested a random sample of loan applications from a large commercial lender in India and received 676 loan files. These loan files contain all information available at the time the application was first processed, and are matched with at least nine months of repayment history for each loan.[12] The information contained in each loan application can be grouped into the following categories, corresponding to the sections of the Lender's standard application format: (1) basic client information including a detailed description of the client's business, (2) list of documents and verification (3) balance sheet and (4) income statement. In addition, participants in the experiment had access to three types of background checks for each applicant: a site visit report on the applicant's (5) business, and (6) residence and (7) a credit bureau report.[13]

Our sample consists of uncollateralized small business loans to self-employed individuals, with a ticket size between Rs 150,000 (US$ 3,000) and Rs 500,000 (US$ 10,000).[14] We consider only term loans to new borrowers, many of whom are first-time applicants for a formal loan.[15] 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).

Based on the Lender's proprietary data on loan repayment, we classify credit files into performing and non-performing loans. Following the standard definition, we classify a loan as delinquent if it has missed two or more monthly payments and remains 60+ days overdue. To calculate the profitability of a loan, we subtract the disbursal amount from the discounted

[12]More than 90% of all defaults occur during the first five months of a loan's tenure, so that our default measure allows for a relatively precise measurement of loan quality.

[13]We focus on loan applications from new customers. A credit bureau report was therefore only available for 66% of the loans in our sample.

[14]To rule out vintage effects and ensure consistency in the initial screening standards applied to loans used in the experiment, we restrict our sample to loans originated in 2009 Q1 and 2009 Q2.

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

stream of repayments.[16] To achieve as representative a sample as possible, we also include a subset of files from clients who applied, but were turned down by the Lender. Throughout the analysis, we report results disaggregated by non-performing and declined loans and show that our results are unaffected by the classification of loans declined ex-ante by the Lender.

Summary statistics for the sample of loan files are reported in Table OA.II. Importantly, the last columns of the table indicate that loan files indeed contain information that makes it possible to infer loan quality, suggesting that there are returns to effort in this setting.

### 3.3 Experimental Protocol

The experimental procedure and presentation of information were designed to closely resemble the actual work environment of the representative loan officer.[17] [18] Incentive treatments, as described in Section 3.4, were randomly and individually assigned at the loan officer and session level. Loan officers were invited to an introductory session and then participated in up to 15 sessions of the experiment, in which they evaluated a set of six randomly assigned loans under a given incentive scheme. Within each session of the experiment, the sequence of loan files was randomly assigned,[19] 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. We chose this ratio to match the distribution that loan officers reported experiencing in their workplaces.

[16] We estimate the Lender's net profit per loan as the net present value of the disbursal plus repayments including interest, discounted by 8%, the approximate rate on Indian commercial paper between January 1 and December 31, 2009, and assuming a 10% recovery on defaulted loans.

[17] Harrison, List and Towe [2007] point out that laboratory behavior may not match field behavior when eliciting risk attitudes ("background risk"). In contrast to that study, we use within-subject variation, and the inclusion of loan officer fixed-effects may reduce the importance of heterogeneous perceptions of background risk from different subjects.

[18] The literature on experiments in economics has pointed out that Hawthorne effects might obscure behavior in experiments that occur under observation (see Levitt and List [2007] and Levitt and List [2011] for a discussion). Note that the only feature that changed in from session to session in our experiments was the compensation scheme, so that any constant "experimenter demand" effects would not affect our estimates.

[19] This was done to ensure that estimates of loan performance would not be biased by factors such as variation in the quality and extent of information contained in the application file.

At the start of each session, loan officers were assigned to an incentive treatment, received a one-on-one introduction to the incentive scheme in place and completed a short questionnaire to verify comprehension. Loan officers then began the loan rating exercise in which they were asked to assess a series of loan files, using a customized software interface. For every loan file under review, the loan evaluation software reproduced each section of the application on a separate tab on the loan officer's screen: this included a description of the applicant's business, balance sheet, trade reference, site visit report, document verification and credit bureau report when available. Each session of the experiment was scheduled to last one hour, although participants could finish early or late if they so chose.

While reviewing loan applications, participants were asked to assess the applicant's credit risk along 15 credit-scoring criteria adapted from the standard format of a leading Indian bank. Internal ratings range from 0 to 100 (with a higher score indicating higher credit quality) and were not binding for the loan officer's lending decision. The risk ratings serve three purposes. First, they add realism to the lab session, as completing a (non-binding) risk rating is a routine part of evaluating applications. Second, they allow us to elicit a measure of perceived credit risk that is not tied to loan officer compensation. Finally, internal ratings serve to assist the loan officer in aggregating information about the application in a systematic way. To ensure that internal ratings are an unbiased reflection of a loan officer's true risk-assessment, participants were reminded that internal risk ratings were not tied to monetary incentives and never reviewed by the administrating staff.

Loan officers were asked to evaluate loans based on their best judgment, but were given no information about the ratio of good and bad loans or the outcome of any particular loan under evaluation.

### 3.4 Incentive Treatments

To test the impact of performance pay on loan officer behavior, we exogenously vary three features of the incentive scheme faced by the loan officer: the incentive power of the contract, the time horizon over which performance incentives are paid, and the degree of limited liability enjoyed by a loan officer. We vary the power of the incentive contract by assigning loan officers to contracts that specify three conditional payments: a payment $\mathrm{w_P}$ made when a loan is approved and performs, a payment $\mathrm{w_D}$, made when a loan is approved and defaults and a payment $\overline{\mathrm{w}}$ that is made when a loan is declined.

Because the outcome of a loan is only observed with some delay, performance incentives, in practice, must be paid with a lag. In our setting, under the non-deferred payment scheme, incentives were paid immediately following an experimental session. In the deferred compensation scheme, incentive payments were delayed by three months.

Finally, we experimentally relax loan officers' limited liability constraint, by providing an initial endowment that the participant can lose if she approves non-performing loans. This mimics proposed 'clawback' schemes. Throughout the paper, we express experimental incentive contracts as as the vector $\mathbf{w} = [\mathrm{w_P}, \mathrm{w_D}, \overline{\mathrm{w}}]$. In addition to these three performance-based conditional payments, loan officers received an unconditional show-up fee of Rs 100 (US$ 2.25), each time they participated in a session of the experiment.

In order to ensure that participants perceived these conditional payoffs as salient, we calibrated the mean payout of experimental incentive schemes to approximately 1.5 times the hourly wage of the median participant in our experiment, a public sector credit officer with ten years of professional experience, an annual income of Rs 240,000 (US$ 4,800) and an approximate hourly wage of Rs 125 (US$ 2.5).

Because understanding the impact of performance pay on costly screening effort is a main objective of the experiment, half of our sessions included a 'costly information' feature. In this treatment condition, loan officers were given an initial information endowment of Rs 108. Under the 'costly information' condition, loan officers were able to review only basic client and loan information items for free[20] and were charged Rs 3 per section for as many of the remaining loan file sections as they chose to view. In these sessions, loan officers received their remaining information endowment at the conclusion of the session, in addition to any incentive payments. Table I summarizes the experimental incentive schemes.

We use the random assignment of incentive contacts to test the following predictions. First, origination incentives will lead to greater risk-taking. Indeed, under this type of incentive, purely rational and profit-maximizing loan officers should indiscriminately approve all applications, and exert no effort to screen out bad applications.[21] 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.[22] Third, high-powered incentives will induce more conservative lending behavior by increasing the utility cost of making a bad lending decision. Fourth, if a loan officer's discount rate is greater than zero, the amount of effort induced by deferred compensation will be less than the amount of effort induced by an immediate bonus.

Finally, if loan officers are intrinsically motivated, or responsive to reputational considerations or career concerns, they may invest in screening even when such effort will not yield additional remuneration.[23]

[20]Two out of nine sections of the loan application could be viewed for free. This included the basic customer profile and the list of verified documentation provided.

[21]It is of course possible that financial incentives interact with loan officers intrinsic motivation. If this is the case, our experiments measure the combined effect of a 'classical' increase in effort, along with any changes in effort due to intrinsic motivation. This is the policy relevant parameter.

[22]Note that this implies that the effort exerted under these treatments can be ranked B > A > C.

[23]Theoretical work has also suggested that monetary incentives may crowd out intrinsic motivation. However, a recurring theme in this literature is that some very restrictive conditions need to be fulfilled for "incentive crowding" to occur. Benabou and Tirole [2003] for example note that incentive crowding requires the employer (bank) to have an information advantage over the employee (loan officer). We believe that this is unlikely to be the case in the setting we study.

# 4 Empirical Strategy and Results

Since treatment status was randomly assigned, our empirical strategy is straightforward and we estimate regressions of the form:

$$y_{il} = \sum_{k=1}^{K-1} \beta_k \mathrm{T}_{ilk} + \theta_i + \theta_l + \zeta' \mathbf{R}_{il} + \xi' \mathbf{X}_{il} + \varepsilon_{il} \tag{1}$$

where $y_{il}$ is the outcome of interest for loan officer $i$ and loan $l$, $T_{il}$ is a vector of treatment dummies for the incentive schemes being compared to the baseline. In all regressions, we use the low-powered baseline incentive $\mathbf{w}_{\mathrm{B}} = [20, 0, 10]$ as the omitted category. We additionally control for loan officer fixed effects, $\theta_i$, loan file fixed effects $\theta_l$, and individual controls $\mathbf{X}_{il}$, including loan officer age, seniority, rank, education, and include dummies for whether the loan officer has management and business experience. Finally, the experiments took approximately one year to complete, and not all incentive schemes were eligible to be assigned in any given session. Hence, our regressions include a set of fixed effects $\mathbf{R}_{il}$ to control for these randomization strata. Standard errors are clustered at the loan officer-session level, the same level at which the treatment is assigned.

Our dataset includes 14,369 lending decisions, representing 206 unique subjects, with three key treatment conditions: (1) Low-powered incentives, which we use as the baseline throughout the empirical analysis; (2) High-powered incentives, which reward loan officers for approving loans that perform and penalizes the origination of loans that default; and (3) Origination bonus, which rewards the loan officer for every originated loan.[24]

In addition to these incentive vectors, we vary conditions under which incentives are paid. In 369 randomly selected sessions (2,214 loan evaluations), we defer incentive payments by 3 months, rather than paying immediately. In further 163 sessions (978 evaluations), we relax

[24]Regressions using all data we collected, which includes the performance bonus schemes which pay only if a loan performs, along with the appropriate treatment dummies, are reported in the Supplemental Appendix.

the participant's limited liability constraint by providing an initial information endowment of Rs 200 (US$ 4.5), which can be lost if a loan officer makes a series of unprofitable lending decisions. Finally, in 137 sessions (3,638 loans), we provide loan officers with an initial information endowment of Rs 108 (US$ 2.25), which they may spend to sections of the loan file. Table I summarizes the sample sizes by treatment condition. Table OA.I in the Supplemental Appendix reports a test of random assignment.

To test our hypotheses, we consider three primary groups of outcome variables: (i) measures of screening effort, (ii) measures of subjective risk-assessment, and (iii) lending decisions (actual risk-taking) and the resulting profitability of originated loans. We construct two measures of screening effort: the number of credit file sections reviewed by a credit officer; and the amount of money spent on reviewing additional information under the costly-information treatment. To measure risk-assessment and risk-taking, we record internal risk ratings assigned to each loan. Finally, to evaluate loan officer decisions and performance, we match the loan officer's lending decision to the actual profitability of the loan to the financial institution.

## 4.1 Descriptive Statistics

Before turning to the main analysis, we report descriptive statistics of loan evaluations during the exercise. We first verify that the experimental task is meaningful, in the sense that it is indeed possible for loan officers to infer credit risk based on hard information contained in an applicant's loan file. To do this, Table OA.II in the Supplemental Appendix presents mean comparisons of loan application information for performing and non-performing loans. There are a number of differences in hard information characteristics that help distinguish ex-post performing from non-performing loans. In particular, borrowers who defaulted on their loans had substantially lower revenue, younger businesses, higher ratios of monthly debt service to income, compared to borrowers who remained current on their obligations. Overdues on credit reports also predicted default. Higher-quality borrowers reported higher levels of debt, consistent with the common observation of low-quality borrowers being excluded from formal credit markets.

