The Information and Agency Effects of Scores: Randomized Evidence from Credit Committees*

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Abstract

Information technologies may affect productivity by reducing agents' information processing costs, and by making agents' private information easier to observe by the principal. We distinguish these mechanisms empirically in the context of the randomized adoption of credit scoring in a bank that lends primarily to small businesses. We find that scores increase credit committees' effort and output on difficult-to-evaluate applications. Output also increases in a treatment where committees receive no new information about an applicant, but the score is expected to become available in the future. This effect is uniquely consistent with scores reducing asymmetric information problems inside credit committees and explains over 75% of the total output increase. Additional evidence suggests that scores improve productive efficiency by decentralizing decision-making and by equalizing the expected marginal returns across loans.

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1 Introduction

The diffusion of information technologies (IT) since the advent of the computer has been associated with increases in productivity in organizations.[1] Empirically identifying the effect of IT on productivity and ascertaining the channel through which it affects performance, however, have proved elusive. The identification problem arises from the fact that IT adoption is usually bundled with other organizational innovations, such as job descriptions, compensation structures or the allocation of authority, which may also affect productivity (see Milgrom and Roberts (1990)).[2] And the main difficulty in isolating the mechanism lies in the dual role played by most IT innovations: they may raise productivity directly by reducing information processing and communication costs, and indirectly through facilitating better monitoring and reducing information asymmetries inside the firm. Distinguishing between the information and agency channels is a key input for understanding the implications of these innovations on firms' internal organization and boundaries.[3] However, existing work attempting to disentangle these two mechanisms has had to rely on ad hoc classifications of whether the information channel or the agency channel will be dominant for each technology.[4]

The present paper uses a randomized control trial design to empirically identify the causal effect of an IT adoption on productivity, and to distinguish the impact through

[1]For early surveys, see Brynjolfsson and Yang (1996) and Brynjolfsson and Hitt (2000).

[2]In addition, IT innovations are typically adopted in response to changes in the environment. In credit markets, for example, it is optimal in theory for lenders to adopt scoring models based on hard information when competition increases (Heider and Inderst (2012)). It is thus difficult to identify the impact of IT innovations from the time series variation of outcomes without imposing structural assumptions (see, for example, Einav, Jenkins and Levin (2012)).

[3]See, for example, Aghion and Tirole (1997) Antras, Garicano and Rossi-Hansberg (2006), and Alonso, Dessein and Matouschek (2008).

[4]For example, Hubbard (2000) identifies two classes of on-board computers in the trucking industry and classifies one as *incentive-enhancing* and the other as *resource-allocation-improving*. Also, Baker and Hubbard (2004) assumes that the introduction of an on-board computer system improves performance through better monitoring. More recently, Bloom, Garicano, Sadun and Van Reenen (2011) classify technologies into communication enhancing and information enhancing, although not for the purpose of separating the information and agency channels.

the information and agency channels. We study how the introduction of a new IT based credit scoring model affects worker effort and output at a bank in Colombia specialized in loans to small enterprises. Prior to the adoption of the scoring model, credit committees evaluate loan applications based on the raw information a loan officer collects in the field from prospective borrowers. The committee determines whether the application should be approved, and conditional on approval, what the terms of the loan should be. If the committee cannot make a decision the loan is passed on to the (higher) manager level for review or an additional round of costly information collection takes place.

We worked with the bank to randomize the roll out of a new credit scoring model in pilot branches. The scoring model provides information about the estimated default probability of a new loan application. Bank headquarters developed this scoring model based on historical loan performance and applicant characteristics such as age, gender, business cash flows and assets, and household expenditure to income. The characteristics used to calculate the score are a subset of those contained in the application file, and are thus observable by the committee before the scores are provided. In the first treatment arm, $T1$, we include the applicant's score in a randomly selected sample of applications submitted to pilot branches before they are evaluated by the credit committee.

There are two ways in which the credit score may lower the cost of acquiring information by the committee. On the one hand it can provide a cheap signal about the default probability that is otherwise impossible to obtain through the analysis of the application or through deliberation by committee members. We label this the *information channel.* On the other hand, the credit score may contain information that is privately observable by the loan officer at some cost —e.g. by analyzing information obtained from direct contact with the prospective borrower in the field. In this case, the score reduces the asymmetry of information between the officer and other committee members, whose only source of information is the "hard" information contained in the application. Making public a signal of the agent's private information reduces the cost of agency problems inside committees that may arise, for example, if loan officers are too conservative, or collude with the borrower. We label this the *agency channel*.

A key innovation in this paper is the design of a second treatment arm ($T2$) aimed at isolating empirically the agency channel. In this randomly selected sample of treatment applications, committees make an interim evaluation of the application *before* observing the value of the score, but knowing that the score will become available to all committee members immediately after the interim decision has been made. This treatment allows us to measure the effect of the expected reduction in information asymmetries between the officer and the committee, while holding constant the information set under which the committee makes decisions. Thus, the effect of $T2$ on interim decisions, before observing the score, measures the agency effect of scores on output.

We find that committees spend more time evaluating applications (more effort) and are more likely to reach a decision on an application (more output) when given access to the credit score in treatment $T1$. The increase in effort is concentrated in marginal —difficult to evaluate– applications that are more likely to be rejected. Despite the upward shift in the difficulty of the tasks performed, the average quality of the decisions, measured as the loan approval amounts and the ex post default rate of the loans approved, remains unaltered. Moreover, we find evidence that treatment improves the cross-sectional allocation of credit: scores equalize the marginal expected return across loans. The increase in committee output substitutes for other, more expensive, inputs in the loan evaluation process. Namely, when committees reach more decisions they reduce the number of application referrals to higher level managers and the collection of additional costly information.

In the second treatment ($T2$) we find that interim committee output also increases relative to the control group, despite the fact that both have the same information at the time of making a decision. Although output increases even further after the committee observes the score, 75% of the output increase in this treatment group occurs before the score is observed. These estimates imply that the adoption of the scoring model has a first order effect on output through the agency channel.

Looking across both treatments we see that the effect of introducing the scores on the bank's overall output is negligible in the short run —holding constant loan prices, number of employees, pay structure and other features of the bank's organizational design. However, one could conjecture that over time the increase in committee productivity and the time savings at the management level could lead to overall increases in output.

Our results present causal evidence on the role of information technologies in shaping the optimal organization of production. Consistent with the predictions in Garicano (2000), our findings imply that innovations that lower the cost of using information leads to more decentralized decision making inside the firm.[5] By introducing the second treatment arm $T2$ we are able to disentangle the alternate mechanisms that explain information costs inside the firm: technological limitations in information processing and agency conflicts between privately informed workers and the rest of the organization. We show that the agency mechanism explains the bulk of the effect of scores on output, suggesting that IT based monitoring policies may provide an adequate, and cheaper, substitute for policies based purely on monetary incentives.

This is an important empirical conclusion because, in theory, innovations that make agents' information and decisions observable by the principal may have ambiguous effects on the productivity of difficult-to-evaluate workers. In moral hazard contexts where the principal and the agent are symmetrically informed about which actions are appropriate, observing the agents' decisions reduces the cost of inducing effort by the agent (Holmstrom (1979)). In contrast, when agents have career concerns (Holmstrom (1999), Dewatripont, Jewitt and Tirole (1999)), have private information about the productivity of their actions

[5] Our setting is remarkably close to that in Garicano (2000), where workers solve common problems and ask for advice to managers on uncommon ones.

(Prat (2005)), or want to conform to the opinion of the principal (Prendergast (1993)), innovations that improve transparency may reduce performance.[6] The results imply that scores help improve the alignment of loan officer incentives with those of the bank and thus suggest that moral hazard costs are of first order importance in our empirical context.

The specific application we focus on, credit scoring, is also of particular importance given the large literature in finance and banking on relationship lending and the role of loan officers in the lending process. This literature has largely focused on the trade off between using soft —less standardized and difficult to communicate— versus hard information. Stein (2002) specifically conjectures that loan officers face weaker incentives in soft information regimes. Our paper provides the first direct evidence to support this conjecture by demonstrating that the adoption of a standardizing technology in the context of a soft information lending process can mitigate agency problems inside the bank.[7]

The rest of the paper proceeds as follows. We provide in Section 2 a description of the tasks and incentives of the credit committees, the characteristics of the credit scoring system. Section 3 describes the experimental design and provides descriptive statistics on the loan applications. Section 4 presents the results of introducing the score on committee output and productivity, Section 5 unpacks the economic mechanism behind the effect. Section 6 concludes.

2 Empirical Setting

The study was implemented with BancaMia, a for profit bank in Colombia that focuses on issuing one- and two-year unsecured loans to micro and small enterprises. The business

[6]Consistent with this interpretation, Berg, Puri and Rocholl (2013) shows evidence that loan officers may "game" the scoring model to pursue private benefits.

[7]A number of empirical studies have analyzed the implications of soft information for bank function and organizational design. See, for example, Berger, Miller, Petersen, Rajan and Stein (2005), and Liberti and Mian (2009).

model of BancaMia, similar to those of other for-profit micro and small business lenders, is based on issuing large numbers of small loans. Only during October 2010, the month prior to the roll out of the study, the bank issued 20,119 loans totalling $US 25,9 million through its 143 branches (average size below $US1,300). Historically the bank relied on a relationship lending model based on two unique sources of information. The first is first-hand verifiable and non-verifiable information about prospective borrowers collected by loan officers in the field. This information collection mechanism is costly but necessary, since micro and small enterprises in Colombia do not have any audited financial statements or other secondary data that a bank could use for credit assessment. The second component is information generated through the repayment history of the riskiest clients: BancaMia offers very small loans to borrowers with high ex ante default probabilities in order to elicit information about their true ex post propensity to repay.[8]

The bank relies on an information technology that allows the loan officer to upload from the field the data collected via PDA (Personal Digital Assistant) devices to a data storage facility in the bank's headquarters. All the information related to an application, including both first hand information collected by the loan officer, past information about the borrower in BancaMia if the borrower has a credit history in the bank at the time of the application, and any external secondary source information (e.g. credit score of the borrower from a private credit rating agency) is put together by the system in a single application file.

2.1 Credit Assessment Process

The application file is then reviewed by a credit committee at the local branch where the loan officer reports to. The committee is composed of the loan officer that collects the information, the branch manager (the loan officer's immediate superior), and one or two

[8]For a theoretical analysis and some evidence of the implications of this learning-by-lending approach, see Rajan (1992) and Petersen and Rajan (1995).

additional credit specialists. The credit specialists are typically other loan officers also employed at the branch.

It is important to highlight three unique aspects of the loan prospecting process. First, although the officer collects both quantitative and qualitative information, in the absence of financial statements all information is "soft" in the sense that it is difficult to verify by anyone other that the agent who produced it. For example, sales figures for a small restaurant may be gathered directly by the loan officer by counting the number of tables served during lunch-time and multiplying by the average price of a meal. Second, the loan officer who collects the information makes an active decision to bring an application to the committee, and screens out applicants who do not fit with the desired profile. Thus, applications that reach the committee do not represent the universe of potential borrowers or applications, but only those that have been pre-selected by the field officer.[9] And third, officers are expected to give advice to the prospective borrower on how to fill the application in order to maximize the likelihood of approval. In particular, the riskiest borrowers are encouraged to request smaller loan amounts. Thus, requested loan amounts do not represent the borrower's unconditional demand for credit. A consequence of these risk-adjustments in loan size is that the rejection rate of loans that reach the committee is very low.

Due to this selection in loan prospecting, we must consider the possibility that the introduction of scores changes the officers' incentives to gather data and select applicants in the field. For example, if the officers expect scores to reduce the cost of making decisions on marginal cases, they may increase the proportion of marginal applications brought to the committee. In the results section we study how the applicant pool changes during the trial weeks along observable characteristic, such as credit scores and requested loan amounts, and find little evidence of a shift in the applicant pool. More importantly, our

[9]All the information regarding potential applicants that do not reach the committee review stage is discarded by BancaMia and is not available for this study.

experimental design, discussed in Section 3, randomizes at the application level once the application reaches the committee to ensure that changes in the application pool do not affect the internal validity of the results.

