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

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September 20, 2012

Abstract

Information technologies may affect productivity by reducing agents' information processing costs, and by making agents' actions easier to evaluate 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 the effort and output of credit committees increases when applications contain a score. Output also increases in a treatment where the committee has no new information, but the score will become available in the future. This effect is uniquely consistent with an agency mechanism, and explains over 75% of the total output increase. Additional evidence suggests that the pure information effect of scores, negligible on average, operates through upwards and downwards adjustments in the intensive margin of lending.

*We are grateful to Heski Bar-Isaac, Greg Fischer, Luis Garicano, Andrea Prat, Lucia Sanchez and John Van Reenen for helpful comments and discussions. We wish to thank BancaMia for their support, and Isabela Echeverry and Santiago Reyes for excellent research assistance. We thank IPA for the funding that made this study possible. Please send correspondence to Daniel Paravisini (d.paravisini@lse.ac.uk) and Antoinette Schoar (aschoar@mit.edu).

1 Introduction

The diffusion of information technologies (IT) since the advent of the computer has been positively associated with increases in productivity in organizations.[1] Ascertaining empirically the channel through which IT affects performance, however, has proved elusive. The main difficulty lies in the dual role played by most IT innovations. The adoption of IT services raises productivity directly by reducing information processing and communication costs as well as allowing for greater standardization of decision rules. At the same time IT raises productivity indirectly through improved monitoring which reduces information asymmetries. Distinguishing between the technological and agency channels is a key input for understanding the implications of these innovations on the internal organization of firms and their boundaries.[2]

Existing empirical work had to rely on ex ante classifications of whether the technology adoption channel or the agency channel will be dominant. For example in the seminal study on the trucking industry, Baker and Hubbard (2004) use the introduction of an on-board computer system to test the impact of better monitoring on incentives and performance.[3] But new technologies usually are a bundle of features that also interact with other dimensions of the organization such as job descriptions, compensation structures or even the allocation of authority (see Milgrom and Roberts (1990)).

The present study explores empirically how the introduction of a new IT based credit scoring model affects worker productivity at a bank in Colombia that lends to small enterprises. We worked with the bank to randomize the roll out of the scoring model across the different bank branches. Prior to the adoption of the IT system, credit committees

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

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

[3] Hubbard (2000) identifies two classes of on-board computers and argues that one helps the principal provide better incentives while the other only improves coordination. Bloom, Garicano, Sadun and Van Reenen (2011) also classify technologies into communication enhancing and information enhancing, although not for the purpose of separating the technology and agency channels.

at each branch perform the first evaluation of a loan application and try to determine whether the application should be approved, and conditional on approving it what the terms of the loan should be. By varying the timing of the roll out along the committee decision process, we are able to cleanly differentiate the individual impact of the scoring model through the technology and agency channels.

For the purpose of our experiment we randomly select a fraction of credit committees (branches of the bank) to receive independent credit scores concerning the estimated default probability of a new applicant. Bank headquarters developed this scoring model based on historical bank data, e.g. using borrower characteristics such as age, gender, leverage, assets etc. The score ranges from zero to one, and is increasing with the default probability of a borrower estimated using past behavior of similar applicants. The characteristics used to calculate the score are a subset of those contained in the application, and are thus fully observable by the committee even before the scores are provided.

There are two ways in which the credit score may improve the decision making of the credit committee: On the one hand it can provide a different weighting of how the applicants characteristics factor into the expected default probability if loan officers use a model that is less well calibrated than the one based on the population data (technology channel). On the other hand providing the score gives an ex ante indication to the credit committee and the manager about which cases are easier or more difficult to analyze and therefore should not be pushed up to the manager (agency channel).

We find that committees exert more effort—spend more time evaluating applications—and are more likely to reach a decision on an application when a credit score is available. The increase in effort appears to be 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 quality of the decisions, measured as the loan approval amounts and the ex post default rate of the loans approved, remains unaltered. The increase in committee output substitutes for other, more expensive, inputs in the loan evaluation process. Namely, when committees reach decisions it reduces the need for collecting additional information or for relying on manager input to make decisions. The overall effect of scores on the banks output is negligible in the short run. However, one could conjecture that over time (and once the organization has been able to observe the change in processing speed) the time savings at the management level could lead to growth in other parts of the firm.