Table OA.III reports summary statistics of loan evaluations by loan type and incentive. We note the following. First, even for a group of highly experienced loan officers, making profitable lending decisions in this lending environment was not a trivial task. On average, loan officers approved 75% of all loans evaluated in the experiment and made correct lending decisions in 65% of all cases. Lending volume responds dramatically to incentives. Lending decisions were, however, profitable under all incentive schemes in the experiment and would have earned the bank an average net present value of US$ 240 (5.9% of the median loan size) per originated loan. Identifying performing loans was substantially easier than identifying non-performing loans or loans that were rejected by the Lender ex-ante. Changes in the incentive power of the contract were especially effective in improving loan officer's success in detecting non-performing loans, and these patterns are directly reflected in the profitability of loans approved under alternative incentives (Column [6]).

Table OA.III Column [2] describes the number of sections a loan officer reviewed prior to making a decision, while Column [3] gives this number for only the subsample which was charged to see additional sections from the loan file. Virtually all loan officers study the basic information and borrower profile sections. However, some chose to reject or accept a loan without viewing the entire application, particularly when the incentive scheme did not reward higher-quality screening.[25]

In addition to observed lending decisions, we analyze loan officer risk assessment, as measured by the rating each loan officer gave to each loan. Since ratings themselves were not incentivized, one might wonder whether these ratings contain useful information. To

[25]When information was costly, loan officers were most likely to review sections of the loan file that contained basic financial information, such as income statements and balance sheet information, and much less likely to pay for additional sections of the file such as site visit reports (results not reported in table).

address this concern, Table OA.V reports tests in which we use internal ratings to predict loan approvals and performance. The results show that loan officer assessments of credit risk are a meaningful and strongly significant predictor of actual lending decisions, the probability of default and the profit of loans evaluated in the experiment. This is true for the overall rating as well as its sub-components measuring perceived personal and financial risk.[26]

Since loan officers complete multiple sessions, one might wonder whether loan officers learn over the course of the study. An affirmative answer might be cause for concern, given that our average loan officer has more than ten years of experience in lending. To verify that learning over the course of the exercise poses no threat to the validity of our results, Figure 2 plots the average fraction of correct decisions and average profit per originated loan as a function of the number of completed sessions. These demonstrate no learning effect, a result confirmed by regression results in Table OA.IV.

## 4.2 Incentivizing Screening Effort

We first analyze the effect of incentives on screening effort. Intuitively, performance incentives can affect the quality of lending decisions if they induce a loan officer to choose higher screening effort, translating into a more thorough evaluation of available information. The design of our experiment provides us with a straightforward measure of screening effort. Specifically, we record how many of the ten sections of the credit file the loan officer chooses to review before making a decision. In a separate set of sub-treatments meant to make the effort trade-off even more stark, we charge loan officers Rs 3 for each section of the loan dossier beyond what would be available on the application form.[27] As human subject considerations precluded an experimental design in which loan officers would pay to participate,

[26]Figure 3 shows the distribution of ratings for performing and non-performing loans, respectively. A Kolgomorov-Smirnov test rejects the equality of these distributions at the 1% level.

[27]Available for free were basic applicant details and list of provided documentation. Loan officers paid to view income statement, balance sheet, site visit reports, and trade and credit reference checks.

we provide each loan officer with an initial information endowment of Rs 108 (approximately US$ 2.25 per experimental session). Participants could choose not to pay to view additional tabs, in which case Rs 108 would be paid to them at the end of the session, in addition to whatever show-up and incentive payments they earn. This information cost was not trivial: purchasing access to all six tabs would cost close to the maximum payout of 20 under the low-powered and origination incentive schemes. We use the amount spent to view loan sections as a second measure of screening effort, capturing the notion of costly information. Because screening effort is not observable to the bank, we do not tie bonus payments to measures of observed effort.

Table III reports the effect of performance pay on screening effort, measured by the number of loan file sections reviewed when the only cost of effort was the loan officer's time (Columns [1] and [2]), as well as when the loan officer was required to pay to view additional tabs (Columns [3] and [4]). High-powered incentives significantly increase screening effort. On average, loan officers facing high-powered incentives viewed .4 additional tabs of information when there was no charge to view tabs (the mean number of tabs viewed was 5.06 when information was free, and 3.99 when information was costly). When information was costly, high-powered incentives had an even stronger effect, increasing the average number of tabs viewed by .8-1.2. These effects are statistically significant across all specifications. Interestingly, we do not observe effort to be significantly lower when loan officers face origination bonuses, although the standard errors are not small enough to rule out meaningful effects. These results confirm that loan officers respond strongly to monetary incentives, and suggest that performance pay can incentivize effort in the review of borrower information.

## 4.3 Risk-Assessment and Risk-Taking

How do performance incentives affect the perception of credit risk and actual risk-taking? We measure loan officers' subjective risk assessment of credit risk using the non-binding internal risk-ratings that participants were asked to complete while evaluating loans.[28]

In Table IV we use these internal ratings to explore the effect of incentives on the perception of credit risk. We find strong evidence that the structure of performance incentives distorts the subjective assessment of credit risk. Loan officers facing incentives that reward loan origination inflate internal ratings by as much as .16 standard deviations. In the specification with loan officer and loan fixed effects (Table IV, Column [2]), we see that the size of the coefficient increases in proportion to the incentive that is placed on origination.

There are two interpretations that are consistent with this finding. Consider a model in which loan officers screen to detect negative signals about a potential borrower. A reduction in effort would result in fewer negative signals, and higher loan ratings. An alternative possibility, which we cannot rule out is that loan officers may fear harm to their reputation if they approve a loan they have rated poorly, and therefore inflate ratings of loans they are going to approve. Finally, our findings are also consistent with a behavioral view of risk-assessment, which is outside the scope of our model: loan officers may change their perception of credit risk if they are not comfortable thinking that the loans they wish to approve under prevailing incentives are indeed of poor quality. This "wishful thinking" effect has been discussed extensively in connection with subprime lending in the United States (see e.g. Barberis [2012]) and documented in lab experiments (Mayraz [2012]). While our experiment does not allow us to disentangle the degree to which each of these forces is at work, an important implication of our results is that irrespective of the underlying mechanism, the same set of clients is judged as collectively less risky when the bank offers

[28] To obtain an unbiased measure of perceived credit risk, loan officers were reminded that risk-ratings were not tied to compensation, and would not be reviewed by the lab staff or the loan officer's employer.

an incentive scheme that places greater emphasis on lending volume.

We next turn to the effect of performance pay on risk-taking. Because the realized outcome of a loan may be a poor proxy of the ex-ante riskiness at the time a loan is originated, we construct a measure of ex-ante risk, by averaging the internal ratings of all loan officers who observed a given file under the baseline incentive. We call this the "loan's average rating." We also calculate the coefficient of variation for the baseline internal score, which is a measure of the degree of disagreement of loan officers about the riskiness of the loan. If high-powered incentives encourage more discerning lending decisions, they will lead loan officers to approve loans with higher average rating and a lower variance. (Indeed, in our data set, the coefficient of variation is strongly correlated with default.)

Table V tests this hypothesis. Rather than using the loan outcome, which is a noisy measure and depends on idiosyncratic risk, we take advantage of the fact that we had over 100 loan officers rate each loan. We therefore define two measures of the riskiness of a loan, based on the ratings given by the loan officers who evaluated loans under the baseline, low-powered incentive scheme. The first measure is simply the mean risk rating. The second is the coefficient of variation of the risk rating, which measures the degree of ex-ante disagreement about the quality of a loan.

In the regressions in Table V, we restrict the sample to loans which a loan officer approved; thus the coefficients give the average risk rating of loans approved under a particular incentive scheme. We find that high-powered incentives lead to more conservative lending, though this result is significant only for the measure of business and financial risk (Columns [5] and [6]). We also find that high-powered incentives cause loan officers to shy away from loans that are risky in the sense that there is greater ex-ante disagreement about the interpretation of information contained in the loan file, as reflected in greater variance of a loan's baseline risk rating. Loans approved under high-powered incentives are characterized by a significantly lower coefficient of variation of their baseline rating.

## 4.4 Lending Decisions and Loan-Level Profit

In Table VI, we turn to the impact of performance pay on lending decisions and loan level profit. We find that loan officers facing compensation schemes that do not penalize default are dramatically more likely to originate loans (Columns [1] and [2]). Compared to the baseline condition, high-powered incentives lead to only slightly more conservative lending decisions, with the share of loans approved dropping by between 3.6 and .04%. This is a small effect relative to the mean acceptance rate of 71% under the baseline. Incentive schemes that reward origination, on the other hand, result in a dramatic increase in the probability of approval. Under the origination bonus treatment, loan approvals increase by approximately 8 percentage points, statistically significant at the 1% level. The probability of approval increases monotonically for the two repayment bonus incentives, with the probability of approval increasing by 9–13.5 and 12.2–15.4 percentage points, respectively.

Of course, incentivizing more or less lending is relatively easy; the more interesting question is whether incentives can make loan officers more discerning. Table VI, Columns [3] and [4] show that laxer incentives increase the fraction of good loan clients who are approved, roughly in proportion to the overall effect on lending. We find a dramatically different pattern for non-performing loans: loan officers facing the high-powered incentive scheme are 11 percentage points less likely to approve these bad loans, a result that is significant at the five percent level in column [5], despite the smaller sample size. In contrast, we find large increases in the fraction of non-performing loans approved under an incentive scheme that does not penalize poor screening decisions. The pattern is similar for the sample of loans that were initially rejected by the bank, though the statistical significance of the high-powered incentive effect is lost.

In Table VI, Columns [9] to [12], we study the effect of performance pay on the profitability of bank lending. Our first measure is the net present value to the lender of repayments, less the amount disbursed, restricting the sample to loans approved by our experimental subjects.[29] This measure is relevant for a lending institution that seeks to maximize average profitability per loan made, such as a capital-constrained lender. Columns [9] and [10] show that high-powered incentives dramatically improve the profitability of lending, raising profit per loan by US$ 149 to US$ 176 per loan, approximately 5% of the median loan size. The final two columns of Table VI consider profit per screened loan, setting the NPV of a loan that is rejected by an experimental subject to zero. This measure makes most sense for a lender whose lending opportunities may be limited and may face difficulties sourcing additional clients. Again, we find that high-powered incentives improve profitability by roughly similar magnitudes, though the result is only statistically significant in the specification with loan officer fixed-effects.

In our setting, the net interest margin is quite high (around 30%), so one might be concerned that high-powered incentives lead loan officers to behave too conservatively, declining profitable loans. In fact, we observe that high-powered incentives improve the quality of origination, and are therefore likely a profitable proposition from the bank's perspective, even when screening costs, reduced volume, and the cost of the incentive payments themselves are taken into consideration.

## 4.5 Deferred Compensation

Efforts to regulate the compensation of loan originators have often focused on the alleged "short-termism" present in many performance contracts in banking and have therefore aimed at extending the time-horizon of incentive payments. If loan officers have higher discount rates than shareholders, however, deferred compensation will blunt the effect of incentives.[30]

[29] Because we do not observe the outcome of loans that were originally rejected by the lender, we do not include these loans in our profit calculations.

[30] One need not assume loan officers are impatient: credit-constraints or concern about separation from employers could also cause loan officers to discount future payments at high rates.

In this subsection, we test how the effects of incentive payments vary when the time horizon of payouts is changed. It is worth noting that any compensation that varies with loan repayment must be paid with some delay, as it takes time to observe whether loans perform or not. The intent of our experimental treatments is to vary the extent of this delay in performance-based compensation. We are primarily interested in understanding whether deferred compensation weakens incentives for costly screening effort. We therefore restrict attention to the subset of "costly information" treatments, in which loan officers pay to access additional sections of the loan application. We operationalize the concept of deferred compensation by comparing loan officer behavior under immediate performance pay (for low-powered, high-powered and origination incentives) to behavior under a series of treatments, in which incentive payments were awarded after a period of 90 days.[31]

Table VII presents the results of the deferred compensation intervention. In Panel A, we report the effect of deferred compensation on screening effort. Panel B reports on the effect of deferred compensation on risk-taking, and treatment effects of deferred compensation on loan-level profits are reported in Panel C. Note that in contrast to the previous tables, the omitted category and relevant basis for comparison here is the low-powered treatment with costly information. At the foot of the table, we report t-tests comparing the effect of immediate versus deferred compensation. Consistent with the predictions of our model, the results show that deferred compensation significantly weakens the impact of high-powered incentives. This is most apparent in the effect of deferred incentives on screening effort, as measured by loan sections purchased (Table VII, Columns [3] and [4]). In Column [3], the difference between immediate high-powered incentive payments and the exact same payments deferred 90 days is large, [1.225 - (-.454)], and significant at the 1 percent level. While

[31] Note that our estimates do not differentiate between the pure effect of deferring incentive payments and the lower real value of the payment at a future date. The setup of our treatments assumes that the relevant comparison in a real world compensation contracts is between the nominal value of payment today versus the same payment at a future date.

high-powered incentives drive loan officers to lend more conservatively (Columns [5] and [6]), deferring those same payments attenuates this effect. High-powered incentives lead loan officers to shy away from loans that appear riskier ex-ante, irrespective of whether the high-powered incentives are deferred (Columns [7] and [8]). Finally, the point estimates of profitability are lower for deferred weak (baseline) incentives, as well as the high-powered incentives, though the difference is significant at the 10% level only for weak incentives.