Once an application reaches the credit review stage, the committee can take four possible actions. First, it can reject the application. Second, it can approve it, in which case the terms of the loan must be decided. The committee may make modifications to the terms of the requested loan —amount and maturity only, the interest rate is fixed– in order to improve profitability. For example, the committee may decide to approve $US500 for a loan application of $US1,000 if the borrower is deemed to be too unlikely to repay the latter amount. Since rejection rates are extremely low, the main task of the committee is to decide the "right" loan amount and maturity given the riskiness of the borrower. When a committee approves or rejects a loan we consider that the committee has reached a decision regarding an application.

The third action available to the committee is to send the application file to a Regional Manager, whom evaluates the application and reaches a decision.[10] Upper level managers are more skilled and have more experience in credit risk assessment than loan officers or branch managers, and are expected to be more likely to reach the "correct" decision on more difficult applications. The fourth action the committee may take is to send the officer to collect additional information about the borrower. In this case, the committee must take an action on the application in a second round of discussion, after the additional information is collected.

BancaMia managers expressed during informal interviews that the third and fourth actions described above, taken when the committee cannot reach a decision regarding an application, represent a substantial cost to the bank in terms of the opportunity cost of

[10]loans above 8 million pesos go directly to the Regional Manager for approval. Randomization insures that this mechanical relationship between loan size and approval level is orthogonal to the scores. Also, adding requested loan amount as a control in the specifications does not change the estimated effect of scores.

time of managers and officers. It is difficult to quantify these costs precisely. The base fixed wage of a Regional Managers is four to eight times that of a loan officers, which gives a lower bound on the incremental evaluation cost of an application by upper management. Further, the Regional Manager must evaluate the application without the officer that collected the information present and must incur in an additional communication costs to access any soft information not reflected in the application. There are additional delay costs when applications sent up are not reviewed immediately, due to the large volume of applications and time constraints of Regional Managers that supervise between 15 and 80 offices.

Committee member bonus compensation is an increasing function of the number, amount, and value-weighted performance of the loans issued by a branch. Performance pay to loan officers based on lending amount and loan performance is common in most types of lending institutions. The combination of bonuses based on the number of loans and value-weighted loan performance are meant to provide incentives to issue small loans to the riskiest borrowers —compensation based solely on the dollar volume of lending would discourage officers from making small loans.

All the bonuses are calculated on the basis of loans issued, regardless of whether the decision was made by the committee or by the upper level manager. There are two potential reasons for measuring performance based on issued loans only. First, pay based on decisions made would penalize committees for asking questions to the skilled upper level managers, and may lead to too many bad decisions at the committee level. Second, committee members must be compensated for monitoring the performance of the loans after origination, even when the decision to approve is made at an upper level of the hierarchy.

The interest rates are set centrally based on the type of loan (first-time versus repeat borrower, urban or rural loan). Thus, neither loan officers, committees, or managers have discretion over the price of loans.

2.2 Credit Scores

In 2010, BancaMia developed a credit risk model to establish the statistical relationship between the bank's historic quantitative and qualitative information in loan applications and the repayment performance of issued loans. For the quantitative part of the score, loan officers are asked to collect information such as: gender, age, location, number of years in business, frequency of late payments in past three years (if the loan applicant already has a credit history with BancaMia), level of overall indebtedness, house expenditures as a percentage of total income, among other variables. For the qualitative part, loan officers are asked to collect information based on more subjective variables such as: overall knowledge of business, general sense of the level of organization, quality of information provided, quality of business location, quality of crops being cultivated (agricultural loans only), stability and diversity of income, among other variables.

The stated objective of introducing the credit scoring system was to improve identification of the best and worst clients, decentralize the loan approval process, and reduce the labor costs involved in loan application evaluation. The idea was to add the score as an input to committees' decision process by including the score in the application file.

The score is a proxy for the expected default probability of the loan. Figure 1, panel (a), plots the out-of-sample relationship between scores and default probabilities in the population of loans issued during October 2010 (the scoring model is calibrated using data for loans issued in 2009). For the purposes of the plot, a loan is considered to be in default if interest or principal payments are more than 60 days overdue at six or twelve months after the loan is issued. There is a strong positive association between credit scores and and default probabilities. The tight standard error band implies that scores have a good out-of-sample predictive power for future default at 6-month and 12-month horizons. This implies, in turn, that the data collected by loan officers in the field is informative about the repayment prospects of borrowers.

There is a strong negative relationship between default probabilities and requested loan amounts in the population (Figure 1, panel (b)). This relationship is consistent with loan officers screening out large loan applications by risky borrowers, or recommending risky borrowers to request smaller loan amounts. Either way, the observed relationship suggests that loan officers have an informative prior about the default probability of a borrower before bringing the application to the committee (and before observing the score).

3 Trial Design and Descriptive Statistics

We design a randomized control trial (RCT) with two goals. The first is to measure the causal effect of scores on the effort and output of the committee, and the total output, loan performance and efficiency of capital allocation of the bank. The objective is to evaluate whether and how credit scores lower the cost of decision making for the committee.

The second goal is to decompose the causal effect of scores into two broad mechanisms: information provision and reduction of agency costs. In the pure information mechanism, scores deliver information that the committee members can otherwise only obtain only at a higher cost, e.g. by analyzing the application and deliberation in the committee. For example, the score may contain information that the loan officer already has but that is costly to communicate to others. Alternatively, the score might simplify the processing of information since it automatically assigns weights —based on population data– to the different dimensions of the application which would otherwise require substantial effort by the committee. In our set up, scores do not provide additional information from what is in the application already, since the score only uses inputs from the application form. Instead, scores are an innovation that lower the cost of communicating information to the committee members and of analyzing information in the application file.

In the pure agency mechanism, scores reduce the information asymmetry between the loan officer and the other committee members. In this scenario the score does not provide any new information to the loan officers; it provides the other committee members with information about the repayment probability of a borrower that is privately known by the loan officer. Reducing the information asymmetry inside the committee will affect output if loan officers' incentives are not fully aligned with the those of the bank —for example, if loan officers are more risk loving than the bank, or if it takes a substantial effort to communicate information about a borrower to the committee.

The fundamental distinction between this agency mechanism and the information one is that scores do not bring new information to the committee: all the information is already in the committee but cannot be used effectively due to agency conflicts. We exploit this difference to isolate the effect of scores through the agency mechanism: we design a treatment that reduces the expectation that the informed agent can exploit the information asymmetry, but holds the information set of the committee constant.

3.1 Design

We implemented a pilot program with an RCT design in eight of BancaMia's 24 branches. The branches were chosen to be representative of the average urban branch of the bank.[11] The pilot consisted of randomizing, at the application level, the introduction of scores in the application file at the time of the committee meeting. At the initiation of the discussion of an application in a committee, the research assistants generated a random number to allocate the application into one of three groups, one control and two treatments. Committee members were informed of the group assignment during the evaluation of the application. As argued above, because the randomization took place in real time

[11] BancaMia also operates rural branches, with a larger fraction of loans associated with agricultural micro-enterprises.

when the application was being evaluated, we guarantee the internal validity of the results in the presence of potential changes in the application selection criteria or the information gathering process introduced by the pilot program.

In the control group, the committee evaluated the application as before and did not rely on the score. In the first treatment group ($T1$), the committee receives the score before beginning the evaluation of the application. This first treatment allows us to measure the overall effect of scores on committee effort, output and productivity.

In the second treatment group ($T2$), the committee is asked to evaluate the application before receiving the score and chooses an interim action. Committees do not have any additional information when evaluating applications in $T2$ relative to control applications. However, the difference is that the committee members know that the score will become available after choosing an interim action. After recording the interim action, the committee receives the score and can revise it to take a final action (for example, a committee may choose to send an application to the Manager in the interim action, but decide to approve the loan after observing the score). Interim actions in this second treatment allow us to measure how committee behavior changes when the information asymmetry between the committee members is expected to decline, while holding constant the information set available to make the decision.

The main advantage of this design is that it allows measuring the effect of reducing information asymmetry on output regardless of the nature of the underlying agency problem. Moreover, we can make inferences about the nature of the agency problem by looking at whether reducing the information asymmetry reduces or increases the level and quality of committee output. Under relatively weak assumptions, Holmstrom (1979) shows that more information about the agent is strictly beneficial to the principal in moral hazard problems. In contrast, more information about the officer may hurt the bank if it reduces her incentives to work hard to prove her worth (Holmstrom (1999)), or if it increases the officer's incentives to disregard useful private information to act according to what is expected by the bank (Prendergast (1993), Prat (2005)). Thus, the sign of the effect of scores on committee output and default rates allows us to gauge the relative importance of two broad classes of agency problems in organizations.

In a short training workshop before the roll-out of the scores, branch directors and loan officers at the eight pilot bank branches were provided with a general explanation of the credit risk model, the scores, and the objective of the study (researching the usefulness of the score as an input to the credit evaluation process). They were also provided with a detailed description of the three treatment groups and the randomization procedure. We report in Appendix Table A.1 the number of control, treatment $T1$ and treatment $T2$ loans per branch in the study sample.

3.2 Descriptive Statistics

We present descriptive statistics of the applications in the control and treatment groups on Table 1, as well as the p-values of difference of means tests between the three groups. Pre-determined application characteristics —characteristics determined before the randomization takes place– are shown in Panel A. In the control group, average loan amount size is US$1,551, average maturity is 20.9 months, average risk score is 0.151, and the fraction of first-time borrowers is 14.6%. Randomization implies that any differences in pre-determined variables between the treatment and control groups are purely by chance. Table 1 corroborates that randomization created groups that are comparable in terms of pre-determined characteristics, with the only significant difference in means occurring for application maturity, which is one month shorter in treatment group $T1$ than in the control group. Our main specification will include pre-determined characteristics to account for chance differences between groups.[12]

[12]The application amount and score distributions are indistinguishable between the treatment and control groups in a two-sample Kolmogorov-Smirnov test for equality of distributions, with corrected

Table 1, Panels B through E, presents the statistics for committee and loan outcomes. Some outcomes, such as the time the committee needs to take an action, are measured for all applications. Others are measured conditional on a particular action of the committee. For example, the indicator for whether the loan was approved or not is measured conditional on the committee reaching a decision, and the approved loan amount is measured conditionally on the committee approving the loan.

The average time spent evaluating an application in the control group, measured as the difference in the time stamp assigned by the research assistant to the beginning and end of each evaluation, is 4.68 minutes (std. Dev. 3.28).[13] Committees reach a decision (accept or reject a loan) in 89% of the applications, and conditional on reaching a decision, in 0.3% of decisions the committee rejects a loan in the control group.

Conditional on loan approval, the committee approves a loan amount different than the requested one in 92% of the applications. The average ratio of approved to requested loan amount is 0.975 indicating that the mean size of approved loans differs little from the mean application amount. Nevertheless, there is substantial variance (Std. Dev. 0.419), and the average absolute value of the difference between the approved and requested amount is $US266, or 17% of the average requested loan amount. Similar patterns can be found for loan maturity, although the proportion of cases in which the committee modifies the loan application maturity is lower (26.2% of the applications in the control group). The low rejection rate and frequent rate of loan size and loan maturity adjustments suggest that committees decisions occur mostly in the intensive margin, e.g. on "how much" to lend as opposed to "whether "to lend or not.

Not all approved loans are issued: 83.5% of the loans approved during the pilot program appear as issued in the bank's information system. The bank does not record the

p-values of 0.81 and 0.94 respectively. We do not perform test for maturity distributions because these are highly concentrated in whole year numbers (12, 24, and 36 months).

[13]Committees see on average 15 applications per day, which implies that committees spend about 70 minutes per day evaluating applications (without considering transitions, breaks, distractions, et cetera).

reason why the loan is not issued, but presumably the borrower either did not need the loan anymore or got credit from a different source. The default rate among the issued loans —fraction of loans more than 30 days late in repayment measured six (twelve) months after the loan was issued— is 3.3% (9.5%) in the control group.

