# Internet Appendix for

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

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This Appendix presents additional materials and results, not reported in the paper. Section A provides additional details on the loan evaluation exercise. Section B reports details on psychometric tests and the measurement of loan officer personality traits. Section C presents a stylized theoretical model of loan officer decision making, and Section D contains Appendix Tables reporting additional robustness checks and results.

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#### A The Loan Evaluation Exercise

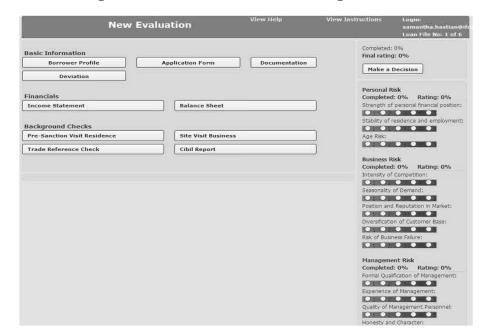


Figure A.1: Screenshot of Loan Rating Interface

Figure A.1 shows a screenshot of the software interface used in the experiment. The format of the loan application displayed on a loan officer's screen followed the standard format of a large Indian bank and contained all applicant information banks are required to collect for loans with comparable terms and ticket size. Loan files were assigned by the software according to the randomization strategy described in Section III.

Loan officers had access to all information submitted by the prospective borrower in the original loan application but were given no information on the realized outcome of the loan. Participants could select a section of the loan file using the tabs at the top of the screen. The information for the selected section was then displayed in the body of the evaluation screen. Loan officers had the option of reviewing all sections of the loan file, but were free to make a decision without having reviewed all parts of the application.

While reviewing the loan file, and prior to making a lending decision, loan officers were asked to provide a subjective evaluation of the loan file under review, using the risk rating categories on the sidebar at the right hand side of the evaluation screen. To ensure that these ratings are an unbiased reflection of the loan officer's perception of credit risk, participants were reminded at the beginning of each session that internal ratings were not binding for the lending decision, not seen by the lab administrator and not tied to monetary incentives.

After reviewing all requested loan file information and assigning an internal risk rating, participants were asked to approve or decline a loan application. Their decision was compared to the realized outcome to the loan and incentive payments were disbursed, as described in Section III. of the paper.

# B 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, Carver and Bridges, 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 B.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 <u>one</u> 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". 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 <a href="http://www.ocf.berkeley.edu/~johnlab/bfi.htm">http://www.ocf.berkeley.edu/~johnlab/bfi.htm</a>. 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 B.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							
							37			
l 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 thoro	ugh job		B.25	is i	is inventive				
B.4	is depressed	, sad		B.26	ha	s an assertive persona	ility			
B.5	is original, co	mes up with new ideas		B.27	ca	n be cold and aloof				
B.6	is reserved			B.28	pe	rseveres until the task	is finished			
B.7	is helpful and	unselfish with others		B.39	ca	n be moody				
B.8	can be some	what careless		B.30	va	lues artistic, aesthetic	experiences			
B.9	9is relaxed, handles stress well			B.31	is sometimes shy, inhibited					
B.10	is curious about many different things			B.32	is o	onsiderate 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 v	vorker		B.35prefers work that is routine			10			
B.14	can be tense			B.36	36is outgoing, sociable					
B.15	is ingenious,	a deep thinker	B.37is sometimes rude to others				ers			
B.16	generates a lot of enthusiasm			B.38	makes plans, follows through with them					
B.17	7has a forgiving nature			B.39	gets nervous easily					
B.18	3tends to be disorganized			B.40	likes to reflect, play with ideas					
B.19	worries a lot			B.41	ha	s only few artistic inter	rtistic interests			
B.20	has an active	imagination		B.42	like	es to cooperate with ot	hers			
B.21	tends to be q	uiet		B.43	is	easily distracted				
B.22	is generally tr	usting		B.44	is s	sophisticated in art, mu	sic 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.<sup>34</sup>

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 B.3: Eliciting monthly discount rates

Please check for each row the option you would prefer:

		Option 1 – Get Money <u>TODAY</u>	Option 2 – Get Money <u>IN 30 DAYS</u> (= 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

<sup>&</sup>lt;sup>34</sup>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, Karlan and Yin [2006], Shapiro [2005], Meier and Sprenger [2010])