## 4.6 Relaxing Limited Liability

In the same way that banks benefiting from deposit insurance and other implicit guarantees may be tempted to take high-risk low-NPV gambles, loan officers seeking to maximize their variable compensation may be tempted to take excessive risks due to the fact that they are protected by limited liability. To test how the presence of limited liability, an inherent characteristic of incentive contracts for loan originators, affects loan officer behavior, we randomly assigned loan officers to a treatment that relaxed the officer's limited liabity constraint. In this treatment, participants received an endowment of Rs 200 (US$ 4.5) at the beginning of each session, which was theirs to take home unless their incentive payments for the session were negative. The worst outcome for a loan officer would be to approve two bad loans and decline four good loans under high-powered incentives, in which case incentive payments would be Rs -200. The endowment therefore completely relaxed the limited liability constraint for the session.

Table VIII presents the results. We find evidence to suggest that relaxing limited liability indeed increases loan officers' screening effort (Columns [3] and [4]), though the differences are not statistically significant. Surprisingly, loan officers approve loans that appear to be on average lower quality (Column [5]) when limited liability is relaxed. When taking lending decisions, loan officers are more conservative without limited liability, though the size of this difference is modest (the difference in coefficients in Column [7] is 2.9 percentage points) and not statistically significant. Taken at face value, these results suggest that ensuring loan officers have more skin in the game has only modest effects on effort and the profitability of lending decisions. Note, however that in a loan officer's real work environment 'unlimited' liability may include career considerations and the possibility of losing one's job. In our experiment, we only partly capture these non-pecuniary factors, so that our results should be interpreted as lower bound estimates.

# 5 Do Loan Officer Characteristics Matter?

The analysis so far documents that the structure of performance pay has important effects on loan officer behavior. However, individual ability and personality traits may play an important role in determining how loan officers respond to incentives.

In this subsection, we use loan officer characteristics to explore the mechanisms by which incentives affect behavior, and to compare their relative importance. We proceed in three steps. First, we benchmark the effect of performance pay against the heterogeneity in performance we observe absent such variation in monetary incentives. Second, we test whether reputational motivations and career concerns can explain heterogeneity in effort, and document the size of the effect. Finally, we examine whether financial incentives interact with loan officer personality traits to determine screening behavior: are greater financial rewards, for example, less effective in eliciting effort from risk-averse individuals?

We are able to answer these questions because our data collection efforts included a detailed elicitation of loan officer characteristics and personality traits, including two widely used personality tests: the 'big five' personality test (John et al. [1991]) and the 'LOT-R' life orientation test (Scheier et al. [1994]). While these tests are widely used, and a small literature has established that individual heterogeneity affects management decisions,[32] there is little work that systematically links employee personality traits to financial decisions. We are aware of only one study in the finance literature, Graham et al. [2013], which uses psychometric tests to link the personality traits of senior executives to firms' financial decisions.

We complement this work in several ways. We show that personality traits are an important determinant of employee behavior, and explain variation in effort, even in a setting without explicit financial incentives. Second, an important finding in Graham et al. [2013] is that growth firms employ less risk-averse executives, suggesting endogenous matching between firm and employee. This, however, leaves open the question whether empoyees with different personality traits vary in their response to incentives. We are able to address this question using exogenous variation in incentive contracts induced by our experiment.

The most direct test for individual heterogeneity is a joint test of significance of the loan officer fixed effects from regression 1. We reject the hypotheses that loan officer heterogeneity does not affect screening effort at the 1 percent level (F-Statistic 71.98, with $N$=204 degrees of freedom). The magnitude of loan officer effects is economically significant, with officers at the 75th percentile of the effort distribution viewing approximately 45 percent more tabs than officers at the 25th percentile of the distribution. This effect size is large, in fact much larger than the increase in effort observed when loan officers transition from baseline to high-powered incentives. This variation helps explain why we observe screening effort even when loan officers face no financial incentives. It also suggests that even in settings where monetary incentives 'work', their efficacy may be bounded by fixed personality traits.

The decision to exert screening effort is likely to depend on more than compensation policy alone: even in settings without explicit monetary incentives, reputational concerns and the prospect of promotion may motivate employees. Our next test examines whether reputational concerns drive screening behavior, by examining whether individuals whose

[32] See Bertrand and Schoar [2003], Malmendier and Tate [2005] and Landier and Thesmar [2009].

characteristics indicate stronger reputational concerns behave differently. To do this, we estimate regressions of the form:

$$y_{il} = \sum_{k=1}^{K-1} \beta_k \mathrm{T} + \sum_{l=1}^{L} \gamma_l g + \sum_{k=1}^{K-1} \sum_{l=1}^{L} \delta_{kl}(T * g) + \theta_i + \theta_l + \zeta' \mathbf{R}_{il} + \xi' \mathbf{X}_{il} + \varepsilon_{il} \tag{2}$$

where $g$ is a personality trait, $\mathbf{X}_{il}$ is a control vector, which includes loan officer age, rank, gender, education, business experience, dummy variables for branch manager experience and employment at a private sector bank, $\mathbf{R}_{il}$ is a matrix of treatment conditions and all other variables are as previously defined. We consider both the main effect of each personality trait, as well as their interaction with the exogenously assigned monetary incentives. The dependent variable is always effort, which is measured by the number of sections of the loan file that the loan officer reviews. Columns [1]–[4] include all observations, while columns [5]–[8] are restricted to the sample of observations in which loan offers faced an explicit monetary cost for viewing additional sections of the loan file.

We first consider the possibility that loan officer behavior is driven by career concerns –a special type of reputational motivation, which would imply that effort is a decreasing function of age. Consistent with the career concerns hypothesis, Panel A of Table IX shows that, ceteris paribus, older loan officers exert less effort. Taking the point estimate from column [5], a loan officer close to retirement (aged 60) will review .36 fewer loan file sections than a 30-year old officer. This represents a ten percent reduction in effort. The presence of career concerns can also explain why loan officers are motivated to exert effort and make appropriate lending decisions even in the absence of explicit financial incentives. The second entry of Table IX, Panel A examines whether loan officers from private sector banks behave differently than those employed by public sector banks. Private banks are likely to be more meritocratic and offer faster promotion paths so that the returns to demonstrating one's type may be higher. Similarly, private banks may attract employees who are more responsive to implicit career incentives. Both mechanisms would suggest stronger career concerns, and imply that private bankers exert greater baseline effort when compared to their public sector counterparts. We find that this is indeed the case: private sector loan officers exert greater baseline screening effort under any monetary incentive scheme.

Second, using data from surveys and psychometric tests, IX, Panel B examines how loan officer behavior varies with fixed personality traits. We find that personality matters: individuals who are risk-averse, altruistic, or state that they wish to live up to personal and professional expectations exert significantly higher effort under any monetary incentive. By contrast, loan officers who are overconfident[33] screen significantly less. Personality also affects risk-ratings and the ability to correctly identify good loans. Optimistic loan officers rate loans significantly higher. Risk-averse loan officers are significantly more likely to approve non-performing loans while the opposite is true for impatient loan officers: a loan officer in the top decile of the discount rate distribution is 16 percent more likely to originate a non-performing loan than the average loan officer.

Finally, to shed light on the mechanism through which performance-based compensation affects loan officer behavior, we test whether monetary rewards affect effort and performance directly, or through their interaction with fixed personality traits. Standard agency theory would, for example, predict that it is more expensive to induce effort when agents are risk-averse. The opposite may be true for traits such as optimism or overconfidence, which might accentuate the response to high-powered incentives. The answer to this question has important implications for financial firms: if the effects of incentives vary by employee type, then firms must not only seek out employees with desirable personality traits, but also consider which type of incentive contract is the best match for their employee population.

By and large, we find only weak evidence that the effects of incentives vary by personal

[33]We identify a loan officer as overconfident if she *incorrectly* ranks herself in the top decile of the performance distribution.

characteristics. In column [3] of Panel B.4, we find that more conscientious individuals alter their behavior less in response to changes in incentives, though this pattern is not consistent across measures of effort (column [7] of Panel B.4). In total, five of the twenty-four possible interactions in Table IX, Panel B are statistically significant at the five percent level. This is more than would be expected by chance, but does not provide overwhelming evidence that incentives are mediated by personality type.

More confident, optimistic, or conscientious loan officers do not respond more strongly to performance-based compensation than their peers. Two interesting exceptions, consistent with the reputational motivations documented above, are worth noting. First, we do find that private sector bankers respond to incentives differently. In particular, we find an asymmetric response when officers are moved from the baseline, low-incentive treatment. When given higher-powered incentives, private sector officers do not increase effort, but when offered the origination bonus scheme, they dramatically reduce effort. Second, loan officers who report a strong "desire to live up to the expectations of others" exert significantly higher effort under origination incentives. That is, they provide effort under conditions where it is most likely to set them apart and signal their type.

In summary, our analysis suggests that career concerns are an important mechanism which generates effort above and beyond what would be expected from immediate financial incentives alone. A second lesson from this section is that personal characteristics are an important determinant of loan officer behavior that may constrain the ability of performance pay to affect screening effort. However, we do not find systematic evidence that incentives work differentially for officers with different personal characteristics.

# 6 Conclusion

Understanding how performance compensation affects risk-taking is a question of first order importance in finance. However, identifying the individual response to incentives is difficult, as we rarely observe decisions under different and truly exogenous incentive environments.

In this paper, we use an experiment with experienced loan officers to identify the effect of performance-based compensation on risk-assessment and risk-taking. We find a strong and economically significant effect of performance pay on risk-assessment and lending behavior. At the same time, we document several factors that constrain the ability of conventional incentive contracts to alter loan officer behavior. First, deferred compensation and limited liability, two standard features of loan officer compensation contracts, severely attenuate the response to performance pay. Second, using psychometric tests, we show that personality traits and demographic characteristics have a strong effect on screening effort that is unrelated to monetary incentives. Irrespective of monetary incentives, effort declines with age, which is consistent with the presence of career concerns. Our results suggest that performance pay affects behavior directly, rather than by accentuating traits such as risk-aversion, conscientiousness or overconfidence. Finally, we provide evidence that monetary incentives distort the perception of credit risk: permissive incentives lead officers to rate loans as significantly less risky than the same loans evaluated under pay-for-performance.

These findings have important implications for the design of performance-based compensation in lending. Lenders have increasingly relied on credit scoring models rather than human judgment. But it is unclear whether credit scoring can outperform human judgment, particularly in informationally opaque credit markets, such as the one we study. 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. The results in this paper are a first step towards answering these important questions.