Comparing the unconditional outcomes in the treatment and control groups in Table 1, shows that on average committees spend more time reviewing applications in the treatment groups, although the difference is only significant for treatment $T2$ (the difference in average time between $T1$ and $T2$ is not significant). Committees were more likely to reach a decision in both treatment groups than in control applications. None of the loan characteristics or outcomes conditional on approval is statistically different in the treatment and control applications, except for the average absolute value of the change in maturity.

Table 2 shows the descriptive statistics for applications in the control group conditional on the action taken by the committee —made decision, sent application to the Regional Manager, or sent the officer to collect additional information. On average, the applications for which the committee reaches a decision are for smaller amounts and are more likely to be submitted by first time applicants than applications where the committee does not reach a decision. Applications where the committee reaches a decision are no different in their credit risk (as measured by the score), to those sent up to the Manager, but have a smaller credit risk than those where the officer is sent to collect additional information. Committees spend less time evaluating applications where they reach decisions than when they send the application up to the Manager or the officer out to collect additional information. If one equates evaluation time with effort, this implies that the committee members employ a substantial amount of effort before being able to determine that a decision cannot be reached.

We can also measure final outcomes for applications when the committee did not make a decision during the experiment by tracking the application after the pilot in BancaMia's information system. This allows us, for example, to measure the disbursed amount and the default rate of loans approved by the Manager, or loans approved after a second round of information collection by the loan officer. Note, however, that due to the fact that not all approved loans are issued, we cannot measure the fraction of the applications rejected by the Manager or in a second round by the committee (rejected applications and approved but non-issued applications are confounded in the ex post data). The final loan outcomes differ substantially depending on the action taken by the committee. For example, loans approved by the manager default with a probability of 8.3% (12-month measure) and have an approved amount that is 95% of the application amount, while loans approved by the committee after a second round of information collection default with probability 13.3% and have an approved amount that is 148% of the application amount.

The above patterns suggest that there is substantial heterogeneity in the observable characteristics of loan applications, and that this heterogeneity is correlated with the likelihood that the committee can reach a decision. The complexity of the task of reaching a decision is unobservable by the econometrician, but we will use the time spent evaluating an application as a measure of effort. In theory, in the presence of task heterogeneity committees should make decisions on the easy-to-evaluate applications and send up to the manager or collect additional information on the difficult-to-evaluate ones (Garicano (2000)). If this is so, the statistics in Table 2 suggest that difficult applications take more time to evaluate, and that applications for larger amounts and with longer maturities are more difficult to evaluate. On the other hand, the difficulty of evaluating an application does not appear to be related with the credit risk of the borrower, as measured by the score. We provide in the Appendix a simple model that has this features and can be used as a framework to evaluate the implications of introducing credit scores.

4 Results

We use the following reduced form equation to estimate the effect of credit scores on committee and loan final outcomes (we delay the discussion on the effect on interim committee decisions for $T2$ until Subsection 5):

$$Y_i = \beta \cdot Treatment_i + X_i' \cdot \eta + \varepsilon_i, \tag{1}$$

where Y_i is an outcome related to loan application i. The variable $Treatment_i$ is an indicator for whether the application is in either treatment group $T1$ or $T2$. In some specifications we also include an indicator equal to one if the application is in treatment $T2$ to evaluate differential effects of the two treatments (we do not find any). The vector X_i contains predetermined application characteristics: applicant's credit score, application loan amount, application loan maturity, a dummy if it is the first loan application of the potential borrower, and the date of the application (in weeks).[14]

We begin by presenting the results for outcomes that are measured unconditionally, such as the action taken by the committee or the application evaluation time. The estimated β using these outcomes measures the Average Treatment Effect (ATE) of having a score as an input to the credit evaluation process.

4.1 Committee Actions

We present in Table 3 the estimated effect of introducing a score on the probability that the committee makes a decision (accepts or rejects an application). The point estimate is 4.6 percentage points, statistically significant at the 5% level (column 1). This implies that when scores are added as an input in the decision process, the number of cases in which committees cannot decide is reduced by 41.8% relative to the baseline proportion

[14]Results without controls are not significantly different, see Appendix Table A.2.

of 11% in the control group. The difference in the effect between $T1$ and $T2$ is positive but not significant (Table 3, column 2).

The data allow identifying two distinct margins through which scores increase committee output: 1) by reducing the need to collect additional information from applicants, and 2) by reducing the need to use upper level manager time in evaluating loan applications. We present in in Table 4 the results of estimating a multinomial logistic specification to model committee choice between between approving a loan, rejecting it, collecting additional information, or sending the application to a manager in a higher hierarchical level to make the decision.[15]

Treatment has a negative and statistically significant effect on the probability of sending the application to the manager and on the probability of collecting additional information.[16] To evaluate the economic significance of the effects, we report on the bottom rows of Table 4 the implied marginal effect of treatment on the probability of each choice. Observing a score decreases the probability of sending the decision up to the manager by 2.3 percentage points, a 48% decline reduction in the baseline probability that an application is sent to the manager in the control group. Scores reduce the probability of collecting additional information by 1.7 percentage points, a 27% decline relative to the baseline.

The results suggest that scores increase committee decision making ability by reducing the degree to which they rely on managers in upper levels of the hierarchy to solve problems

[15]We estimate:

$$\ln \frac{P\left(D_i = m\right)}{P\left(D_i = 1\right)} = \beta_m \cdot Score_i + X_i' \cdot \chi_m + \varepsilon_{mi}, \tag{2}$$

where D_i represents the committee choice. We use the committee's decision to approve a loan, $D_i = 1$, as the reference category. All right-hand side variables are as in equation (1). There is one predicted log odds equation for each choice relative to the reference one, e.g. there is a β_m for rejecting a loan, one for collecting more information, and one for sending the application to the manager. A positive estimate for β_m implies that committees are more likely to take action m than to approve a loan in the treatment group relative to the control group.

[16]The coefficients on the treatment regressors β_m are significant at the 1% level in a joint test across the four choices)

and on costly information acquisition by the loan officer. This effect implies that scores reduce the cost of decision-making by committees, and are consistent with the prediction in Garicano (2000).

4.2 Committee Effort

Our evaluators recorded in real time the beginning and ending time of each application's evaluation. We use the time spent evaluating an application as a measure of committee effort. The estimated effect of introducing a score on the time it takes to evaluate and application is 0.76 minutes, statistically significant at the 1% level (column 3). This implies that committees spend on average 16.2% more time per application when scores are available, measured at the mean evaluation time in the control group of 4.7 minutes. Treatment $T2$ has a larger effect on evaluation time than $T1$, but the difference is not statistically significant (column 4). Some difference is expected since committees must make two decisions in $T2$: an interim one without observing the score and then revise it after observing the score.

One would conjecture these results are the result of committees making more decisions and taking more time on the marginal cases, i.e. applications that require a higher than average effort to evaluate, when scores are available. To test that this is how the committee is reallocating its time (as opposed to spending more time on all applications), we characterize the effect of scores on the distribution of decision time. Table 3, columns 5 through 10, shows the result of estimating specification (1) using simultaneous quantile regressions for the 25th, 50th, 75th quantiles of evaluation time. The results indicate that only percentiles at or above the median are affected by the introduction of scores, and the point estimates increase monotonically with the quantile (columns 5, 7 and 9).

This indicates that scores do not shift the entire distribution of evaluation times. Instead, the availability of credit scores increases the evaluation time on applications that take longer than the median time to evaluate in the first place. This is consistent with scores increasing the time committees spend evaluating more difficult applications. In contrast, the additional effect of $T2$ relative to $T1$ on evaluation time appears to be constant across all quartiles (columns 6, 8 and 10). So the additional time spent per application due to the additional decision required in $T2$ does not seem to be related to problem difficulty.

We can further explore the relationship between effort and evaluation difficulty in the data by looking at the cross section of applications. We expect that committees are less likely to make decisions (more likely to ask for help) when applications are more difficult to evaluate. The descriptive statistics on Table 2 suggested that loan application amount is correlated with the probability of making a decision. We confirm this non-parametrically in Figure 2, panel (a): the probability of making a decision drops non-linearly with application amount in the control group applications. The figure also shows that treatment increases the probability of making a decision for the largest applications.

Figure 2, panel (b), explores the cross sectional patterns in evaluation time by application amount. The non-parametric estimate of the average evaluation time in the treatment applications is above the average for control applications for every application amount. More importantly, evaluation time is increasing with application amount in the control group, and treatment increases the average time spent on the largest applications. These patterns suggest that application amount is correlated with the difficulty of evaluating an application.

We repeat in Figure 3 the nonparametric analysis of the treatment effect by scores instead of application amounts. Treatment does not appear to have a heterogeneous impact on applications of different scores. This would suggest that, unconditionally, the *level* of the forecast of the default probability is not correlated with the difficulty of evaluating an application. A potential interpretation of this pattern is that the committee has an unbiased signal about the creditworthiness of the borrower, and the the score changes the precision of the signal. The difficulty of evaluating an application is correlated with this precision.

Put together, the cross-sectional patterns in the treatment effect imply that scores reduce the cost of deciding for any given default probability, and that the reduction is larger for larger loan amounts, where the committee members have more at stake. Although our experimental setting is not designed to establish the link between output and compensation, these results are potentially related to the fact that committee compensation is a (negative) function of the value of defaulted loans, and not their frequency (see Cole, Kanz and Klapper (2012) for randomized evidence on compensation and risk taking by loan officers).[17]

4.3 Loan Outcomes

The only loan outcome that we can measure unconditionally is whether the loan was issued or not. All other outcomes —e.g. amount issued, default probability– are measured only conditionally on the loan being issued. Moreover, when we focus on committee outcomes the conditioning criterion is narrower —e.g. the probability that the *committee* approves a loan can be measured only if the committee makes a decision, as opposed to referring the application to the manager or postponing the decision to collect additional information.

For outcomes that are measured conditionally the interpretation of β in specification (1) is complicated by the fact that it captures a combination of two effects: 1) a direct causal effect of treatment on the outcome, and 2) a selection effect driven by the effect of treatment on the conditioning variable. And the results so far suggest that the selection

[17]We also perform a parametric exploration of treatment heterogeneity by augmenting specification (1) with interactions between the treatment dummy and application size and score. These interaction terms are not statistically significant at the standard levels. This is to be expected given the observed patterns in non-parametric plots, where the treatment effect heterogeneity appears to be severely non-linear in loan size, and negligible in score.

component may be important when measuring committee outcomes, given that treatment affects substantially the probability of making a decision. We begin by evaluating the effect of treatment without conditioning on the committee's action, and we turn to outcomes conditional on committee action in the next subsection.

In Table 5 we present the estimates obtained from specification (1) using dependent variables that we can measure ex post from the bank's information system. The effect of scores on the probability that the loan is issued is close to zero and not statistically significant (Table 5, column 1). This implies that the addition of scores to the loan production process does not affect the overall extensive margin of lending. This also means that the selection component of the β estimates for outcomes measured conditioning on the loan being issued (loan amount, default) is negligible.

Scores do not have a statistically significant effect on the average level of any of the measured outputs: loan size, probability that loan amount and application amount are different, absolute value of the loan amount adjustment, and default probability (Table 5, columns 2 through 6). Note that if banks have an unbiased signal of the creditworthiness of the borrower and scores increase the precision of the this signal, the effect of the score on loan amount and default are ambiguous. Banks will lend less to some borrowers and more to others, and this will increase the default probability of some borrowers and lower it for others. The net effect will depend on the distribution of borrower characteristics in the population.