#### C 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  $u'_{\rm w}>0$ ,  $u''_{\rm w}<0$  and  $\lim_{{\rm w}\to\infty}u'({\rm w},\cdot)=0$ . 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  $\pi p$  and earn expected return  $\pi p(1+r)-1$ . 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

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

It follows that the posterior probability of a firm being bad after receiving a bad signal is  $P(\theta_B|\sigma_B)=1$ , and the probability of the firm being good after observing a good signal is  $P(\theta_G|\sigma_G)=\frac{\pi}{\pi+(1-\gamma)(1-\pi)}$ . 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

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

Contracts. The bank may offer the loan officer a contract  $\mathbf{w} = [w, w_D, \overline{w}]$  to induce screening effort. The contract specifies a payment  $\overline{w}$  for declining a loan application, and contingent payments for approving a loan that subsequently performs  $w_P$  and for approving a loan that subsequently defaults,  $w_D$ , where  $w_P, \overline{w} \in [0, r]$  and  $w_D \in [-1, 0]$ . The bank's problem is to choose  $\mathbf{w} = [w_P, w_D, \overline{w}]$  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  $u_{\rm R} = u(\overline{\rm w})$ . If the loan officer approves a loan without screening, her expected utility is

$$u_{\rm NS} = \pi p u(w_{\rm P}) + (1 - \pi p) u(w_{\rm D})$$
 (A.4)

If an officer screens and approves only when no negative signal is observed, her utility is  $^{35}$ 

$$u_{S}(\mathbf{w}) = \pi p u(\mathbf{w}_{P}) + [1 - \pi p - \gamma(1 - \pi)] u(\mathbf{w}_{D}) + [(1 - \pi)\gamma] u(\overline{\mathbf{w}}) - e$$
(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:  $u_{\rm S} \geq u_{\rm NS}$  and  $u_{\rm S} \geq u_{\rm R}$ . The first constraint requires that the returns to effort be greater than the cost of effort. This condition simplifies to:

$$\gamma \left[ u(\overline{\mathbf{w}}) - u(\mathbf{w}_{\mathbf{D}})(1-\pi) \right] \ge e^* \tag{A.6}$$

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

$$\pi p u(\mathbf{w}_{\mathbf{P}}) + [1 - \pi p + \gamma(\pi - 1)] u(\mathbf{w}_{\mathbf{D}}) - [1 + \gamma(\pi - 1)] u(\overline{\mathbf{w}}) \ge e^*$$
 (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  $w_P$  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)  $\frac{\partial e^*}{\partial w_D}$  and  $\frac{\partial e^*}{\partial w_D} < 0$  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

<sup>&</sup>lt;sup>35</sup>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  $\Pi_{NS} = \pi p(r-w_P) - (1-\pi p)(1+w_D)$ , 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.<sup>36</sup> 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

$$v(b,e) = \int_{B} h(b)\phi(b,e)db$$
 (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

$$u_{\mathcal{S}}(\mathbf{w}, e) = u_{\mathcal{S}}(\mathbf{w}) + \lambda^{i}(\mathbf{z}, \bar{t} - t) \int_{B} h(b)\phi(b, e)db - e$$
(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  $\tilde{e}$  in which the agent exerts non-zero screening effort independent of monetary incentives with  $\frac{\partial \tilde{e}}{\partial \lambda} > 0$ ,  $\tilde{e} > 0$  and  $\tilde{e} \leq e^*$ .

**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  $\frac{\partial \tilde{e}}{\partial (\bar{t}-t)} > 0$ .

<sup>&</sup>lt;sup>36</sup>This requires the assumption that all agents will, in equilibrium, form the same expectations.

<sup>&</sup>lt;sup>37</sup>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].

# D Appendix Tables

## Table D.I Test of Random Assignment

This table reports a test of random assignment. We regress loan officer characteristics on an indicator variable for loans evaluated under high-powered and origination incentives, week-of-experiment fixed effects and dummy variables controlling for the the randomization strata described in Section IV.. In all regressions, the low-powered baseline incentive is the omitted category. Male is a dummy variable equal to one if the participant is male. Age is the loan officer's age. Rank is the loan officer's level of seniority in the bank, ranging from 1 (lowest) to 5 (highest). Experience is the number of years the loan officer has been employed by the bank.  $Private\ sector\ banker$  is a dummy variable equal to one if a loan officer is employed by a private sector bank. Standard errors, in parentheses, are heteroskedasticity robust and clustered at the loan officer level. \* p<0.10 \*\*\* p<0.05 \*\*\*\* p<0.01.