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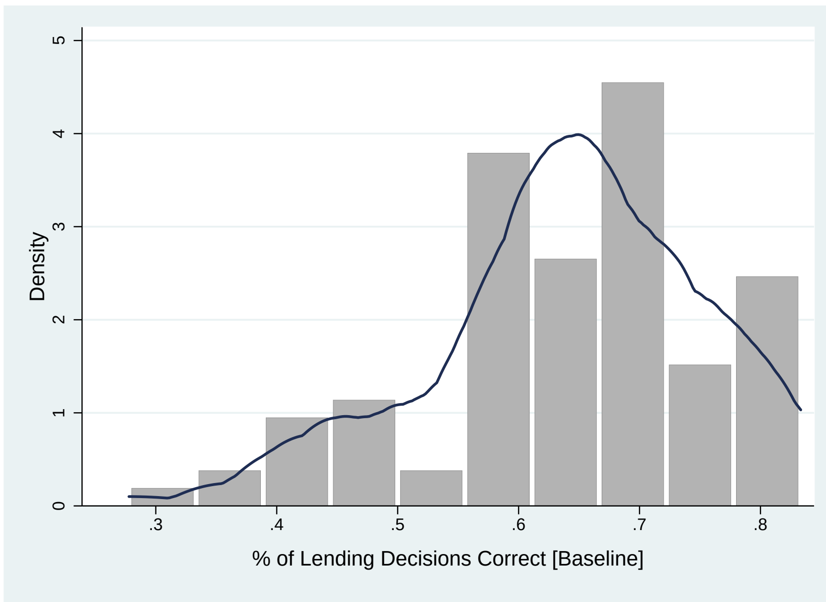
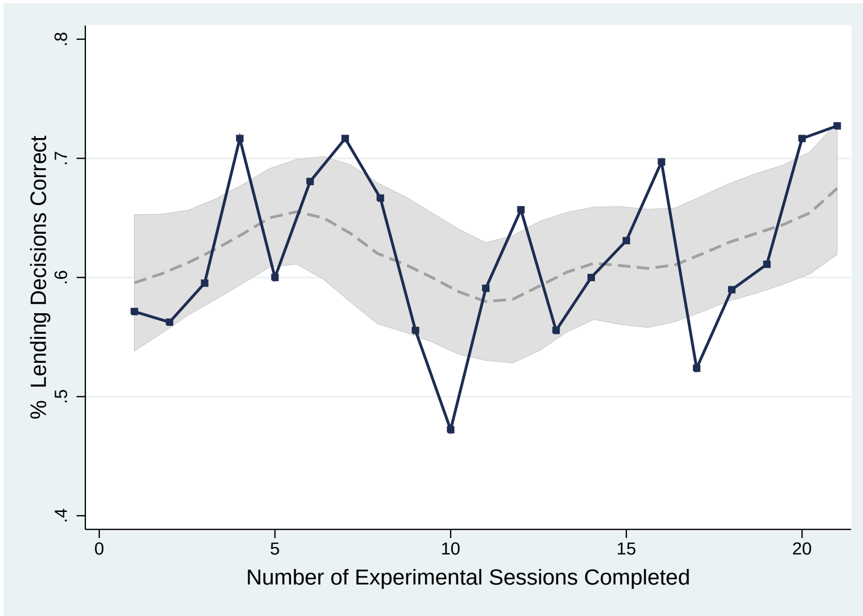
# Figures and Tables

Figure 1: Loan Officer Performance

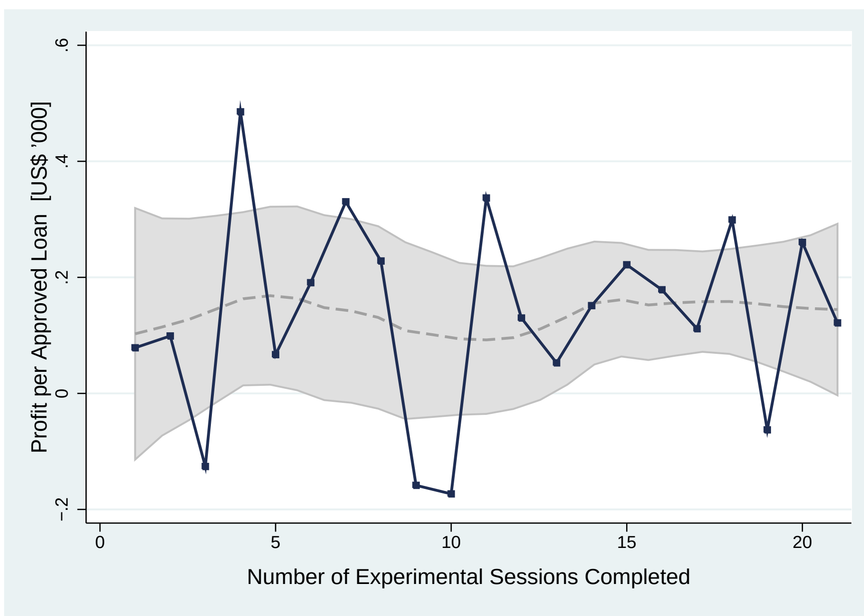



Notes: This figure shows the distribution of loan officer performance, measured by the average percentage of correct decisions per session under the Baseline treatment. The line plots the Kernel density of the performance distribution. We define a correct lending decision as approving an ex-post performing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

Figure 2: Learning During the Experiment




(a) Accuracy of Lending Decisions

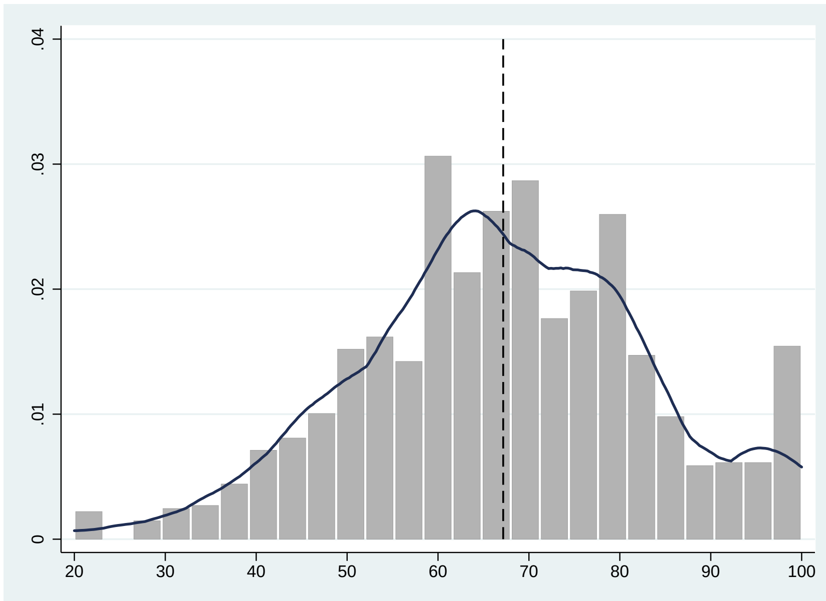



(b) Profitability of Lending Decisions

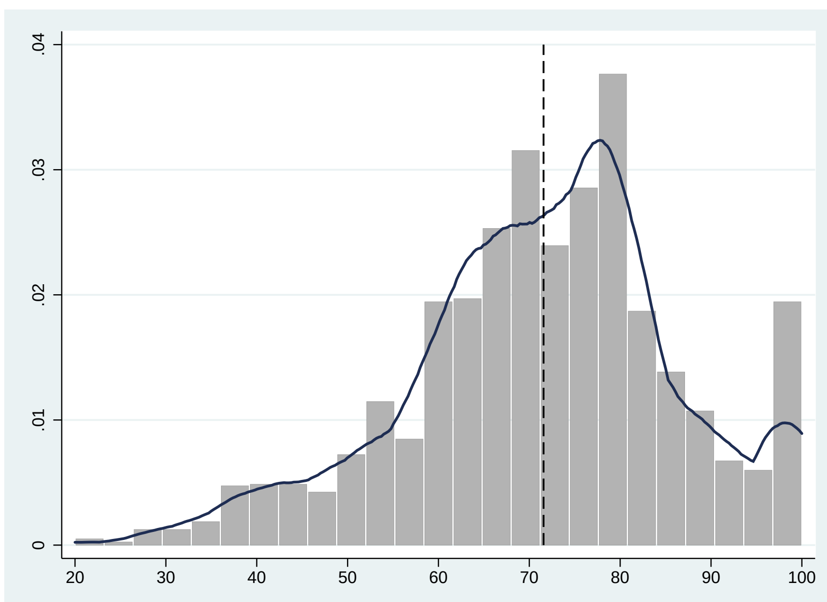
Notes: This figure examines the presence of learning effects over the course of the experiment by plotting (a) the percentage of correct decisions by the total number of experimental sessions completed and (b) the profit per approved loan by the number of experimental sessions completed. A correct lending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

Figure 3: Distribution of Internal Ratings

(a) Non-performing Loans




(b) Performing Loans




Notes: This figure plots the distribution of internal ratings assigned to loans evaluated under the baseline treatment. Panel (a) shows the distribution of risk-ratings for the sample of non-performing loans and loans that were declined by the Lender ex-ante; panel (b) plots the distribution for performing loans. Vertical lines show the median of the distribution. A Kolgomorov-Smirnov test rejects equality of distributions at 1% (p-value¡0.001).

## Table I: Summary of Incentive Treatments

The table summarizes the experimental incentive schemes. Each incentive scheme consists of a conditional payment $w_P$ for approving a loan that performs, a conditional payment $w_D$ for approving a loan that subsequently defaults and an outside payment $\overline{w}$ for declining a loan, in which case the outcome of the loan is not observed. All incentives refer to conditional payoffs for an individual lending decision.

| | **Incentive Treatment** | **Incentive Payments [amount in Rs]** | **Observations** | **Costly Information** | | **Deferred Compensation** | | **Limited Liability** | |
|---|---|---|---|---|---|---|---|---|---|
| | | [Perform \| Default \| Decline] | | No | Yes | No | Yes | No | Yes |
| **A** | Low-Powered [Baseline] | [20, 0, 10] | 7,420 | 3,782 | 3,638 | 6,568 | 852 | N/A | 7,420 |
| **B** | High-Powered | [50, -100, 0] | 2,946 | 654 | 2,292 | 2,496 | 450 | 978 | 1,968 |
| **C** | Origination Bonus | [20, 20, 0] | 2,548 | 762 | 1,786 | 1,632 | 916 | N/A | 2,548 |

## Table II: Loan Officer Summary Statistics

Panel A reports demographic summary statistics of the participants (Columns [1] to [4]), comparing experiment participants to the staff of all loan officers of a large public sector bank in the state in which the experiment was carried out (Columns [5] to [8]). Rank is the loan officer's seniority level in the bank ranging from 1 (lowest) to 5 (highest). 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. Panel B shows summary statistics for the various tests of attitudes and personality characteristics completed by participants of the experiment. Details on the personality tests and construction of variables are provided in Supplemental Appendix A.

**Panel A: Demographics**

| | **Experiment participants** [N=209] | | | | **Bank sample** [N=3,111] | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | Median | StdDev | N | Mean | Median | StdDev |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Male | 206 | 0.90 | 1.00 | 0.30 | 3,111 | 0.9 | 1.00 | 0.30 |
| Age | 206 | 37.60 | 35.00 | 10.94 | 3,111 | 37.9 | 35.00 | 12.0 |
| Experience in banking [Years] | 206 | 12.76 | 10.00 | 11.30 | 3,111 | 13.90 | 11.00 | 13.00 |
| Rank [1 (Lowest) - 5 (Highest)] | 206 | 1.94 | 2.00 | 1.00 | 3,111 | 1.60 | 2.00 | 0.75 |
| Education [Master's degree] | 200 | 0.33 | 0.00 | 0.47 | N/A | N/A | N/A | N/A |
| Private sector banker [Yes=1] | 206 | 0.20 | 0.00 | 0.40 | 3,111 | 1.00 | 1.00 | 0.00 |

**Panel B: Personality traits**

| | **Experiment participants** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | Median | StdDev | p10 | p25 | p75 | p90 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Impatient | 74 | 0.12 | 0.00 | 0.33 | 0.00 | 0.00 | 0.00 | 1.00 |
| Risk averse | 172 | 0.75 | 1.00 | 0.43 | 0.00 | 0.50 | 1.00 | 1.00 |
| | | | | | | | | |
| Optimism [LOT-R] | 64 | 2.37 | 2.33 | 0.46 | 1.83 | 2.17 | 2.67 | 3.00 |
| Conscientiousness [BFI] | 72 | 3.81 | 3.89 | 0.47 | 3.11 | 3.50 | 4.17 | 4.44 |
| Confidence | 71 | 0.73 | 0.78 | 0.20 | 0.50 | 0.60 | 0.85 | 0.99 |
| Overconfidence | 69 | 0.19 | 0.00 | 0.39 | 0.00 | 0.00 | 0.00 | 1.00 |
| Altruism | 172 | 0.70 | 1.00 | 0.46 | 0.00 | 0.00 | 1.00 | 1.00 |