This reallocation across applications should have, in contrast, a strong effect on the relationship between loan contract characteristics and default probability in the cross section. In the simple framework provided in the Appendix, we show that in the extreme case where the bank has a zero-variance signal of the borrower's creditworthiness (measured as the sensitivity of the borrower's default probability to loan size), the cross sectional relationship between loan size and default probability becomes flat. The reason is that without any uncertainty about the borrower's creditworthiness, the optimal cross sectional allocation is the one that equalizes the marginal expected return across borrowers, which in turn implies that loan sizes do not predict default probabilities in the cross section (conditional on the information set of the bank). On the other hand, when there is uncertainty about the borrower's type, this relationship depends on how the precision of the signal varies in the cross section of borrowers.

There is a strong cross-sectional correlation between loan amount and default in the control group applications. The slope of loan amount is negative and on loan maturity is positive in a linear probability model after conditioning for pre-determined observable characteristics (see Appendix Table A.3). In Table 6 we document how these slopes change with treatment. Both slopes become flatter: the slope on loan amount increases by 0.073 (from -0.262) and the slope on maturity decreases by 0.119 (from 0.094). Thus, treatment reduces the cross-sectional correlation between loan size and default by 28% and that between loan maturity and default probability essentially disappears. This implies that the addition of scores to the loan production process substantially decreases the equilibrium cross-sectional correlation between loan contract characteristics that potentially affect default, and ex post default probabilities. This is consistent with the interpretation that scores reduce the uncertainty about the borrower's creditworthiness.

4.4 Committee Conditional Output

To illustrate the complication introduced by measuring the effect of treatment on outcomes that are conditional on committee actions, consider the case of loan size approved by the committee. This loan size can be measured conditional on the committee approving an application, as opposed to rejecting it, sending it to the manager, or postponing the decision until more information is collected. Scores may have direct effect on approved loan size, holding constant the set of applications. This is the Local Average Treatment

Effect (LATE) of scores on loan amount. Scores also change the set of applications that the committee decides on. An these marginal applications are likely to be different along dimensions that are correlated to loan size. In fact, we already documented that this is the case: marginal applications are more difficult to evaluate than the infra-marginal ones and marginal applications are for larger loan amounts. Thus, treatment changes the composition of applications approved by the committee in a way that will likely affect average loan size even if the LATE is zero.

Disentangling the Local Average Treatment and selection effects is typically difficult without an additional instrumental variable for the selection effect.[18] Our setting, however, provides a unique advantage: we can evaluate outcomes of marginal committee decisions due to selection, because these decisions are made anyway either by the manager or by the committee in a second evaluation. To follow our example above, suppose that we find that committees approve loans that are significantly larger when the score is available. We know from the results in Table 5 that the final loan amount does not change. This implies that the entire observed effect of treatment on the approved loan size by the committee is due to selection: the marginal applications approved by the committee are larger than the infra marginal ones (these larger applications would have been approved anyway by the manager or in a second round of decisions). Moreover, since we found that treatment does not have any effect on the average level of final outcomes, *any* difference that we find between treatment and control groups at the committee level is due to selection.

We present the estimates of β using outcomes conditional on committee actions in Table 7, which includes the conditioning variable on the first row. Conditional on making a decision, the probability that a committee rejects an application increases by 0.9 percentage points in the presence of scores, significant at the 10% level (column 1). This estimate

[18]See Lee (2008) for a recent discussion.

implies three-fold increase in the proportion of applications rejected by the committee relative to the baseline probability of 0.3% in the control group. Moreover, assuming that all the additional rejections come from the marginal decisions, the estimate implies that committees reject 13% of the marginal cases they decide on when scores are used as an input $((0.9 - 0.3)/4.6)$. Given that the overall probability that the loan is issued is unchanged, the entire increase must come from applications that would have been rejected by the manager or by the committee in a second decision.

Conditional on the committee approving the loan, scores do not have a significant effect on other committee outcomes. So even though committees are deciding on a larger proportion of marginal cases when the score is available, the average credit supply and loan maturity do not change, and neither do the frequency or amount of revisions to the requested amounts and maturities.

4.5 Loan Prospecting and Branch Output

The introduction of scores may affect the behavior of loan officers in the information collection and loan prospecting stage. For example, in anticipation of the availability of scores in the committee stage of the evaluation process loan officers may change their information gathering effort or shift their attention to particular types of information (from soft information to hard), they may manipulate the entry of data into the system to game the score, or even influence the borrower to change the requested loan amount in the application. In addition, officers may postpone certain types of applications to the committee until the pilot ends.[19]

In this subsection we investigate the effect the effect of scores on loan prospecting and the selection of applications by looking at whether the experiment changes the pool of applications that reaches the committee. We cannot use the experimental design to

[19] See Heider and Inderst (2012) for a theoretical discussion on loan officer incentives and loan prospecting.

study this because the randomization occurs at the committee level, after the selection has occurred. Instead, we perform non-experimental tests that compare outcomes of the pilot branches during the weeks of the trial relative to other weeks, and relative to propensity score-matched non-pilot branches of the bank during the same weeks, using the following difference-in-differences specification:

$$Y_i = \gamma \cdot ExperimentWeek_i + Z_i' \cdot \psi + \varepsilon_i, \tag{3}$$

where Y_i is either the score of the borrower, the approved loan amount, or a dummy equal to one if the loan is in default six months after issued. $ExperimentWeek_i$ is a dummy equal to one if the loan was approved during an experimental week in the branch. Z_i is a vector of control variables that includes a full set of branch and week dummies, and branch-specific trends.

We present the results in Table 8, columns 1 through 4, estimated using all the loans approved starting four weeks before the experiment began on the first branch of the pilot (week 41 of 2010), and four weeks after the pilot ended (week 26 of 2011). The propensity score is estimated using the branches' number and total amount of loans approved, average approved loan size and borrower score in October 2010, the month prior to the beginning of the pilot. We find no statistically significant change in the score or requested loan amount of approved loans during experimental weeks. These results imply that the introduction of scores either did not substantially affect the applicant pool, or the change in the applicant pool was exactly offset by the effect of scores on the composition of approved loans.

With the caveat that the source of variation is not random, we can also use this difference-in-differences approach to evaluate whether the pilot affected the total branch output. We estimate specification (3 aggregated at the branch-week level and present the results in Table 8, columns 5 through 9. We estimate specifications using as dependent variable the (log) number of loans issued at the branch, the (log) sum of requested and approved amounts, the fraction of loans that default, and the fraction of debt that defaults (value-weighted defaults). The point estimates on the number and amount of lending are positive, and those on default (unweighed and value-weighted) are negative, but only the coefficient on the fraction of loans that defaults is significant. Overall, we do not find that scores affected total output in the short run. Since scores potentially free up loan officer and Manager time, it is possible that the results are lower bound estimates on the long run effect of scores on total output.

4.6 Discussion

The results in this Section imply that the introduction of scores in the loan evaluation process increases committee effort, measured as time evaluating applications, and output, measured as final decisions regarding an application. The introduction of scores appears to change the difficulty composition of the problems solved by committees, as it enables committees to reach decisions on applications that are more difficult to evaluate. Despite the upward shift in the difficulty of the tasks performed, the average level of loan amounts and default rates remain unaltered.

The addition of scores has first order consequences on the reallocation of credit across borrowers. The evidence suggests that capital is reallocated in a way that equalizes the expected marginal return across loans, which is consistent with an scores reducing the uncertainty about borrower quality. An explanation in which scores provide a mean zero signal of borrowers' riskiness can explain all the findings.

The increased output by committees substitutes for other, more expensive, inputs to the production of loans. In particular, scores reduce the rate at which committees refer applications to managers at higher hierarchical levels of the organization. This implies that scores increase the decentralization of the decision making process of the bank and reduces the workload of managers.

The measured effect on output is a partial equilibrium outcome because in the time frame of our study there are endogenous variables that do not adjust to the potential change in the committee productivity induced by the scores. In particular, the interest rates on loans, which should decline in response to a drop in the cost of lending, are fixed during the study period. Also, manager span of control is fixed and may potentially increase given the effect that the new technology had on the decentralization of the decision-making process.

5 The Information and Agency Channels

The results presented so far measure the effect of scores on the final choices by the committee and the manager. In this section we turn our attention to evaluating the effect of treatment $T2$ on interim decisions. In treatment $T2$ the committee performs an evaluation of the application and reaches an interim conclusion before observing the score. That is, they chose an interim action with the same information set as in the control applications, except for the knowledge that the score would become observable by all committee members immediately after the action is chosen.

In theory, we can use this treatment to isolate the agency mechanism. If scores change committee decision making behavior exclusively through the information channel, e.g. by providing information about borrower creditworthiness at a lower cost to the committee, then $T2$ will not lead to an increase in the committees' output (decisions made) before observing the score. On the contrary, in the pure information channel the score and committee effort are complements, so it will be optimal for the committee to put zero effort in evaluating the application before receiving the score, leading to fewer decisions reached in the interim actions. Thus, the pure information channel predicts that the entire increase in committee output relative to the control group will be observed after the score becomes available in treatment $T2$.

In the pure agency mechanism, the future availability of the score reduces the scope for a privately informed loan officer to distort the loan evaluation process. As a result, the entire effect of $T2$ on output may occur in anticipation of the score becoming available —in the interim action. The direction of the agency mechanism on output is ambiguous a priori, since it depends on the exact nature of the agency problem and how it interacts with the rest of the organization.

The results in the previous section allow ruling out some interpretations. In particular, since we do not observe an effect on average lending or defaults, scores cannot be de-biasing the assessments made by officers. If scores reduce agency costs, it is not because officers are systematically underestimating or overestimating the default probability. Rather, it is because officers provide signals that are too noisy relative to the first best. This would occur if producing a precise signal requires costly effort, or if the loan officer is more risk averse than the bank and prefers to overstate the uncertainty about borrower quality to reduce the variance in her compensation. The framework in the appendix is based on this observation.

The information and agency mechanisms are not mutually exclusive, and the results so far based on final outcomes measure the net effect of the two. If both mechanisms are at work, we will observe that $T2$ has an effect on interim actions, and then we will observe committees modify their actions after observing the score.

5.1 Interim Decisions before Observing Scores

We estimate the OLS equation (1) with interim committee decisions as the left-hand side variable, and using for estimation only the control and $T2$ applications. The right hand side variable of interest is a dummy equal to one if application i belongs to treatment $T2$. The coefficient on this dummy measures the effect of making the score available on committee actions *before* the committee observes the score, and thus reflects the gross effect before receiving a new signal about borrower creditworthiness.

We present in Table 10 the results. For comparison, the table includes the estimation of the effect on final outcomes for $T2$, after the committee has observed the score. The effect of the score on the probability of making an interim decision is positive and significantly different from zero at the 5% confidence level (Column 1). The magnitude of the estimated effect is 0.039, smaller than the estimated magnitude on the probability of making final decision, 0.052 (Column 2), but not statistically distinguishable. Committees thus make more decisions in anticipation of receiving the score, and then make even more decisions after observing it. The point estimates suggest that 75% (.039/0.052) of the increase in output occurs before observing the scores. In addition, the expectation of receiving a score reduces significantly the probability that committees send an application to the manager in the interim decisions (see Appendix Table A.5).

Conditional on making a decision, committees are also more likely to reject applications during the interim action and before observing the score. In this case, the increase in the probability of rejection in the interim action, 1.3 percentage points (column 3), is larger than the increase in the final outcomes, 1.1 percentage points (column 4), although again the estimates are not statistically distinguishable. Appendix Table A.4 presents in matrix form the transitions between interim and final decisions for all the applications in treatment $T2$, and shows that committees never revise an interim decision to reject an application. This implies that the decline in the point estimate on approval probability between interim and final action occurs due to an increase in number of decisions made and approved.

The estimated effect on approved loan amounts, on the probability of adjusting the application loan size, and on the absolute value of the adjustment, are all statistically insignificant for both interim decisions and final ones. These figures hide a substantial heterogeneity in the decisions between the interim and the final stages. Appendix Table

XX shows that committees changed the amount of 81.8% of the applications at the interim stage, while the proportion of applications that were further changed between the interim and final stage was only 22.8%. Something similar happens when one considers the change in the average size of the loan or the absolute value of the changes: most of the changes occur between the application an the interim stage and the differences are statistically significant. This further suggests that treatment $T2$ induces most of the changes in committee behavior before the committee observes the score.