	Male	A cro	Education	Experience	Rank	Private Sector Banker
		Age		1		
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline, omitted						
Origination	-0.023	-0.385	0.023	0.016	-0.123*	-0.016
	(0.02)	(0.68)	(0.03)	(0.66)	(0.07)	(0.02)
High-powered	-0.003	0.017	-0.054	0.659	-0.068	-0.009
	(0.02)	(0.64)	(0.04)	(0.62)	(0.08)	(0.03)
Observations	14,675	14,675	14,405	14,675	14,675	14,675
R-squared, adjusted	0.059	0.401	0.060	0.379	0.076	0.584

Table D.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	Panel A: Entire sa	sample	Panel E	Panel B: Performing loans	ing loans	Panel	C: Non-per	Panel C: Non-perf & declined	Difference in means	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)	(9)	(7)	(8)	(6)	(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	6	7.99	11.64	6	8.35	9.5	∞	8.0	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 D.III 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 pe	r loan
	correct	approved	screened
	(1)	(2)	(3)
Number of experimental	-0.001*	0.003	-0.003
sessions completed	(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 D.IV 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 pe	r loan
	Approved=1	Performing=1	approved	screened
	(1)	(2)	(3)	(4)
Panel A: Final Rating				
Log internal rating	1.348***	0.323***	0.449*	1.000***
	(0.04)	(0.03)	(0.238)	(0.089)
R-squared	0.443	0.059	0.023	0.027
Number of observations	13,979	13,979	8,956	11,478
Panel B: Personal and Manager	nent Risk			
Log internal rating	1.159***	0.282***	0.368*	0.851***
Personal and management risk	(0.04)	(0.03)	(0.221)	(0.094)
R-squared	0.368	0.055	0.023	0.025
Number of observations	13,979	13,979	8,956	11,478
Panel C: Business and Financia	ıl Risk			
Log internal rating	1.265***	0.321***	0.31	0.918***
Business and financial risk	(0.04)	(0.02)	(0.226)	(0.082)
R-squared	0.439	0.060	0.023	0.026
Number of observations	13,979	13,979	8,956	11,478
Loan fixed effects	No	No	No	No
Loan officer fixed effects	Yes	Yes	Yes	Yes

Table D.V Heterogeneity in the Response to Incentives, Additional Results

This table presents additional 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. In addition to the fixed effects indicated at the foot of the table, all regressions control for loan officer age, rank, gender, education, experience in other business areas. Regressions additionally control for all measured personality traits included in Table X, including all non-reported categories of the "Big Five" personality test. Standard errors, in parentheses, are clustered at the loan officer  $\times$  session level. \* p<0.10 \*\* p<0.05 \*\*\*\* p<0.01.

	Screen	ing Effo	ort							
	Sections	s reviewe	ed		Information credits spent					
	Main E	ffect	Intera	ction	Main Eff	Interacti	on			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
A. Male	-0.46	(0.52)			-0.88	(0.88)				
High-powered	-0.47	(1.15)	1.06	(1.17)	-2.11	(1.40)	3.69**	(1.12)		
Origination	0.56	(1.25)	-0.36	(1.27)	-2.21	(1.47)	2.09*	(1.23)		
R-squared, N	0.498	6,102			0.424	3,828				
B. Seniority rank	0.15	(0.14)			0.64**	(0.28)				
High-powered	0.55	(0.69)	-0.04	(0.29)	2.26	(1.96)	-0.60	(0.59)		
Origination	0.49	(0.67)	-0.12	(0.28)	1.18	(1.62)	-0.78**	(0.39)		
R-squared, N	0.498	6,102			0.422	3,828				
C. Confidence	0.10	(0.73)			-1.07	(1.36)				
High-powered	0.82	(0.84)	-0.43	(1.22)	-0.33	(1.93)	-0.60	(2.05)		
Origination	0.12	(0.89)	0.21	(1.26)	-1.79	(1.85)	-0.03	(1.68)		
R-squared, N	0.496	6,102			0.425	3,828				
D. Altruism	0.64**	(0.27)			3.37***	(0.47)				
High-powered	0.89*	(0.49)	-0.48	(0.55)	-0.06	(1.04)	-0.80	(0.86)		
Origination	0.65	(0.47)	-0.46	(0.55)	-1.29	(1.06)	-1.11	(0.85)		
R-squared, N	0.498	6,102			0.421	3,828				

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