# Table III: The Effect of Incentives on Effort

This table reports treatment effects of performance pay on screening effort. Each column reports results from a separate regression. The omitted treatment category is the low-powered baseline incentive. The dependent variable in Column [1] and [2] is number of sections of the loan file viewed; the dependent variable in Columns [3] and [4] is the number of loan file sections reviewed when loan officers were required to pay for additional information. The regressions in Columns [1] and [2] include the entire sample, while Columns [3] and [4] limit the data to evaluations to the "costly information setting." All regressions include a lab fixed effect, randomization stratum and week fixed effects, as well as dummies to control for treatment conditions not reported in this table. Loan officer controls include age, seniority, rank, education, and indicators for branch manager and business experience. Standard errors, in parentheses, are clustered at the loan officer × session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Free information** | | **Costly information** | |
|---|---|---|---|---|
| | Loan file sections reviewed | | Loan file sections reviewed | |
| | (1) | (2) | (3) | (4) |
| Baseline, omitted | | | | |
| High-powered | 0.434* | 0.400*** | 1.225*** | 0.794*** |
| | (0.23) | (0.14) | (0.42) | (0.25) |
| Origination bonus | 0.083 | 0.005 | -0.147 | -0.156 |
| | (0.22) | (0.14) | (0.40) | (0.21) |
| Loan fixed effects | No | Yes | No | Yes |
| Loan officer fixed effects | No | Yes | No | Yes |
| Loan officer controls | Yes | No | Yes | No |
| Number of observations | 14,405 | 14,675 | 8,520 | 8,688 |
| R-squared, adjusted | 0.232 | 0.689 | 0.271 | 0.725 |

## Table IV: The Effect of Incentives on Risk-Assessment

This table reports the effect of performance pay on loan officers' subjective assessment of credit risk. Each column shows results from a separate regression. The omitted treatment category is the low-powered baseline incentive. The dependent variable in regressions [1] and [2] is the overall risk rating, standardized to have mean zero. The dependent variable in Columns [3] and [4] is the normalized sub-rating for all categories that pertain to the personal risk of a potential applicant. In Columns [5] and [6] the dependent variable is the normalized sub-rating for all rating categories that pertain to the business, management and financial risk of a loan applicant. All regressions include a lab fixed effect, randomization stratum and week fixed effects, as well as dummies to control for treatment conditions not reported in this table. Loan officer controls include age, seniority, rank, education, and indicators for branch manager and business experience. Standard errors are clustered at the loan officer × session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Internal rating** | | | | | |
|---|---|---|---|---|---|---|
| | Overall rating | | Personal and management risk | | Business and financial risk | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Baseline, omitted | | | | | | |
| High-powered | 0.029 | 0.006 | 0.011 | -0.001 | 0.054 | 0.02 |
| | (0.09) | (0.04) | (0.09) | (0.04) | (0.09) | (0.04) |
| Origination bonus | 0.144* | 0.006 | 0.130* | -0.015 | 0.156** | 0.021 |
| | (0.08) | (0.04) | (0.08) | (0.04) | (0.08) | (0.04) |
| Loan fixed effects | No | Yes | No | Yes | No | Yes |
| Loan officer fixed effects | No | Yes | No | Yes | No | Yes |
| Loan officer controls | Yes | No | Yes | No | Yes | No |
| Number of observations | 14,405 | 14,675 | 14,405 | 14,675 | 14,405 | 14,675 |
| R-squared, adjusted | 0.151 | 0.640 | 0.142 | 0.644 | 0.161 | 0.626 |

## Table V: The Effect of Incentives on Risk-Taking

This table reports treatment effects of performance pay on risk-taking. Each column reports results from a separate regression. The omitted treatment category is the low-powered baseline incentive. The dependent variable in Columns [1] through [6] is a measure of the perceived quality of the loan: the average internal rating of each loan reported by all loan officers under the baseline treatment. To capture the degree of ex-ante uncertainty about the quality of a loan, Columns [7] to [12] repeat the exercise using the coefficient of variation of internal rating assigned to a given loan under the baseline treatment as the dependent variable. The internal rating is normalized to have mean zero and standard deviation of 1, hence effect sizes are standard deviations. All regressions include a lab fixed effect, randomization stratum and week fixed effects, as well as dummies to control for treatment conditions not reported in this table. Loan officer controls include age, seniority, rank, education, and indicators for branch manager and business experience. Standard errors, in parentheses, are clustered at the loan officer × session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Perceived quality of approved loans** | | | | | | **Perceived loan quality of approved loans** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | [Mean rating][a] | | | | | | [Coefficient of variation][b] | | | | | |
| | Overall rating | | Personal and management risk | | Business and financial risk | | Overall rating | | Personal and management risk | | Business and financial risk | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Baseline, omitted | | | | | | | | | | | | |
| High-powered | -0.039 | -0.046 | -0.024 | -0.03 | -0.058* | -0.065* | -0.015*** | -0.015*** | -0.018*** | -0.018*** | -0.013** | -0.013** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Origination bonus | 0.027 | 0.025 | 0.031 | 0.032 | 0.025 | 0.022 | -0.008* | -0.007 | -0.007 | -0.006 | -0.010** | -0.009* |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Loan fixed effects | No | No | No | No | No | No | No | No | No | No | No | No |
| Loan officer effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Loan officer controls | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Observations | 10,180 | 10,402 | 10,180 | 10,402 | 10,180 | 10,402 | 9,349 | 9,555 | 9,349 | 9,555 | 9,349 | 9,555 |
| R-squared, adjusted | 0.08 | 0.096 | 0.07 | 0.087 | 0.082 | 0.098 | 0.06 | 0.081 | 0.062 | 0.084 | 0.062 | 0.082 |

[a] Mean rating assigned to loan application $l$ by all loan officers evaluating the loan under the baseline treatment.

[b] Coefficient of variation of ratings assiged to loan application $l$ by all loan officers reviewing the loan under the baseline treatment.

## Table VI: Incentives, Lending Decisions and Profit

This table reports the effect of performance pay on loan approvals and the profitability of lending. Each column reports results from a separate regression. The omitted treatment category is the low-powered baseline incentive. The dependent variable in Columns [1] to [8] 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, and estimates in Columns [7] and [8] are based on the sample of loans that were initially declined by the Lender. Columns [9] to [12] report treatment estimates of incentives on profit per approved loan and profit per screened loan, in units of US$ '000. All regressions include a lab fixed effect, randomization stratum and week fixed effects, as well as dummies to control for treatment conditions not reported in this table. Loan officer controls include age, seniority, rank, education, and indicators for branch manager and business experience. Standard errors, in parentheses, are clustered at the loan officer × session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Panel A: Approved** | | | | | | | | **Panel B: Profit** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total | | Performing | | Non-performing | | Declined by bank | | per approved loan | | per screened loan | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Baseline, omitted | | | | | | | | | | | | |
| High-powered | -0.036* | -0.004 | -0.010 | 0.015 | -0.110** | -0.063 | -0.042 | -0.014 | 148.986* | 175.907** | 84.900 | 114.930* |
| | (0.02) | (0.02) | (0.03) | (0.03) | (0.06) | (0.06) | (0.06) | (0.06) | (85.01) | (86.81) | (62.51) | (63.76) |
| Origination bonus | 0.083*** | 0.079*** | 0.087*** | 0.068*** | 0.048 | 0.082* | 0.098* | 0.102* | 29.489 | -4.182 | 80.193 | 56.500 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.05) | (0.05) | (0.06) | (0.05) | (78.04) | (79.02) | (60.96) | (61.21) |
| Loan fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | No | No | No |
| Loan officer fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Loan officer controls | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Number of observations | 14,405 | 14,675 | 9,398 | 9,575 | 2,730 | 2,778 | 2,277 | 2,322 | 9,242 | 9,435 | 11,853 | 12,074 |
| R-squared, adjusted | 0.025 | 0.212 | 0.025 | 0.203 | 0.054 | 0.244 | 0.080 | 0.300 | 0.009 | 0.020 | 0.007 | 0.016 |

# Table VII: Deferred Compensation

This table reports treatment effects of deferring performance pay by three months. Each column reports results from a separate regression. The omitted treatment category is the low-powered baseline condition. The dependent variable in Columns [1] and [2] is the number of loan file sections reviewed for each evaluated loan. The dependent variable in Columns [3] and [4] is the amount spent on reviewing additional information under the "costly information" condition. In Columns [5] and [6] we consider the effect of deferred compensation on risk-taking. The dependent variable is the mean and coefficient of variation of internal ratings assigned to each loan under the baseline for loans approved by participants in the experiment as the outcome of interest, with the sample restricted to loans the loan officer approves. The dependent variable in Columns [7] and [8] is a dummy equal to 1 if a loan evaluated in the experiment was approved and 0 otherwise. The dependent variables in Columns [9] and [10] report treatment estimates of monetary incentives on profit per approved loan and profit per screened loan, in units of US$ '000. All regressions include a lab fixed effect, randomization stratum and week fixed effects, as well as dummies to control for treatment conditions not reported in this table. Loan officer controls include age, seniority, rank, education, and indicators for branch manager and business experience. Test statistics at the foot of the table refer to t-tests for the equality of coefficients between the deferred and non-deferred treatment dummies. Standard errors, in parentheses, are clustered at the loan officer × session level. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

| | **Panel A: Screening effort** | | | | **Panel B: Risk-taking** | | **Panel C: Lending and profit** | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Loan file sections reviewed | | Amount spent on information | | Average Internal Rating | | Approved | | Profit per loan | |
| | | | | | Mean | cv | | | approved | screened |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Baseline, omitted | | | | | | | | | | |
| Baseline, deferred | -0.448* | -0.519*** | -0.538 | -0.248 | 0.100*** | -0.013*** | 0.000 | 0.025 | -144.137* | -133.337* |
| | (0.24) | (0.11) | (0.35) | (0.20) | (0.04) | (0.00) | (0.02) | (0.02) | (73.79) | (70.03) |
| High-powered | 0.102 | -0.125 | 1.225*** | 0.794*** | 0.081** | -0.011** | -0.048** | -0.060*** | 39.656 | 78.682 |
| | (0.25) | (0.13) | (0.42) | (0.25) | (0.03) | (0.01) | (0.02) | (0.02) | (71.50) | (65.68) |
| High-powered, deferred | -0.512* | -0.364** | -0.454 | 0.034 | 0.048 | -0.012* | -0.021 | -0.017 | -60.365 | -52.466 |
| | (0.28) | (0.15) | (0.50) | (0.29) | (0.04) | (0.01) | (0.03) | (0.03) | (105.13) | (100.10) |
| Origination bonus | -0.409* | -0.497*** | -0.147 | -0.156 | 0.184*** | -0.016*** | 0.110*** | 0.093*** | -165.972** | -65.190 |
| | (0.25) | (0.12) | (0.40) | (0.21) | (0.04) | (0.00) | (0.02) | (0.02) | (74.73) | (69.84) |
| Origination bonus, deferred | -0.319 | -0.517*** | -0.207 | -0.387* | 0.185*** | -0.008* | 0.079*** | 0.090*** | -55.138 | -15.003 |
| | (0.24) | (0.12) | (0.37) | (0.23) | (0.04) | (0.00) | (0.02) | (0.02) | (65.11) | (62.48) |
| Loan effects | No | Yes | No | Yes | No | No | No | Yes | No | No |
| Loan officer effects | No | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Loan officer controls | Yes | No | Yes | No | No | No | Yes | No | No | No |
| *Test: immediate=deferred* | | | | | | | | | | |
| Baseline | [0.06] | [0.00] | [0.12] | [0.21] | [0.01] | [0.01] | [1.00] | [0.19] | [0.05] | [0.06] |
| High-powered | [0.01] | [0.09] | [0.00] | [0.02] | [0.38] | [0.90] | [0.33] | [0.10] | [0.35] | [0.19] |
| Origination bonus | [0.56] | [0.81] | [0.88] | [0.28] | [0.97] | [0.07] | [0.08] | [0.88] | [0.10] | [0.44] |
| Observations | 8,520 | 8,688 | 8,520 | 8,688 | 8,090 | 7,263 | 8,520 | 8,520 | 5,619 | 7,741 |
| R-squared, adjusted | 0.282 | 0.724 | 0.271 | 0.725 | 0.075 | 0.104 | 0.054 | 0.191 | 0.654 | 0.43 |