Two conclusions can be drawn from these results. First, the bulk of the effect of scores on committee output occurs holding committees' information set constant. Consistent with the agency mechanism, scores induce committees to make more decisions with information that its members already possess, and this information is relevant for deciding and rejecting marginal applications. These findings are complementary with prior evidence in other settings that shows that privately informed loan officers tend to hide bad news about borrowers (see Hertzberg, Liberti and Paravisini (2010)). In this setting, the results indicate that loan officers tend to produce estimates that are too noisy.

Second, we find little evidence to suggest that the pure information mechanism has first order implications for loan outcomes. This implies that most of the relevant information contained in the scores is already known by the committee members, and that the fundamental problem of the bank is to provide incentives so that the information is used effectively. The results suggest that innovations that reduce informational asymmetries inside the committees may be an efficient way of providing such incentives.

6 Conclusions

In this paper we use a randomized controlled trial to identify the incentive effect of an information technology innovation at a Colombian bank that specializes in lending to small enterprises. We measure the effect of providing credit scores on the productivity of credit evaluation committees. We find that credit scores increase the effort committees put into solving more difficult problems. As a result, scores increase committee's overall output and reduce the need for higher-level manager involvement in the decision process. Thus, the paper presents direct evidence on how information technologies can lead to the decentralization of decision processes inside organizations.

There are two potential mechanisms that drive the increase in committee productivity: (1) reducing committees' information processing costs (information channel), and (2) making loan officers' private information easier to observe by the committee members (agency channel). To disentangle these two channels in treatment $T2$ we do not provide the committee with a score, but we tell them that the score will be made available to all committee members soon after they have reached a decision. We find that the expected future availability of the score increases committee output. Moreover, 75% of the total increase in output occurs before committees see the score in this treatment. This suggests that scores increase output by reducing asymmetric information problems between the loan officer and the committee.

These findings have interesting implications regarding the design of incentives inside organizations. IT based solutions that increase the ease with which the principal can monitor the actions of the agents may have first order effects on productivity and organizational design. These results are particularly surprising in our context, since even without the score the supervisors would have been able to ultimately observe loan officers' choices, for example, when they review the loan officers' performance and bonus payments on a quarterly basis. So the intervention improved the *immediacy and ease with which the principal can monitor the agents but not* whether they get reviewed. It also affected how salient the information is to both the agent and the principal, and thus related to the work by Cadenas and Schoar (2011) who change the frequency of incentives to help loan officers overcome procrastination issues. It is suggestive that these relatively subtle changes in how agents are monitored provide very such significant changes in behavior. As such IT solutions may represent an effective and low cost alternative to steepening or increasing monetary incentives.

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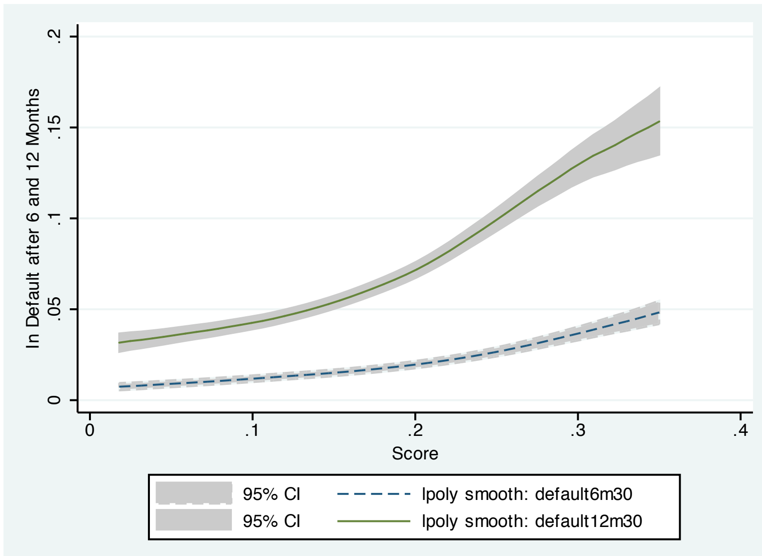
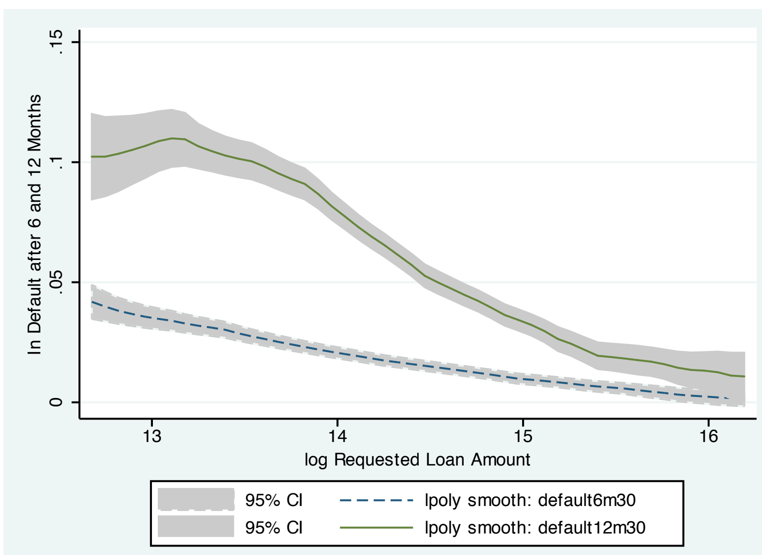
Figure 1: Population Relationships between Default Probability and Credit Scores/Requested Loan Amount

(a) Default Probability, by Score



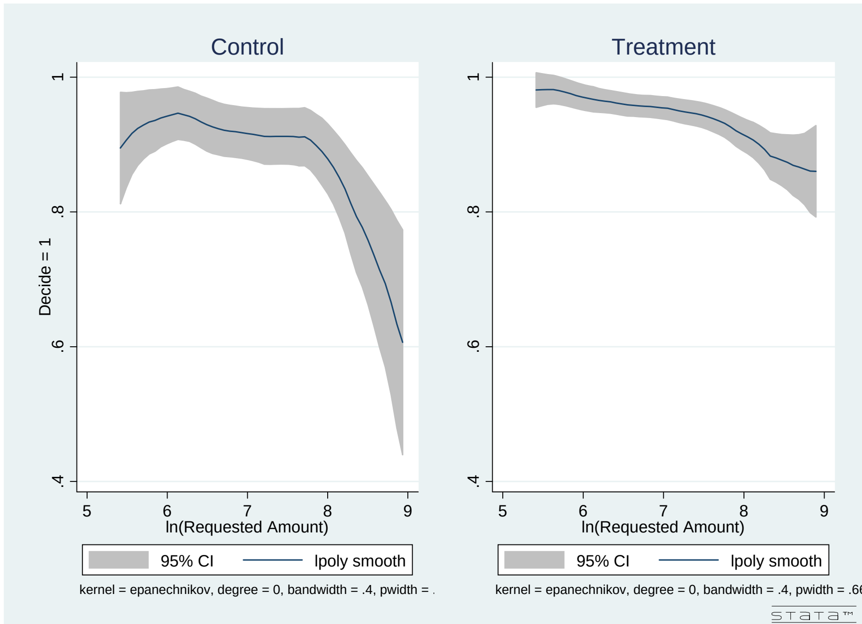
(b) Default Probability, by Requested Loan Amount (log)



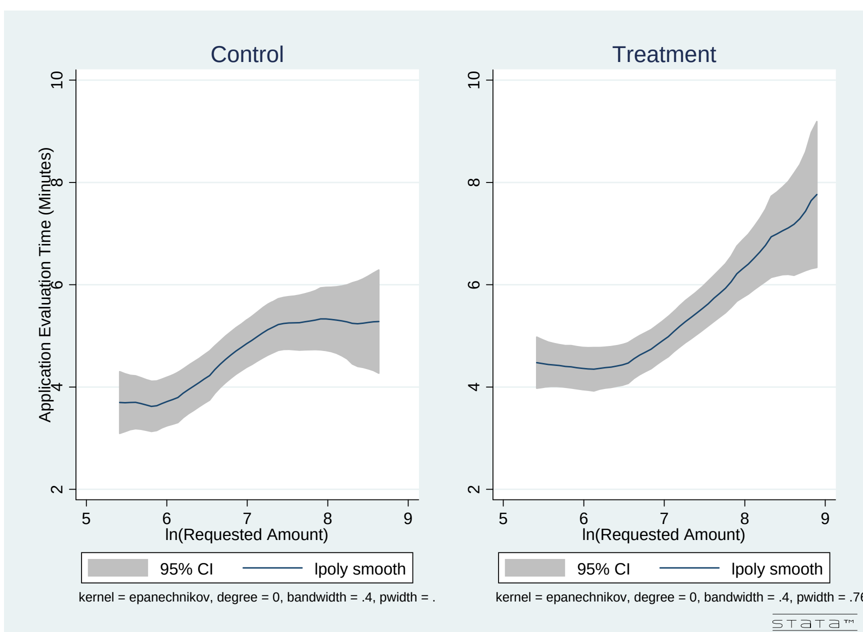
Non-parametric relationship between 6-month and 12-month default probabilities and (a) credit score, (b) requested loan amount, estimated on the sample of *all* loans approved by BancaMia during October 2010, one month before the roll out of the randomized pilot program.

Figure 2: Probability of Decision and Evaluation Time, by Application Amount

(a) Probability that Committee Makes Decision



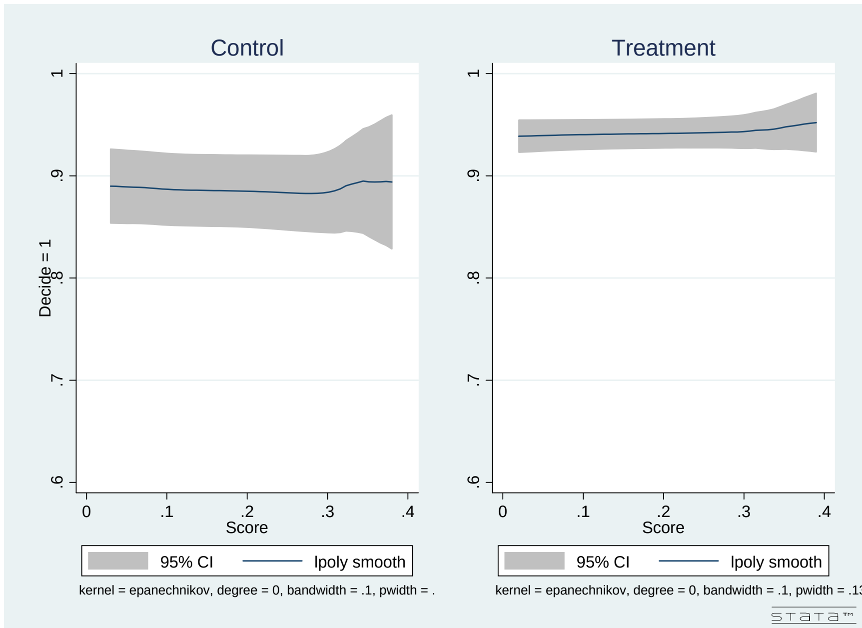
(b) Application Evaluation Time



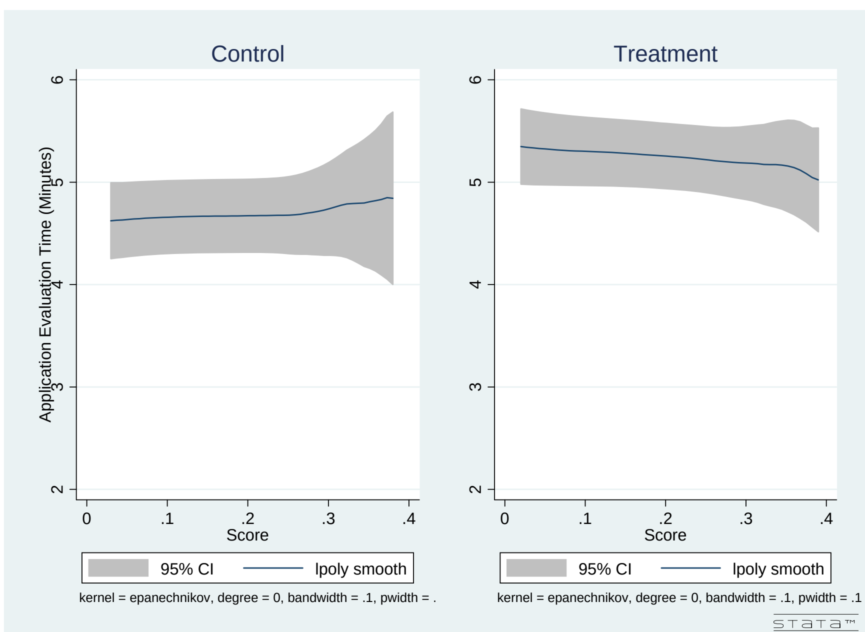
Non-parametric relationship of (a) probability that committee makes a decision on an application (approve or reject) and (b) evaluation time, with application amount.

Figure 3: Probability of Decision and Evaluation Time, by Score

(a) Probability that Committee Makes Decision



(b) Application Evaluation Time



Non-parametric relationship of (a) probability that committee makes a decision on an application (approve or reject) and (b) evaluation time, with application score.

Table 1: Descriptive Statistics by Randomized Subsample

	(1) Control (n = 335)		(2) Treatment T1 (n = 563)		(3) Treatment T2 (n = 523)		(4) p-value		
	Mean	SD	Mean	SD	Mean	SD	(1) = (2)	(1) = (3)	(2) = (3)
Panel A. Ex Ante Application Characteristics									
Application Amount (USD)	1,551.5	1,321.4	1,571.7	1,405.6	1,532.3	1,256.8	0.832	0.852	0.649
Application Maturity (Months)	20.9	9.8	22.0	10.4	22.1	10.4	0.109	**0.086**	0.880
Credit Risk Score	0.151	0.068	0.155	0.074	0.158	0.080	0.459	0.201	0.512
First Application (Dummy)	0.146	0.354	0.147	0.355	0.159	0.366	0.962	0.631	0.616
Panel B. Committee Outcomes									
Evalutation Time (minutes)	4.68	3.28	5.13	5.24	5.43	5.34	0.156	**0.021**	0.353
Committee Approves/Rejects (Dummy)	0.890	0.314	0.931	0.254	0.950	0.218	**0.032**	**0.001**	0.221
Panel C. Committee Outcomes, Conditional on Reaching decision									
Loan Approved (Dummy)	0.997	0.058	0.987	0.11	0.984	0.13	0.161	0.100	0.717
Panel D. Committee Outcomes, Conditional on Approval									
Amount Approved $\neq$ Application (Dummy)	0.698	0.460	0.737	0.441	0.692	0.462	0.230	0.849	0.108
Approved Amount/Application Amount	0.979	0.435	0.975	0.318	0.950	0.293	0.905	0.271	0.187
|Approved Approved - Application Amount|	266.4	478.8	249.8	484.3	245.6	486.0	0.635	0.557	0.892
Maturity Approved $\neq$ Application (Dummy)	0.262	0.440	0.278	0.449	0.307	0.462	0.609	0.174	0.314
Approved Maturity/Application Maturity	0.985	0.290	1.000	0.264	0.983	0.371	0.471	0.922	0.404
|Approved Maturity - Application Maturity|	2.3	4.7	2.4	5.0	3.2	6.0	0.616	**0.023**	**0.032**
Loan Issued (Dummy)	0.835	0.372	0.855	0.353	0.840	0.367	0.447	0.840	0.524
Panel E. Final Outcomes, Conditional on Loan Issued									
Disbursed Amount/Application Amount	0.959	0.382	0.965	0.297	0.974	0.549	0.828	0.702	0.755
In Default after 6 Months (Dummy)	0.036	0.188	0.039	0.193	0.037	0.190	0.881	0.954	0.917
In Default after 12 Months (Dummy)	0.095	0.293	0.088	0.283	0.089	0.284	0.757	0.781	0.976
Defaulted Amount (6 months)	27.26	166.22	26.43	147.97	35.04	193.26	0.947	0.604	0.476
Defaulted Amount (12 months)	62.67	238.07	71.84	257.73	74.11	265.39	0.650	0.584	0.902

Column (4) presents p-values of t test of equality of means between columns (1), (2), and (3). The requested amounts in dollars are calculated at prevailing exchange rate of 1,779 pesos per dollar. The credit risk score is a number between zero and one assigned by BancaMia's credit risk model. The time to decision was calculated from begin and end time of each application's discussion, recorded by the study's research assistants in the field.

Table 2: Descriptive Statistics by Committee Action, Control Group Applications

	Decide (n = 298) (1)		Send Up (n = 16) (2)		More Information (n = 21) (3)	
	mean	sd	mean	sd	mean	sd
Panel A. Ex Ante Application Characteristics						
Application Amount (US$)	1,443	1,170	2,480	2,126	2,476	1,994
Application Maturity (Months)	20.3	9.3	26.3	12.2	25.1	13.3
Credit Risk Score	0.152	0.069	0.155	0.060	0.138	0.046
First Loan (Dummy)	0.154		0.125		0.048	
Panel B. Outcomes						
Time to decision (minutes)	4.608	3.188	5.438	3.405	5.105	4.508
Loan Issued (Dummy)	0.832		0.750		0.714	
Amount Approved $\neq$ Application (Dummy)	0.924		1.000		1.000	
Approved Amount/Application Amount	0.945	0.272	0.950	0.227	1.486	1.807
|Approved Approved - Application Amount|	287.4	499.1	262.9	309.8	1477.0	2153.0
In Default after 6 Months (Dummy)	0.028		0.000		0.200	
In Default after 12 Months (Dummy)	0.093		0.083		0.133	
Defaulted Amount (after 6 Months)	25.8	164.0	0.0	0.0	121.4	321.2
Defaulted Amount (after 12 Months)	66.4	246.6	28.6	99.2	0.0	0.0

Comparison of application characteristics where the officer reaches a decision—approves or rejects application— (column 1), those where the officer sends the application up for review by the Regional Manager (column 2), and those where the committee decides to send the loan officer out to collect additional information (column 3).

Table 3: Average Treatment Effect of Scores on Committee Output – OLS and LAD

Estimation:	OLS		OLS		LAD (Quantile Regression)					
Dependent Variable:	Committee Decides		Evaluation Time		Evaluation time					
					25th %ile		50th %ile		75th %ile	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment (T1 and T2)	0.046**	0.038**	0.760***	0.624**	0.183	0.123	0.426***	0.383**	0.663***	0.662***
	(0.018)	(0.019)	(0.229)	(0.273)	(0.192)	(0.194)	(0.157)	(0.193)	(0.231)	(0.254)
Treatment (T2)		0.016		0.283		0.057		0.133		0.113
		(0.013)		(0.321)		(0.170)		(0.171)		(0.249)
ln(Requested Amount)	-0.032***	-0.032***	0.751***	0.747***	0.084	0.053	0.239*	0.238	0.664***	0.617***
	(0.012)	(0.012)	(0.226)	(0.226)	(0.145)	(0.140)	(0.133)	(0.145)	(0.183)	(0.185)
ln(Requested Maturity)	-0.026	-0.026	0.653**	0.656**	0.676***	0.692***	0.680***	0.670***	0.227	0.265
	(0.018)	(0.018)	(0.332)	(0.330)	(0.222)	(0.222)	(0.208)	(0.225)	(0.308)	(0.303)
Credit Risk Score	-0.105	-0.107	-1.28	-1.301	-1.181	-1.175	-1.970**	-1.464	-1.761	-1.971
	(0.111)	(0.111)	(1.457)	(1.458)	(0.752)	(0.818)	(0.945)	(1.077)	(1.564)	(1.558)
First Application	0.009	0.009	0.695*	0.692*	0.408**	0.426**	0.541***	0.571***	0.764	0.757
	(0.018)	(0.018)	(0.387)	(0.388)	(0.187)	(0.194)	(0.186)	(0.204)	(0.509)	(0.535)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,406	1,406	1,397	1,397	1,397	1,397	1,397	1,397	1,397	1,397
R-squared	0.041	0.042	0.048	0.049						

OLS estimates of the effect of treatment on committee and loan outcomes: probability that committee reaches decision (column 1), evaluation time in minutes (column 2), with robust standard errors in parenthesis. LAD estimates of the effect of treatment on evaluation time, with bootstrapped standard errors (500 repetitions) estimated via simultaneous quantile regressions in parenthesis (columns 3 through 5). ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 4: Costly Information and Referrals

Committee Choice	Approves (Omitted) (1)	Rejects (2)	More Information (3)	Send to Manager (4)
Treatment (T1 and T2)		1.3236	-0.5439*	-0.9038***
		(1.049)	(0.305)	(0.344)
ln(Application Amount)		0.0851	0.7971***	0.1790
		(0.466)	(0.243)	(0.308)
ln(Application Maturity)		-0.2176	-0.1358	1.7474***
		(0.731)	(0.386)	(0.570)
Credit Risk Score		4.8843**	0.2146	2.8701*
		(2.121)	(2.001)	(1.537)
First Application		0.4442	-0.6193	0.2574
		(0.673)	(0.487)	(0.419)
Trend		Yes	Yes	Yes
Observations	1405			
Pseudo R-squared	0.0875			
Fraction in Control Subsample	0.8866	0.0030	0.0627	0.0478
Marginal Effects:				
Treatment	0.0281	0.0124	-0.0174*	-0.0231**
	(0.0166)	(0.0100)	(0.0104)	(0.0094)

Multinomial Logistic Regression estimates of the effect of treatment on final committee actions: make a decision on an application (approve or reject), postpone until the loan officer collects additional information, or send the application to the manager (referrals). The first action, make a decision, is the omitted category. The bottom rows present the proportion of each action in the control group and the estimated marginal effect of treatment on the probability that the committee takes an action. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 5: Effect of Scores on Overall Output – OLS

Sample Conditioning:	None	Loan Issued				
Dependent Variable:	Loan	ln(Issued	Issued $\neq$	|Issued -	In Default after	
Percentile	Issued	Amount)	Application	Application|	6 months	12 months
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (T1 and T2)	0.0020	0.0107	-30.1268	0.0107	-0.0038	-0.0158
	(0.024)	(0.018)	(38.713)	(0.025)	(0.013)	(0.020)
ln(Application Amount)	-0.0018	-0.0082	307.2***	0.7760***	-0.0036	-0.0327**
	(0.020)	(0.015)	(49.378)	(0.029)	(0.009)	(0.013)
ln(Application Maturity)	-0.0314	0.0445*	14.51	0.0987**	-0.0075	0.0229
	(0.032)	(0.026)	(59.88)	(0.042)	(0.015)	(0.021)
Credit Risk Score	0.0603	0.2064***	568.5***	-0.6069***	0.3256***	0.6472***
	(0.142)	(0.068)	(207.829)	(0.165)	(0.086)	(0.135)
First Application	0.0421	0.0198	12.2255	0.0244	0.0087	-0.0197
	(0.026)	(0.018)	(50.211)	(0.027)	(0.016)	(0.021)
Trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,406	1,048	1,048	1,046	1,165	1,165
R-squared	0.007	0.013	0.195	0.773	0.022	0.043

OLS estimates of the effect of treatment on overall application outcomes, without conditioning on whether the committee made the decision during the experiment, or the decision was made outside the experiment by either the committee in a later evaluation or by the Regional Manager. Column (1) is estimated on all applications, and columns (2) through (6) on the subsample of applications where the loan was approved. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 6: Effect on Relationship between Default and Contract Characteristics – OLS