# Table VIII: Relaxing Limited Liability

This table reports the effect of relaxing loan officers' limited liability constraint. Each column reports results from a separate regression, the omitted category in each regression is the low-powered baseline treatment. Panel A (Columns [1] to [4]) report treatment effects on screening effort, Panel B (Columns [5] and [6]) report treatment effects on risk-taking and Panel C (Columns [6] to [8]) report treatment effects on loan approvals and profit per approved loan. The dependent variable in Columns [7]-[8] is a dummy equal to 1 if a loan evaluated in the experiment was approved and 0 otherwise. The dependent variable in Columns [9] and [10] are the bank's profit per approved loan, and the bank's profit per screened loan, respectively, denominated in units of US$ '000. All regressions include a lab fixed effect, randomization stratum and week fixed effects, as well as dummies to control for treatment conditions not reported in this table. Loan officer controls include age, seniority, rank, education, and indicators for branch manager and business experience. Test statistics at the foot of the table refer to t-tests for the equality of coefficients between the high-powered treatment dummies when limited liability is present vs. relaxed. Standard errors, in parentheses, are clustered at the loan officer × session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Panel A: Screening effort** | | | | **Panel B: Risk-taking** | | **Panel C: Lending and profit** | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Loan file sections reviewed | | Information credits spent | | Internal rating [baseline] | | Approved | | Profit per loan | |
| | | | | | Mean | cv | | | approved | screened |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Baseline, omitted | | | | | | | | | | |
| [credit] | | | | | | | | | | |
| High-powered | 0.345** | 0.248** | 1.225*** | 0.794*** | 0.081** | -0.011** | -0.048** | -0.060*** | 39.656 | 78.682 |
| [credit] | (0.16) | (0.10) | (0.42) | (0.25) | (0.03) | (0.01) | (0.02) | (0.02) | (71.50) | (65.68) |
| High-powered | 0.555*** | 0.372*** | 1.900*** | 1.260*** | -0.057* | 0.006 | -0.077*** | -0.074*** | 49.900 | 22.940 |
| [credit+endowment] | (0.16) | (0.08) | (0.44) | (0.22) | (0.03) | (0.01) | (0.02) | (0.02) | (80.04) | (69.50) |
| Loan effects | No | Yes | No | Yes | No | No | No | Yes | No | No |
| Loan officer effects | No | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Loan officer controls | Yes | No | Yes | No | No | No | Yes | No | No | No |
| *Test: High-Powered no endowment=* | | | | | | | | | | |
| *High-powered with endowment:* | [0.34] | [0.34] | [0.25] | [0.17] | [0.00] | [0.00] | [0.33] | [0.63] | [0.92] | [0.53] |
| Observations | 8,520 | 8,688 | 8,520 | 8,688 | 6,100 | 5,463 | 8,520 | 8,688 | 5,694 | 7,222 |
| R-squared, adjusted | 0.282 | 0.724 | 0.271 | 0.725 | 0.073 | 0.076 | 0.054 | 0.240 | 0.661 | 0.511 |

Table IX: Heterogeneity in the Response to Incentives

This table examines the interaction between incentive schemes and loan officer personality traits. In each panel, the first two columns report the main effect of the personality characteristic indicated in the panel heading. Additional controls include loan officer age, rank, gender, education, experience in other business areas, dummy variables for branch manager experience and employment by a private sector bank, loan officer confidence and all categories of the "big five" personality test. All personality traits are as defined in Appendix A. Standard errors, in brackets, are clustered at the loan officer×session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Screening Effort** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Sections reviewed | | | | Information credits spent | | | |
| | Main Effect | | Interaction | | Main Effect | | Interaction | |
| **Panel A Career Concerns** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ***A.1 Age*** | -0.02*** | (0.01) | | | -0.12*** | | | |
| High-powered | -0.71 | (0.68) | 0.03* | (0.02) | 7.43* | (4.39) | 0.02 | (0.03) |
| Origination | -0.92 | (0.67) | 0.03 | (0.02) | 9.14** | (4.49) | -0.07 | (0.05) |
| R-squared / N | 0.455 | 14,405 | | | 0.42 | 3,828 | | |
| ***A.2 Private Banker*** | 0.39** | (0.17) | | | 1.50*** | (0.45) | | |
| High-powered | 0.78** | (0.33) | -0.69 | (0.43) | 1.59* | (0.85) | -0.71 | (0.79) |
| Origination | 0.31 | (0.31) | -0.46 | (0.42) | 0.72 | (0.94) | -1.76** | (0.75) |
| R-squared / N | 0.456 | 14,405 | | | 0.284 | 8,520 | | |
| **Panel B: Personality traits** | | | | | | | | |
| ***B.1 Impatience*** | -0.55 | (0.55) | | | -0.41 | (1.06) | | |
| High-powered | 0.28 | (0.28) | 3.00*** | (0.76) | 1.20* | (0.62) | 3.01 | (2.43) |
| Origination | 0.14 | (0.29) | 1.38 | (0.91) | -0.28 | (0.69) | 2.65 | (1.99) |
| R-squared / N | 0.50 | 6,102 | | | 0.44 | 3,828 | | |
| ***B.2 Risk-aversion*** | 1.55*** | (0.32) | | | 1.46** | (0.57) | | |
| High-powered | -0.86 | (0.88) | 1.32 | (0.91) | 3.86** | (1.79) | -2.00 | (1.51) |
| Origination | 1.27 | (0.87) | -1.21 | (0.92) | 0.23 | (1.39) | 0.52 | (1.08) |
| R-squared / N | 0.504 | 6,102 | | | 0.425 | 3,828 | | |
| ***B.3 Optimism*** | 0.47 | (0.33) | | | 0.27 | (0.64) | | |
| High-powered | 0.55* | (0.29) | -0.80 | (0.56) | 0.32 | (0.65) | -2.24** | (1.07) |
| Origination | 0.33 | (0.30) | -1.01 | (0.91) | 1.39** | (0.65) | -3.91*** | (1.26) |
| R-squared / N | 0.500 | 6,102 | | | 0.42 | 3,828 | | |
| ***B.4 Conscientiousness*** | -0.43 | (0.30) | | | -1.24** | (0.57) | | |
| High-powered | -5.97*** | (1.71) | 1.78*** | (0.46) | -0.97 | (5.27) | 1.63* | (0.94) |
| Origination | -6.94*** | (2.17) | 1.96*** | (0.59) | 1.90 | (5.18) | 0.42 | (0.88) |
| R-squared / N | 0.507 | 6,102 | | | 0.426 | 3,828 | | |
| ***B.5 Overconfidence*** | -1.01** | (0.46) | | | -1.07 | (0.67) | | |
| High-powered | 0.53* | (0.28) | -0.19 | (0.86) | 1.13* | (0.68) | 1.51 | (1.37) |
| Origination | 0.04 | (0.29) | 1.18 | (0.84) | -0.32 | (0.80) | 1.47 | (1.07) |
| R-squared / N | 0.501 | 6,102 | | | 0.434 | 3,828 | | |

# Supplemental Appendix

*Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers*

**Shawn Cole** **Martin Kanz** **Leora Klapper**

# A Measurement of Personality Traits

## A.1 Personality tests

This section describes the tests used to measure loan officer personality traits. We use a number of standard psychometric tests that are used in the behavioral economics literature, specifically the literature on managerial attitudes and personality traits (see e.g. Landier and Thesmar [2009], Graham, Harvey and Puri [2013]).

*Optimism*: We measure optimism using the revised LOT-R Life Orientation Test [Scheier et al., 1994]. This psychometric test is widely used in the psychology literature. It measures an individual's level of optimism based on the following six salient questions which are administered as part of a questionnaire including additional filler questions. Respondents are asked to answer these questions on a scale ranging from "I agree a lot" to "I disagree a lot". The LOT-R score is calculated from the questions: [1] "In uncertain times, I usually expect the best", [2] "If something can go wrong for me, it will" [3] "I'm always optimistic about my future" [4] "I hardly ever expect things to go my way" [5] "I rarely count on good things happening to me" [6] "Overall, I expect more good things to happen than bad". Responses are coded from 0 to 4, so that higher values indicate greater optimism.

Figure A.1: The LOT-R personality test

Please answer the following questions. There are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer. Please check only **one** box per row

| | | Strongly Disagree | Disagree a little | Neither Agree nor Disagree | Agree a little | Strongly Agree |
|---|---|---|---|---|---|---|
| D.1 | In uncertain times, I usually expect the best. | | | | | |
| D.2 | I am a better driver than most people. | | | | | |
| D.3 | It's easy for me to relax. | | | | | |
| D.4 | Compared to others I know, I am worse at using computers. | | | | | |
| D.5 | If something can go wrong for me, it will. | | | | | |
| D.6 | I am better than most of my friends at card and board games. | | | | | |
| D.7 | I am always optimistic about my future. | | | | | |
| D.8 | I am worse at standardized tests than most of my friends. | | | | | |
| D.9 | Overall, I expect more good things to happen to me than bad. | | | | | |
| D.10 | I am worse at spelling that most people I know. | | | | | |
| D.11 | It's important for me to keep busy. | | | | | |
| D.12 | I have better decision making skills than most people. | | | | | |
| D.13 | I hardly ever expect things to go my way. | | | | | |
| D.14 | Even when I'm sure about the right choice, I still ask others for advice before making an important decision. | | | | | |
| D.15 | I don't get upset too easily. | | | | | |
| D.16 | I am better at very difficult tasks than most of my friends. | | | | | |
| D.17 | I rarely count on good things happening to me. | | | | | |
| D.18 | I shy away from hard problems because I am not good at them. | | | | | |
| D.19 | When working on a team project, I want to do the most difficult task because I know I'll be able to do it well. | | | | | |

*Altruism*: We measure altruism based on responses to the following question: "Suppose you win Rs 1,00,000 in the lottery tomorrow and have a choice of keeping the money for yourself or sharing it with friends and family. How will you divide the money?". There were seven choices, arranged in increasing order of generosity from "Keep the money for myself", "Keep 90,000 and give 10,000 to family or friends" [...] "Keep 10,000 and give 90,000 to family or friends", "Give all of the money to family or friends". We obtain the distribution of responses for all participants and code a loan officer as 'altruistic' if she would give more to family and friends than the median respondent.

*Conscientiousness*: We measure conscientiousness using standard questions from the "Big Five" personality test [John, Donahue and Kentle, 1991]. The test asks respondents to express their agreement or disagreement with 44 brief questions relating to personality traits. The full questionnaire and details about the construction of the personality trait variables are available at http://www.ocf.berkeley.edu/˜johnlab/bfi.htm. Based on responses to the test we calculate measures of "extroversion", "agreeableness", "conscientiousness", "neuroticism" and "openness". In our analysis, we focus on the correlation between "conscientiousness" on loan officer behavior. We control for the remaining dimensions of the "Big Five" personality test. Results are available upon request.

Figure A.2: The BFI personality test

Below are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who *likes to spend time with others*? Please write a number next to each statement to indicate the extent to which **you agree or disagree with that statement**.

| 1 Disagree Strongly | 2 Disagree a little | 3 Neither agree nor disagree | 4 Agree a little | 5 Agree strongly |
|---|---|---|---|---|

| I am someone who... | | | | | |
|---|---|---|---|---|---|
| B.1 | ...is talkative | | B.23 | ...tends to be lazy | |
| B.2 | ...tends to find fault with others | | B.24 | ...is emotionally stable, not easily upset | |
| B.3 | ...does a thorough job | | B.25 | ...is inventive | |
| B.4 | ...is depressed, sad | | B.26 | ...has an assertive personality | |
| B.5 | ...is original, comes up with new ideas | | B.27 | ...can be cold and aloof | |
| B.6 | ...is reserved | | B.28 | ...perseveres until the task is finished | |
| B.7 | ...is helpful and unselfish with others | | B.39 | ...can be moody | |
| B.8 | ...can be somewhat careless | | B.30 | ...values artistic, aesthetic experiences | |
| B.9 | ...is relaxed, handles stress well | | B.31 | ...is sometimes shy, inhibited | |
| B.10 | ..is curious about many different things | | B.32 | ..is considerate and kind to almost everyone | |
| B.11 | ...is full of energy | | B.33 | ...does things efficiently | |
| B.12 | ...starts quarrels with others | | B.34 | ...remains calm in tense situations | |
| B.13 | ...is a reliable worker | | B.35 | ...prefers work that is routine | |
| B.14 | ...can be tense | | B.36 | ...is outgoing, sociable | |
| B.15 | ...is ingenious, a deep thinker | | B.37 | ...is sometimes rude to others | |
| B.16 | ...generates a lot of enthusiasm | | B.38 | ...makes plans, follows through with them | |
| B.17 | ...has a forgiving nature | | B.39 | ...gets nervous easily | |
| B.18 | ...tends to be disorganized | | B.40 | ...likes to reflect, play with ideas | |
| B.19 | ...worries a lot | | B.41 | ...has only few artistic interests | |
| B.20 | ...has an active imagination | | B.42 | ...likes to cooperate with others | |
| B.21 | ...tends to be quiet | | B.43 | ...is easily distracted | |
| B.22 | ...is generally trusting | | B.44 | ...is sophisticated in art, music and literature | |

*Confidence* and *overconfidence*: To measure confidence and overconfidence, loan officers were asked the question "how would you compare your performance in the loan rating exercise". The question was asked after an initial familiarization session and participants were given the choice of "top 5%", "top 10%", "top 25%" "above average" and "below average". Respondents were classified as "confident" if they answered either "top 5%" or "top 10%". Respondents were classified as "overconfident" if they wrongly self-assessed their performance to be in the top 10th percentile of all participants.

### A.2 Time preference and risk-aversion

*Time preference*: We elicit monthly discount rates using a standard Becker-DeGroot-Marschak procedure, in which subjects were given a series of binary choices between *Rs 200* to be paid out in one month and and *Rs 200-x* to be paid out today. The resulting discount factor between today and one month from today is our discount rate variable "delta". Participants were told that there was a 20% chance that their choices would actually be paid out.[34]

*Risk-aversion:* We used answers to the survey question *"Do you regularly play the lottery?"* as a simple proxy of risk aversion. Respondents were classified as risk-averse if they stated that they never played the lottery.

Figure A.3: Eliciting monthly discount rates

Please check **for each row** the option you would prefer:

| | | **Option 1 – Get Money TODAY** | **Option 2 – Get Money IN 30 DAYS (= 1 MONTH)** |
|---|---|---|---|
| T4.1 | **Row 1** | ☐ 196 Rs. today | ☐ 200 Rs. in 30 days |
| T4.2 | **Row 2** | ☐ 188 Rs. today | ☐ 200 Rs. in 30 days |
| T4.3 | **Row 3** | ☐ 176 Rs. today | ☐ 200 Rs. in 30 days |
| T4.4 | **Row 4** | ☐ 160 Rs. today | ☐ 200 Rs. in 30 days |
| T4.5 | **Row 5** | ☐ 140 Rs. today | ☐ 200 Rs. in 30 days |
| T4.6 | **Row 6** | ☐ 116 Rs. today | ☐ 200 Rs. in 30 days |
| T4.7 | **Row 7** | ☐ 88 Rs. today | ☐ 200 Rs. in 30 days |
| T4.8 | **Row 8** | ☐ 56 Rs. today | ☐ 200 Rs. in 30 days |
| T4.9 | **Row 9** | ☐ 20 Rs. today | ☐ 200 Rs. in 30 days |

[34] There is a growing literature indicating that discount rates elicited in the lab using this standard procedure predict a range of real world behaviors, including saving and credit card borrowing (see e.g. Ashraf et al. [2006], Shapiro [2005], Meier and Sprenger [2010])

# B Theoretical Framework

In this section, we develop a simple theoretical framework that highlights how changes in loan officer incentives affect screening behavior and lending decisions.

*Agents.* The model encompasses firms, loan officers, and the bank. The bank is risk-neutral, while loan officers are risk-averse with $u'_{\mathrm{w}} > 0$, $u''{}_{\mathrm{w}} < 0$ and $\lim_{\mathrm{w}\to\infty} u'(\mathrm{w}, \cdot) = 0$. Firms seek to borrow 1 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 $\theta_G$ with probability of investment success $p$, and bad firms of type $\theta_B$, with probability of investment success 0. The ex-ante fraction of good firms is $\pi$. We assume that the bank has a net cost of capital normalized to 0, and charges interest rate $r > 0$. If the bank makes a loan that is repaid, it earns net interest margin $r$. If the loan defaults, the bank loses 1 unit of capital. If the bank were to lend 1 unit of capital to all applicants, a loan would be repaid with probability $\pi \mathrm{p}$ and earn expected return $\pi \mathrm{p}(1+r)-1$. We assume this amount to be negative, so that it is not profitable to lend to all applicants.

*Information and Screening.* While firm type is not observed, a loan officer may screen a loan application in an attempt to determine the firm's type. This requires effort, which comes at private cost $e > 0$ to the loan officer. We assume $e$ to be specific to the loan officer and independent of monetary incentives. If a loan officer screens, she observes either a fully informative "bad news" signal, $\sigma_B$, indicating that the firm is type $\theta_B$, and will default with certainty, or the "no bad news" signal $\sigma_G$. Bad firms generate a bad signal with probability $\gamma$, and a good signal with probability 1-$\gamma$. Good firms generate a good signal with certainty. Hence, the probability of observing a bad signal conditional on firm type is

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

It follows that the posterior probability of a firm being bad after receiving a bad signal is $\mathrm{P}(\theta_{\mathrm{B}}|\sigma_{\mathrm{B}}) = 1$, and the probability of the firm being good after observing a good signal is $\mathrm{P}\left(\theta_{\mathrm{G}}|\sigma_{\mathrm{G}}\right) = \frac{\pi}{\pi+(1-\gamma)(1-\pi)}$. We assume that it is profitable to lend to a firm with a good signal, even when screening costs are taken into consideration, so that

$$\pi\left[p\mathrm{r} + (1-p)(-1)\right] + (1-\pi)\left[\gamma \cdot 0 + (1-\gamma)(-1)\right] \geq e \tag{A.3}$$

*Contracts.* The bank may offer the loan officer a contract $\mathbf{w} = [\mathrm{w}, \mathrm{w_D}, \overline{\mathrm{w}}]$ to induce screening effort. The contract specifies a payment $\overline{\mathrm{w}}$ for declining a loan application, and contingent payments for approving a loan that subsequently performs $\mathrm{w_P}$ and for approving a loan that subsequently defaults, $\mathrm{w_D}$, where $\mathrm{w_P}, \overline{\mathrm{w}} \in [0, r]$ and $\mathrm{w_D} \in [-1, 0]$. The bank's problem is to choose $\mathbf{w} = [\mathrm{w_P}, \mathrm{w_D}, \overline{\mathrm{w}}]$ to maximize profitability. The bank does not observe the outcome of a loan that is screened out by the loan officer.

*Expected Utility.* Loan officers choose the return to three possible actions: declining a loan without screening, approving the loan without screening, or screening the loan application and approving the loan only if no bad signal is observed. We consider the outcome of each action in turn. If a loan officer rejects a loan without screening, her expected utility is simply $u_{\mathrm{R}} = u(\overline{\mathrm{w}})$. If the loan officer approves a loan without screening, her expected utility is

$$u_{\mathrm{NS}} = \pi p u(\mathrm{w_P}) + (1 - \pi p) u(\mathrm{w_D}) \tag{A.4}$$

If an officer screens and approves only when no negative signal is observed, her utility is[35]

$$u_{\mathrm{S}}(\mathbf{w}) = \pi p u(\mathrm{w_P}) + [1 - \pi p - \gamma(1-\pi)]\, u(\mathrm{w_D}) + [(1-\pi)\,\gamma]\, u(\overline{\mathrm{w}}) - e \tag{A.5}$$

*Incentive Compatibility.* We begin by remarking that, in the case of a risk-neutral loan officer with unlimited wealth, the efficient outcome can be obtained by setting $\mathbf{w} = [r, -1, 0]$, effectively selling the loan to the loan officer and making her the residual claimant. However, this contract is not feasible in practice, as the loan officer would be liable for the total amount of the loan in case of default. Hence, if the bank is to motivate the loan officer to exert screening effort, it needs to offer a contract that satisfies two incentive constraints: $u_{\mathrm{S}} \geq u_{\mathrm{NS}}$ and $u_{\mathrm{S}} \geq u_{\mathrm{R}}$. The first constraint requires that the returns to effort be greater than the cost of effort. This condition simplifies to:

$$\gamma\, [u(\overline{\mathrm{w}}) - u(\mathrm{w_D})(1-\pi)] \geq e^* \tag{A.6}$$

The second constraint requires that the loan officer prefer screening to declining all loans:

$$\pi p u(\mathrm{w_P}) + [1 - \pi p + \gamma(\pi - 1)]\, u(\mathrm{w_D}) - [1 + \gamma(\pi - 1)]\, u(\overline{\mathrm{w}}) \geq e^* \tag{A.7}$$

In practice, since both constraints are upper bounds for the cost of effort, only one will bind. No matter which constraint binds, it is always weakly easier to induce effort when the cost of effort is lower, the penalty for making a non-performing loan increases, and the outside option of declining a loan decreases. The effect of increasing $\mathrm{w_P}$ depends on which incentive compatibility constraint binds. Loan officers can always be induced to lend, although not necessarily in a manner that is profitable for the bank.

We focus on the following testable predictions that characterize incentive schemes commonly employed in commercial lending. Taken literally, the model predicts that loan officers will either screen all loans, or not screen any loans. However, a simple extension in which $e$ varies by loan, in a way that is observable only to the loan officer, would generate non-corner solution in screening effort, with the following comparative statics.

**Proposition 1** (Incentive power) $\frac{\partial \mathrm{e}^*}{\partial \mathrm{w_D}}$ *and* $\frac{\partial e^*}{\partial \mathrm{w}_D} < 0$ *and* $\frac{\partial e^*}{\partial w_P} > 0$. *An origination piece rate, as often employed in commercial lending, leads to low effort, indiscriminate lending and high defaults. By contrast, high-powered incentives that reward performing loans and penalize the approval of bad loans lead to greater effort, more conservative lending and lower defaults.*

**Proposition 2** (Deferred compensation) *Let* $\delta \in (0, 1)$ *denote the time discount rate of*

[35] From these conditions, we can also derive the profit of the bank in each case. If a loan officer rejects a loan without screening, the bank's profit is $\Pi_R = -\overline{w}$. If the loan officer approves a loan without screening, the bank's profit is $\Pi_{NS} = \pi \mathrm{p}(r - w_P) - (1 - \pi \mathrm{p})(1 + w_D)$, and if the loan officer screens and approves a loan only if no bad signal is observed, expected profit is $\Pi_S = \pi p(r - w_P) - [\pi(1-p) + (1-\pi)(1-\gamma)](1 + w_D) - [(1-\pi)\gamma]\overline{w}$.

*loan officer $i$. Then $\delta u < u \; \forall \; \delta$. Deferred compensation weakens the incentive power of the contract, as monetary incentives are discounted while the cost of effort is not.*

**Proposition 3** (Limited liability) *Because $\frac{\partial e^*}{\partial w_D}$ and $\frac{\partial e^*}{\partial w_D} < 0$, increasing a loan officer's liability for non-performing loans from $w_D \geq 0$ to $w_D \in (-r, 0)$ leads to greater screening effort. More generally, relaxing the limited liability constraint increases the incentive power of any performance based contract.*

*Reputational concerns*: To complete the model, we allow for the possibility that loan officers are responsive to reputational concerns.

Suppose that a loan officer's type is not directly observable, so that others must infer it from her actions. Specifically, let $h(b)$ denote the esteem accorded to a loan officer considered to be of type $b$, and let $\phi(b, e)$ the inference function which, for each effort choice $e$, assigns a probability to each possible inference about the loan officer's type.[36] In the population, types are distributed over interval $B$ with cumulative density function $F(\cdot)$. Hence, a loan officer who is responsive to reputational concerns derives non-pecuniary utility

$$v(b, e) = \int_B h(b)\phi(b, e)db \tag{A.8}$$

from screening, where the inference function satisfies $v(b, e) = \int_B \phi(b, e)db = 1$ for all $e \in E$.[37] Finally, we assume loan officers to be heterogeneous in their responsiveness to reputational concerns, with $\lambda^i \in [0, 1]$ denoting an agent's responsiveness to non-monetary incentives. We allow $\lambda^i$ to vary with a vector of measurable personality traits $\mathbf{z}$ and a loan officer's age, or distance to retirement, $\bar{t} - t$ This modifies the private utility from screening as follows

$$u_{\mathrm{S}}(\mathbf{w}, e) = u_{\mathrm{S}}(\mathbf{w}) + \lambda^i(\mathbf{z}, \bar{t} - t) \int_B h(b)\phi(b, e)db - e \tag{A.9}$$

and generates the following additional predictions.