Dependent Variable:	In Default after	
	6 months	12 months
	(1)	(2)
Treatment (T1 and T2)	0.0409	-0.1752
	(0.091)	(0.171)
ln(Loan Amount)	-0.0948***	-0.2619***
	(0.031)	(0.051)
ln(Loan Amount) × Treatment	0.0209	0.0733**
	(0.020)	(0.035)
ln(Loan Maturity)	0.0401	0.0944*
	(0.041)	(0.056)
ln(Loan Maturity) × Treatment	-0.0628*	-0.1190**
	(0.033)	(0.050)
ln(Application Amount)	0.2993***	0.5325***
	(0.084)	(0.129)
ln(Application Maturity)	0.0655**	0.1477***
	(0.026)	(0.042)
Credit Risk Score	0.0004	0.0236
	(0.035)	(0.043)
First Application	0.0037	-0.0221
	(0.017)	(0.023)
Trend	Yes	Yes
Observations	1,100	1,100
R-squared	0.047	0.091

Table 7: Scores and Conditional Committee Outcomes – OLS

Sample Conditioning:	Committee Decides	Committee Approves					
			Loan Amount			Loan Maturity	
Dependent Variable:	Committee Approves Dum.	Approved (log USD)	Approved $\neq$ Application	|Approved - Application|	Approved (log Months)	Approved $\neq$ Application	|Approved - Application|
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment (T1 and T2)	-0.0092*	-0.0001	0.0322	-29.2229	0.0282	0.0197	0.3434
	(0.005)	(0.020)	(0.030)	(28.585)	(0.029)	(0.019)	(0.317)
ln(Application Amount)	-0.0006	0.8752***	0.0357	212.5798***	0.0092	0.1075***	-0.0333
	(0.005)	(0.015)	(0.022)	(28.189)	(0.020)	(0.028)	(0.316)
ln(Application Maturity)	0.0016	-0.0002	-0.0360	59.7938**	0.0382	-0.3075***	2.1669***
	(0.009)	(0.024)	(0.036)	(29.936)	(0.034)	(0.053)	(0.540)
Credit Risk Score	-0.0886	-0.5715***	0.5898***	452.2661***	0.4515**	-0.0730	5.4257**
	(0.082)	(0.128)	(0.168)	(165.744)	(0.180)	(0.099)	(2.131)
First Application	-0.0056	-0.0002	0.0230	51.1913	-0.0228	0.0212	-0.1109
	(0.009)	(0.024)	(0.034)	(41.627)	(0.034)	(0.022)	(0.422)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,315	1,314	1,314	1,314	1,314	1,314	1,314
R-squared	0.007	0.840	0.022	0.165	0.010	0.136	0.051

OLS regressions of conditional outcomes on treatment status. Column (1) estimated on subsample of applications where the committee reaches a decision (approves or rejects), columns (2) through (7) estimated on subsample of applications where the committee approved an application. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 8: Aggregate Effects on Branch Outcomes - Difference-in-Differences Estimate

Unit of Observation:	Loan				Branch-Week				
	Score	ln(Application Amount)	ln(Issued Amount)	In Default after 12 Months	ln(Number of Loans)	ln(Sum Application Amount)	ln(Sum Issued Amount)	Fraction of Loans that Defaults	Fraction of Amount that Defaults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Experiment Week	-0.0014	-0.0194	-0.0185	-0.0065	-0.0273	-0.0074	-0.0108	-0.0121*	0.0007
	(0.002)	(0.020)	(0.019)	(0.007)	(0.044)	(0.047)	(0.047)	(0.006)	(0.005)
Branch Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,270	18,270	18,270	18,270	525	525	525	525	525
R-squared	0.044	0.028	0.033	0.016	0.754	0.699	0.705	0.283	0.170

OLS regression of loan characteristics on a dummy equal to one if the application was evaluated during a week in which the randomized pilot study was taking place in the branch. Sample contains only approved loans from the eight pilot branches and eight propensity score matched branches (branch matching based on number and total amount of loans approved, average approved loan size and borrower score measured in October 2010). The sample period is from week 41 of 2010 to week 26 of 2011 (four weeks before and after the pilot program began and ended). Columns 1 through 3 are estimated at the loan level, and 3 through 9 at the branch-week level. Robust standard errors clustered at the branch level in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 9: Amount Adjustment Statistics: Application, Interim and Final Amount in $T2$

Comparison:	Interim versus Application Amount (1)	Final versus Interim Amount (2)	Mean Difference (3)
Amount Change Dummy	0.818	0.228	0.590***
Amount After/Amount Before	0.958	1.001	-0.0437***
	(0.305)	(0.107)	(0.349)
|Amount change|	279.0	35.9	243.1***
	(517.7)	(102.5)	(514.5)

Measures of loan amount change adjustments between the interim action and the application (panel A) and the interim action and the final approved amount ((Panel B).

Table 10: Information versus Incentives: Effect on Interim and Final Actions in $T2$ – OLS

Outcome:	Committee Decides Dummy		Committee Approves Dummy		ln(Approved Amount)		Approved $\neq$ Application Dummy		|Approved - Application|	
Choice:	Interim	Final	Interim	Final	Interim	Final	Interim	Final	Interim	Final
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment T2	0.0388**	0.0524***	-0.0136**	-0.0113*	-0.0023	-0.0064	0.0060	0.0016	-28.8	-39.73
	(0.019)	(0.018)	(0.007)	(0.006)	(0.023)	(0.022)	(0.029)	(0.034)	(31.43)	(31.93)
ln(Application Amount)	-0.0257	-0.0378**	0.0013	0.0012	0.746***	0.776***	0.0028	0.0640**	288.5***	285.1***
	(0.016)	(0.015)	(0.007)	(0.007)	(0.022)	(0.021)	(0.026)	(0.029)	(42.20)	(42.50)
ln(Application Maturity)	-0.0572**	-0.0352	-0.0015	-0.0012	0.280***	0.237***	0.0397	-0.0399	-90.5*	-103.4*
	(0.024)	(0.023)	(0.015)	(0.015)	(0.036)	(0.035)	(0.041)	(0.047)	(52.80)	(53.20)
Credit Risk Score	-0.0925	-0.1607	-0.1877	-0.1632	-0.821***	-0.762***	0.456**	0.549**	708.3***	690.4***
	(0.132)	(0.132)	(0.129)	(0.129)	(0.155)	(0.152)	(0.212)	(0.238)	(204.20)	(201.30)
First Application	0.0402*	0.0318	-0.0034	-0.0052	-0.0197	-0.0152	0.0487	0.0682	61.7	70.7
	(0.021)	(0.021)	(0.010)	(0.010)	(0.031)	(0.031)	(0.035)	(0.043)	(52.30)	(53.20)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	851	851	787	793	783	793	789	793	789	793
R-squared	0.050	0.056	0.023	0.019	0.838	0.845	0.015	0.022	0.188	0.178

OLS estimates the treatment effect on interim committee outcomes before observing the score (odd columns) and on final outcomes after observing the score (even columns). Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

A Appendix

This simple framework is provided to characterize the optimal committee choices. We choose the assumptions to fit the decision-making environment in BancaMia. In particular, we assume that the main decision variables of the committee are loan amount and effort for any application, and that the key input of interest is the precision of the signal that the committee has about the borrower's creditworthiness.

We make an additional shortcut: the incentive problem of the loan officer is modeled in reduced form. There is some incentive problem in the background that the bank must solve with a combination of formal and informal incentives. Providing incentives to the loan officer costs λ per unit of effort, and by a revelation principle argument, after being adequately incentivized, the officer's effort level is observed.

A.1 Committee Decision Making

The committee receives an application and must choose a loan size, L, and an effort level by the officer, e. The loan produces a gross return to the bank of R with probability $1-p$ and the cost of capital is zero. Default probability is increasing in the amount of the loan and increasing and convex in a borrower-specific risk parameter θ_i:

$$p = L\theta_i^2$$

with $\theta_i << 1$ so that the probability is between 0 and 1.

The committee observes an unbiased (mean θ_i) signal of the risk parameter $\tilde{\theta}_i$, with variance $\tilde{\sigma}_i^2$. The variance of the signal in increasing with a borrower-specific baseline variance σ_i^2 (reflects how difficult it is to evaluate a borrower's riskiness), and decreasing with the effort of the officer:

$$\tilde{\sigma}_i^2 = \frac{\sigma_i^2}{e}$$

The risk-neutral committee maximizes the expected returns for each loan, net of the cost of incentivizing the officer: $E\left[L\left(1-p_i\right)R-L-\lambda e\right]$. The expectation of the default probability can be re-written as: $E\left[p_i\right] = LE\left[\tilde{\theta}_i^2\right] = L\left[\theta_i^2+\tilde{\sigma}_i^2\right]$.

Note: the only reason why a risk-neutral committee cares about the variance of the signal is because of the convexity of the default probability on the risk parameter, θ. Given that committees approve many small loans, it seems natural to assume that committees are approximately risk neutral on any one of them. Convexity is the simplest assumption that makes them risk averse towards the uncertainty on p (make the effort cost convex is an alternative that leads to similar conclusions).

Substituting in the objective function, the expected return from a loan is defined by the following maximization problem:

$E\left(\pi\right) = \max_{L,e} L\left(1-L\left[\theta_i^2+\frac{\sigma_i^2}{e}\right]\right)R-L-\lambda e$

$s.t.\ \ L \geq 0;\ \ e \geq 0$

The committee observes the borrower-specific parameters θ_i and σ_i^2. The gross return R is also treated as a parameter, since the committee does not decide the interest rate of the loan.

A.2 Optimal L and e

We'll assume that the parameters are such that we have an interior solution ($L > 0$). The F.O.C. for L is $L(e) = \frac{R-1}{2R\left(\theta_i^2 + \frac{\sigma_i^2}{e}\right)}$, and for e: $e\left(L\right) = L\sqrt{\frac{R\sigma_i^2}{\lambda}}$.

Solving gives:

$$L^* = \frac{R-1}{2R\theta_i^2} - \frac{\sigma_i}{\theta_i^2}\sqrt{\frac{\lambda}{R}}$$

$$e^* = \frac{\sigma_i}{\theta_i^2}\left[\frac{R-1}{2\sqrt{\lambda R}} - \sigma\right]$$

Note: to have $L > 0$ and $e > 0$ requires that the following condition holds: $\frac{R-1}{2\sqrt{R}} > \sigma_i\sqrt{\lambda}$. This implies that the committee will reject applications that are too difficult (high σ_i) for any given cost of inducing effort.

A.3 Comparative statics

The randomized Control Trial moves exogenously σ_i and/or λ, depending on whether the information channel or the agency channel are at work. So comparative statics with respect to variations in these parameters give us the predicted changes in actions by the committee in the treatment group.

The optimal loan size is decreasing in σ_i, and λ:

$\frac{\partial L^*}{\partial \sigma_i} = -\frac{1}{\theta_i^2}\sqrt{\frac{\lambda}{R}} < 0$

$\frac{\partial L^*}{\partial \lambda} = -\frac{1}{2}\frac{\sigma_i}{\theta_i^2}\sqrt{\frac{1}{\lambda R}} < 0$

Thus, the introduction of a technology that lowers σ_i or λ, should increase average loan size, ceteris paribus.

Optimal effort is decreasing in λ, but the effect of changing σ_i is ambiguous:

$\frac{\partial e^*}{\partial \lambda} = -\frac{1}{2}\frac{\sigma_i}{\theta_i^2}\frac{R-1}{2\sqrt{R}}\lambda^{-3/2} < 0$

$\frac{\partial e^*}{\partial \sigma_i} = \frac{1}{\theta_i^2}\left[\frac{R-1}{2\sqrt{\lambda R}} - 2\sigma_i\right] \geq 0$ if $\frac{R-1}{2\sqrt{R}} > 2\sigma_i\sqrt{\lambda}$

so $\frac{\partial e^*}{\partial \sigma_i} \geq 0$ for easier applications (applications with a low σ_i) and negative for difficult applications. The effect of a technology that lowers σ_i on average effort thus will depend on the distribution of σ_i in the cross section of applications.