**Proposition 4** (Reputational concerns). *For any $\lambda^i > 0$, there exists a unique level of optimal effort $\widetilde{e}$ in which the agent exerts non-zero screening effort independent of monetary incentives with $\frac{\partial \widetilde{e}}{\partial \lambda} > 0$, $\widetilde{e} > 0$ and $\widetilde{e} \leq e^*$.*

**Proposition 5** (Career concerns). *If a loan officer is motivated by career concerns, she will exert non-zero screening effort in the absence of monetary incentives and screening effort is decreasing in age, or distance to retirement so that $\lambda^i > 0$ and $\frac{\partial \widetilde{e}}{\partial (\bar{t} - t)} > 0$.*

[36] This requires the assumption that all agents will, in equilibrium, form the same expectations.

[37] We choose this general specification to encompass a range of reputational concerns, including self-signaling, social norms [Bernheim, 1994], and identity [Akerlof and Kranton, 2000].

# C Appendix Tables

## Table OA.I: Test of Random Assignment

This table presents a test of random assignment across the four main treatments. We regress treatment dummies on demographic variables, controlling for randomization strata, lab and week fixed effects. Age is the loan officer's age in years, Male is a dummy variable taking a value of 1 if the participant is male. Rank is the loan officer's level of seniority in the bank. Experience is the number of years the loan officer has been employed by the bank. Branch Manager is a dummy variable indicating whether the participant has ever served as a branch manager. * p<0.10 ** p<0.05 *** p<0.01.

| | **Incentive Treatment** | |
|---|---|---|
| | High-powered | Origination bonus |
| | (1) | (2) |
| Male | 0.006 | -0.017 |
| | (0.03) | (0.03) |
| Age | -0.002 | -0.001 |
| | (0.002) | (0.002) |
| Education [Master's degree] | -0.031 | 0.014 |
| | (0.019) | (0.020) |
| Experience [Years] | 0.002 | 0.001 |
| | (0.001) | (0.001) |
| Rank [1 Lowest - 5 Highest] | -0.005 | -0.009 |
| | (0.008) | (0.008) |
| Branch manager experience | -0.007 | -0.012 |
| | (0.023) | (0.024) |
| Number of observations | 9,268 | 9,806 |
| R-squared, adjusted | 0.314 | 0.322 |

## Table OA.II: Loan File Summary Statistics

This table reports summary statistics for the 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 p-values from a test of equality. Monthly revenue includes business revenue and other sources of household income. Personal Expenses measure a client's monthly personal expenses and Business Expenses measure a client's total monthly required cash expenses, including all inputs to production. Monthly Debt Service is the sum of all monthly installments on the applicant's outstanding loans, not including the proposed loan. All variables are denominated in US$. * p<0.10 ** p<0.05 *** p<0.01.

| | **Panel A: Entire sample** | | | **Panel B: Performing loans** | | | **Panel C: Non-perf & declined** | | | **Difference in means** | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | [N=676] | | | [N=592] | | | [N=84] | | | (B)-(C) | |
| | Mean | Median | StDev | Mean | Median | StDev | Mean | Median | StDev | Difference | $p > \|t\|$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| **Loan characteristics** | | | | | | | | | | | |
| 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 | 9.04 | 31.8 | 36 | 7.57 | 37.9 | 36 | 14.35 | -6.10*** | (0.00) |
| **Business income** | | | | | | | | | | | |
| Monthly revenue | 11,680 | 6,383 | 18,621 | 12,126 | 6,383 | 19,257 | 7,850 | 5,309 | 11,224 | 4,276* | (0.07) |
| Monthly business expenses | 9,818 | 5,191 | 17,438 | 10,529 | 5,559 | 18,354 | 5,368 | 3,514 | 8,771 | 5,161*** | (0.01) |
| Monthly EBIT | 1,844 | 1,007 | 6,523 | 1,904 | 991 | 7,002 | 1,467 | 1,074 | 1,388 | 437 | (0.55) |
| **Debt** | | | | | | | | | | | |
| Total debt | 6,776 | 0 | 31,572 | 6,820 | 0 | 33,425 | 6,504 | 955 | 15,887 | 316 | (0.93) |
| Monthly debt service | 227 | 0 | 733 | 226 | 0 | 777 | 234 | 112 | 358 | -8.00 | (0.92) |
| **Personal** | | | | | | | | | | | |
| Age of business | 11.27 | 9 | 7.99 | 11.64 | 9 | 8.35 | 9.5 | 8 | 5.8 | 2.14** | (0.02) |
| Monthly personal expenses | 283 | 223 | 304 | 285 | 223 | 317 | 270 | 231 | 209 | 15 | (0.66) |
| Credit report, accts overdue | 0.2 | 0 | 0.4 | 0.18 | 0 | 0.38 | 0.32 | 0 | 0.47 | -0.14** | (0.04) |

## Table OA.III: Loan Evaluation Summary Statistics

This table reports summary statistics on lending decisions in the experiment by incentive treatment. The table displays unconditional means and standard deviations. Columns [2] and [3] report summary statistics for screening effort measured as the number of loan file sections reviewed and the number of information credits spent by loan officers for treatments that included the "costly information" condition, under which participants were charged to access additional information. Column [4] reports the internal rating (normalized to have mean zero and standard deviation 1) assigned to loans evaluated under each treatment condition, and Column [6] reports profit per approved loan by incentive treatment in units of US$ '000. Columns [7] to [10] report the percentage of correct lending decisions by incentive treatment. A "correct" decision is defined as approving a loan that ex-post performs, or rejecting a loan that ex-post does not perform, or which the bank rejected.

| | **N** | **Effort** | | **Risk rating** | **Approved** | **Profit** | **Evaluations Correct** | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Sections reviewed | Amount spent on information | | % | US$ '000 | Sample | Performing | Non-performing | Declined by bank |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Entire sample | 14,675 | 5.06 | 4.17 | 0.07 | 0.75 | 553.89 | 0.65 | 0.80 | 0.30 | 0.45 |
| | | (2.44) | (4.41) | (1.01) | (0.44) | (1882.85) | (0.48) | (0.40) | (0.46) | (0.50) |
| Baseline | 8,398 | 5.25 | 4.80 | 0.00 | 0.72 | 527.84 | 0.65 | 0.78 | 0.32 | 0.52 |
| | | (2.35) | (4.57) | (1.00) | (0.45) | (1859.50) | (0.48) | (0.42) | (0.47) | (0.50) |
| High-powered | 1,968 | 5.01 | 4.78 | 0.23 | 0.69 | 576.10 | 0.65 | 0.75 | 0.42 | 0.48 |
| | | (2.33) | (4.66) | (1.01) | (0.46) | (1732.70) | (0.48) | (0.43) | (0.49) | (0.50) |
| Origination | 2,548 | 4.60 | 3.59 | 0.13 | 0.84 | 554.83 | 0.66 | 0.87 | 0.21 | 0.29 |
| | | (2.18) | (3.84) | (1.02) | (0.37) | (1986.07) | (0.48) | (0.33) | (0.41) | (0.45) |

## Table OA.IV: Test for Learning During the Experiment

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

| | **Lending decisions** | **Profit per loan** | |
|---|---|---|---|
| | correct | approved | screened |
| | (1) | (2) | (3) |
| Number of experimental sessions completed | -0.002* | 0.003 | -0.003 |
| | (0.00) | (0.00) | (0.00) |
| Loan fixed effects | Yes | No | No |
| Loan officer fixed effects | Yes | Yes | Yes |
| Number of observations | 14,675 | 9,357 | 13,084 |
| R-squared | 0.322 | 0.652 | 0.415 |

## Table OA.V: Predictive Content of Internal Ratings

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

| | **Lending** | **Performance** | **Profit per loan** | |
|---|---|---|---|---|
| | Approved=1 | Performing=1 | approved | screened |
| | (1) | (2) | (3) | (4) |
| *Panel A: Final Rating* | | | | |
| Log internal rating | 1.348*** | 0.322*** | 0.659*** | 0.305*** |
| | (0.04) | (0.03) | (0.19) | (0.05) |
| Number of observations | 13,979 | 13,979 | 8,834 | 12,411 |
| R-squared | 0.443 | 0.064 | 0.03 | 0.024 |
| *Panel B: Personal and Management Risk* | | | | |
| Log internal rating | 1.159*** | 0.279*** | 0.476*** | 0.251*** |
| Personal and management risk | (0.04) | (0.03) | (0.17) | (0.06) |
| Number of observations | 13979 | 13979 | 8834 | 12,411 |
| R-squared | 0.368 | 0.061 | 0.03 | 0.023 |
| *Panel C: Business and Financial Risk* | | | | |
| Log internal rating | 1.265*** | 0.318*** | 0.572*** | 0.282*** |
| Business and financial risk | (0.04) | (0.02) | (0.18) | (0.05) |
| Number of observations | 13,979 | 13,979 | 8,834 | 12,411 |
| R-squared | 0.439 | 0.066 | 0.03 | 0.024 |
| Loan fixed effects | No | No | No | No |
| Loan officer fixed effects | Yes | Yes | Yes | Yes |

Table OA.VI: Heterogeneity in the Response to Incentives, Additional Results

This table presents evidence on the interaction between incentive schemes and loan officer personality traits. In each panel, a pair of columns report the main and hetergenous effects of each incentive treatment, by the personality characteristic indicated in the panel heading. Even columns indicate the interactions, odd columns report the main effects of the personality characteristic and treatment conditions. Additional controls included in all regressions include loan officer age, rank, gender, education, experience in other business areas, a dummy equal to one if a loan officer has ever served as a branch manager and a dummy equal to one if a loan officer is employed by a private bank, loan officer confidence and all categories of the "big five" personality test. Standard errors are clustered at the loan officer×session level. * p<0.10 ** p<0.05 *** p<0.01.

| | **Screening Effort** | | **Risk-assessment** | | **Lending and Profit** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sections reviewed | | Internal rating | | Approved | | | | | | Profit | |
| | | | | | Total | | Performing | | Non-performing | | Per screened loan | |
| | Main Eff | Interaction | Main Eff | Interaction | Main Eff | Interaction | Main Eff | Interaction | Main Eff | Interaction | Main Eff | Interaction |
| **[A] Confidence** | 0.03 | | 1.89*** | | 0.02 | | 0.06 | | -0.09 | | 268.88 | |
| | (0.74) | | (0.30) | | (0.07) | | (0.08) | | (0.14) | | (201.17) | |
| High-powered | 0.81 | -0.41 | 0.62** | -0.84** | -0.03 | -0.06 | -0.03 | -0.06 | -0.05 | -0.01 | 94.42 | -194.67 |
| | (0.84) | (1.22) | (0.30) | (0.42) | (0.08) | (0.11) | (0.11) | (0.14) | (0.17) | (0.23) | (289.08) | (355.18) |
| Origination | 0.09 | 0.24 | 0.54* | -0.84* | -0.07 | 0.12 | -0.01 | 0.03 | -0.21 | 0.30 | 394.71* | -467.05* |
| | (0.90) | (1.27) | (0.32) | (0.43) | (0.09) | (0.11) | (0.09) | (0.12) | (0.16) | (0.21) | (211.28) | (274.82) |
| R-squared [N] | 0.50 | [6,102] | 0.38 | [6,102] | 0.127 | [6,102] | 0.102 | [3,970] | 0.145 | [2,132] | 0.760 | [5,067] |
| **[B] Desire to live** | -0.03 | | 0.02 | | 0.00 | | 0.00 | | 0.01 | | -9.45 | |
| **up to expectations** | (0.05) | | (0.02) | | (0.00) | | (0.01) | | (0.01) | | (12.71) | |
| High-powered | 0.46 | 0.01 | -0.18 | 0.03 | -0.05 | -0.00 | -0.09 | 0.00 | -0.00 | -0.01 | -204.38 | 25.44 |
| | (0.55) | (0.09) | (0.17) | (0.03) | (0.06) | (0.01) | (0.07) | (0.01) | (0.11) | (0.02) | (166.81) | (23.12) |
| Origination | -0.86 | 0.18** | -0.22 | 0.03 | 0.06 | -0.01 | 0.01 | 0.00 | 0.16 | -0.02* | -157.14 | 35.12* |
| | (0.59) | (0.09) | (0.19) | (0.03) | (0.05) | (0.01) | (0.07) | (0.01) | (0.10) | (0.02) | (146.38) | (20.94) |
| | 0.504 | [6,102] | 0.386 | [6,102] | 0.127 | [6,102] | 0.099 | [3,970] | 0.143 | [2,132] | 0.759 | [5,067] |