We cannot take these comparative statics straight to the data because treatment induces changes in two extensive margins : 1) the probability or rejection, and 2) the probability that the committee refers the application to the boss. These comparative statics are based on looking at the same application, before and after a change in the parameter.

A.4 Referrals

Finally we model the possibility that the committee can ask for help at a cost C. When the committee refers the problem to the boss, the boss sees the true risk parameter θ_i, so the net return from a loan after a referral is: $E\left(\pi^R\right) = \max_L L\left(1 - L\theta_i^2\right) R - L - C$

The committee refers the application when $E\left(\pi^R\right) \geq E\left(\pi^*\right)$. The optimal loan size with a referral is $L^R = \frac{R-1}{2R\theta_i^2}$. This implies that for any given borrower risk parameter, the boss approves a larger amount than the committee.

A decline in σ_i and/or λ leads to an decrease (weakly) in the number of referrals. This follows from the fact that $\frac{dE(\pi^*)}{d\sigma_i} < 0$ and $\frac{dE(\pi^*)}{d\lambda} < 0$, while $\frac{dE\left(\pi^R\right)}{d\sigma_i} = \frac{dE\left(\pi^R\right)}{d\lambda} = 0$. $\frac{dE(\pi^*)}{d\sigma_i} < 0$ also suggests that the marginal applications, those that are decided by the boss in the absence of scores and by the committee when the score is available, are those that are more difficult to evaluate (although this is a cross sectional statement and thus depends on the sign of $Cov\left(\theta_i, \sigma_i^2\right)$).

The loan amount drops for the marginal applications because $L^R > L^*$ for all θ_i. This implies that the average effect on the size of approved applications is ambiguous (including those approved by the boss). Ambiguity in the average loan amount also implies ambiguity in the expected default probability.

To characterize the effect on loan size and effort of applications approved by the committee only, one would need to characterize the marginal applications (the least profitable applications referred to the boss). To characterize the marginal applications in the cross-section one needs to know what the joint distribution of θ_i and σ_i^2 is in the data. If we assume they are independent, then $\frac{dE(\pi^*)}{d\sigma_i} < 0$ indicates that the marginal applications will be more difficult to evaluate (have a higher σ_i^2) than the inframarginal ones. This implies that marginal applications require more effort than inframarginal ones.

A.5 Loan Allocation in the Cross-Section

Although the introduction of scores improves the allocation of credit across borrowers, the model has ambiguous implications for the average *level* of observable outcomes (committee effort, loan amount, and default). In order to derive testable implications we are interested in characterizing the cross sectional implications of improving the efficiency of loan allocation. To evaluate cross-sectional relationships, however, we cannot rely on comparative statics on the parameters, which assume that the parameters are independently distributed in the cross section of loans. In the data it is more likely that θ_i and σ_i are jointly distributed with some correlation. We can use the data together with the model to tell us what the correlation between θ_i and σ_i is in the population. This requires taking the model seriously as the description of the relationships observed in the data and make inferences that are not causal but solely identified through the assumptions in the model.

We find a negative relationship in the cross section between loan amounts and the default probability. Let's start by assuming θ_i and σ_i are independent. If so, then we have that $p = L^* \theta_i^2$, and $L^* \left(\theta_i, \sigma_i^2\right) \sim 1/\theta_i^2$, so p should be constant in the cross section when there is heterogeneity in both θ_i or σ_i^2. The second one is obvious, since the only effect of σ_i on p is through L^*. The first one can be shown by looking at the total derivative of p with respect to θ:[20]

$$\frac{dp}{d\theta} = \theta^2 . \frac{\partial L^*}{\partial \theta} + 2\theta L^* = \theta^2 \left(-2\right) \left[\frac{R-1}{2R\theta_i^3} - \frac{\sigma_i}{\theta_i^3}\sqrt{\frac{\lambda}{R}}\right] + 2\theta \left[\frac{R-1}{2R\theta_i^2} - \frac{\sigma_i}{\theta_i^2}\sqrt{\frac{\lambda}{R}}\right] = 0$$

Intuitively, to get the negative relationship between default and loan size observed in the data through heterogeneity in θ_i, one requires that L^* drops at a rate higher than $1/\theta_i^2$. From inspection of the equation for L^* this occurs if θ_i and σ_i are positively associated in the cross section ($Cov\left(\theta_i, \sigma_i\right) > 0$). That is, if borrowers that are riskier are also more difficult to evaluate. To see this, suppose that the relationship is deterministic and linear: $\sigma_i = a\theta_i$, with $a > 0$. Then:

$$\frac{dp}{d\theta} = \theta^2 \left[\left(-2\right) \frac{R-1}{2R\theta_i^3} + \frac{a}{\theta_i^2}\sqrt{\frac{\lambda}{R}}\right] + 2\theta \left[\frac{R-1}{2R\theta_i^2} - \frac{a}{\theta_i^2}\sqrt{\frac{\lambda}{R}}\right] = -a\sqrt{\frac{\lambda}{R}}\left(\frac{2}{\theta} - 1\right) < 0$$

Note that we can think of the technology that reduces σ_i as a technology that reduces a. So anything that reduces a or that reduces λ will lead to a decline in the absolute value of $\frac{dp}{d\theta}$, or a flattening of the relationship between the default probability and loan amounts in the cross section. This implication can be directly tested in the data.

[20] In a more direct way we can evaluate the total derivative: $\frac{dp}{dL^*} = \frac{\partial p}{\partial \theta_i^2} \frac{\partial (L^*(\theta))^{-1}}{\partial L^*} + \frac{\partial p}{\partial L^*} = L^* \left[-\frac{1}{L^{*2}}\left(\frac{R-1}{2R} - \sigma_i \sqrt{\frac{\lambda}{R}}\right)\right] + \theta_i^2 = 0$ where $\left(L^*\left(\theta\right)\right)^{-1}$ is the inverse of the L^* function (θ expressed as a function of L^*).

Table A.1: Study Sample: Number of Applications per branch and per Treatment Status

	Control	T1	T2	Total
Branch #:				
1	44	67	62	173
2	89	153	132	374
3	26	51	66	143
4	69	88	87	244
5	18	28	27	73
6	22	26	14	62
7	20	45	38	103
8	47	105	98	250
Total	335	563	524	1,422

Control: the committee makes decision without observing the score. $T1$: the borrower's score is made available at the beginning of the application evaluation. $T2$: the committee makes an interim decision before the score is made available, and the allowed to revise the decision after observing the score.

Table A.2: Effect of Scores on Committee Output, No Controls

Sample Conditioning:	None		Committee Decides	Committee Approved		Loan Issued	
Dependent Variable:	Evaluation Time	Committee Decides	Committee Approves	ln(Approved Amount)	Loan Issued	ln(Issued Amount)	Defaults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Score Dummy	0.5962**	0.0506***	-0.0113**	0.0281	0.0182	0.0541	0.0099
	(0.242)	(0.019)	(0.005)	(0.050)	(0.028)	(0.056)	(0.014)
Observations	1,412	1,421	1,319	1,315	1,303	1,001	1,001
R-squared	0.003	0.007	0.002	0.000	0.000	0.001	0.000

OLS estimates of the effect of treatment on committee and loan outcomes. Columns (1) and (2) are estimated on all applications, columns (3) and (4) on the subsample of applications where the committee reached a decision, column (5) on the subsample of approved applications, and columns (6) and (7) on the subsample of issued loans. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table A.3: Default Probability Correlates in the Cross Section of Control Group Applications

Dependent Variable:	In Default after			
	6 months		12 months	
	(1)	(2)	(3)	(4)
ln(Application Amount)	-0.0069	0.0520	-0.0572**	0.1463*
	(0.012)	(0.049)	(0.029)	(0.079)
ln(Application Maturity)	0.0064	-0.0527	0.0646*	-0.0539
	(0.015)	(0.039)	(0.038)	(0.063)
Credit Risk Score	0.3325*	0.2850*	0.7426**	0.5823*
	(0.181)	(0.164)	(0.325)	(0.320)
First Application	0.0284	0.0208	-0.0171	-0.0329
	(0.041)	(0.043)	(0.052)	(0.055)
ln(Loan Amount)		-0.0777		-0.2545***
		(0.054)		(0.085)
ln(Loan Maturity)		0.0794		0.1563**
		(0.052)		(0.071)
Trend	Yes	Yes	Yes	Yes
Observations	248	248	248	248
R-squared	0.040	0.056	0.058	0.103

Linear probability model of default using ex ante application characteristics and ex post loan characteristics as independent variables. Estimated on the subsample of applications in the control group that were approved by the committee.

Table A.4: Interim and Final Decisions in Treatment $T2$

	Final Decision (after Observing Score):				Total
	Accept Loan	Reject Loan	Obtain More Information	Send Decision to Manager	
Interim Decision:					
Accept Loan	482	0	0	1	483
Reject Loan	0	8	0	0	8
Obtain More Information	0	0	20	0	20
Send Decision to Boss	7	0	0	5	12
Total	489	8	20	6	523

Each observation in the matrix represents the two sequential decision made by a committee regarding the *same* application in treatment $T2$. Interim decisions (rows) are the decisions made before observing the score and final decisions (columns) are the revised decisions after observing the score.

Table A.5: Information versus Incentives: Effect on Interim and Final Actions in $T2$ – ML

Estimation	Interim Outcomes				Final Outcomes			
Action:	Approve (Omitted)	Reject	More Information	Send to Manager	Approve (Omitted)	Reject	More Information	Send to Manager
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment T2		1.5208	-0.4868	-0.8152**		1.4762	-0.5112	-1.5197***
		(1.071)	(0.347)	(0.392)		(1.058)	(0.346)	(0.483)
ln(Application Amount)		-0.1783	0.8793**	-0.1355		-0.1558	0.9058**	0.5286
		(0.698)	(0.359)	(0.453)		(0.701)	(0.358)	(0.501)
ln(Application Maturity)		0.1960	0.0517	1.8806***		0.1588	0.0159	1.0678*
		(1.352)	(0.575)	(0.652)		(1.342)	(0.568)	(0.618)
Credit Risk Score		6.3225**	1.1175	1.7954		6.4498**	1.3050	4.2580
		(2.507)	(1.738)	(2.708)		(2.566)	(1.774)	(2.806)
First Application		0.2935	-0.9911	-0.5589		0.3135	-0.9733	-0.4016
		(0.642)	(0.644)	(0.656)		(0.644)	(0.643)	(0.766)
Trend		Yes	Yes	Yes		Yes	Yes	Yes
Observations	850				850			
R-squared								
Pseudo R-squared	0.0975				0.114			
Fraction in Control Subsample	0.8866	0.0030	0.0627	0.0478	0.8866	0.0030	0.0627	0.0478
Marginal Effects:								
Treatment T2	0.0279	0.0140	-0.0172	-0.0247*	0.0392*	0.0138	-0.0170	-0.0360***
	(0.0201)	(0.0104)	(0.0131)	(0.0128)	(0.0204)	(0.0102)	(0.0129)	(0.0136)

Multinomial Logistic Regression estimates of the effect of treatment on interim committee choices before observing the score (columns 1 through 4) and on final choices after observing the score (columns 5 through 8). The bottom rows present the proportion of each action in the control group and the estimated marginal effect of treatment on the probability that the committee takes an action. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table A.6: Amount Changes: Application, Interim and Final in Treatment $T2$

Comparison:	Interim versus Application Amount (1)	Final versus Interim Amount (2)	Mean Difference (3)
Amount Change Dummy	0.818	0.228	0.590***
Amount After/Amount Before	0.958	1.001	-0.0437***
	(0.305)	(0.107)	(0.349)
|Amount change|	279.0	35.9	243.1***
	(517.7)	(102.5)	(514.5)

Statistics of the frequency and magnitude of loan amount changes that occur between the application and the interim decision (column 1) and the interim decision and the final one (column 2). Column 3 shows the difference in means. *** indicates significance at the 1% levels in a difference in means t-test.