This productivity improvement can be driven by a pure information effect: scores provide a signal about the applicant's creditworthiness that allows committees to reach decisions on more complicated cases. Alternatively, scores can reduce agency problems between the manager and the committee by providing a signal of the difficulty of the committees task to evaluate the loan and make a decision. To differentiate these two explanations we add a separate treatment arm where we introduce a credit score for the manager but hold constant the information set for the credit committee. In a randomly selected sample of treatment applications, committees are asked to make an interim evaluation of the application *before* observing the value of the score. We find that interim committee output 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, 78% 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 mechanism.

The results taken together imply that the introduction of scores improves committee decision-making through both the information and agency mechanisms. The information mechanism is consistent with the theories of the optimal organization of knowledge in production, as in Garicano (2000). The agency mechanism is consistent with theories of optimal delegation, surveyed in Mookherjee (2006). In our set up the agency mechanism explains the bulk of the effect of scores on output, highlighting the importance of improved monitoring via IT solutions to encourage decision making lower down in the hierarchy. It can ultimately facilitate the decentralization of work and organizations.

The specific application we focus on, credit scoring, is 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 (see for example, Rajan (1992) and Petersen and Rajan (1995)). Stein (2002) specifically conjectures that loan officers face weaker incentives in soft information regimes, but this link has not received much attention in the empirical literature.[4] Our paper provides the first direct evidence to support this conjecture and characterizes an economic mechanism behind it: the adoption of a standardizing technology in the context of a soft information lending process can mitigate agency problems inside the bank.

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, and the specifics of the experimental design. Section 3 presents the results of introducing the score on committee output and productivity, Section 4.2 explores the channel through which scores improve the productivity of committees in the loan evaluation process, and attempts to unpack the economic mechanism behind the effect. Section 5 concludes.

2 Setting and Study Design

The study was implemented with BancaMia, a for profit bank in Colombia that focuses on micro and small enterprises. In October 2010, the month prior to the roll out of the

[4]A number of studies have analyzed the implications of soft information for bank function and organizational design. See, for example, Berger, Miller, Petersen, Rajan and Stein (2005), Liberti and Mian (2009), and Hertzberg, Liberti and Paravisini (2010)).

study, the bank issued 20,119 loans totalling \$US 25,9 million through its 143 branches. Historically the bank relied on a relationship lending model were loan officers go into the field and collect detailed information from the potential applicants. This information collection mechanism is necessary since small enterprises in Colombia do not have any audited financial statements or other secondary data that a bank could use for credit assessment. The bank relies on a sophisticated information system that allows the data collected by loan officers in the field to be automatically uploaded via PDA devices to a data storage facility in the bank's headquarters. All the information related to an application, including both new 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

An application file is reviewed at the branch level by a credit committee, composed of the loan officer that collected the information in the field, the head of the branch, and one or two additional credit specialists, who are typically other loan officers associated with the branch. The credit assessment is based on the information that loan officers collected from the borrower in the field. General information about the industry and a macroeconomic outlook are taken into account as well. It is important to highlight that the officer that collects the information makes the decision to bring an application to the committee. 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. 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.

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 can adjust the terms of the loan at will in order to improve the acceptance rate. For example, the committee may decide to approve a $500 loan when the requested loan amount in the application is $1,000. When a committee takes any of these two actions we consider that the committee has reached a decision regarding an application. When a committee cannot reach a decision, it has two additional actions at its disposal. The first is to send the application file to a regional manager, whom evaluates the application and reaches a decision.[5] The second is to postpone the decision and send the officer out to collect additional information about the borrower.

During informal interviews, bank managers expressed that such non-decisions by committees represent a substantial cost to the bank in terms of the opportunity cost of time of managers and officers. It is difficult to quantify these costs precisely. The base fixed wage of a Regional/Zonal 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/Zonal 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/Zonal managers that supervise between 15 and 80 offices.

Despite all the above, committee member bonus compensation is a function of the number, amount, and performance of the loans issued by a branch, regardless of whether

[5]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.

the decision was made by the committee or by the upper level manager. There are two potential reasons for this compensation scheme. First, penalizing committees for asking questions to upper level managers may lead to too many bad decisions at the committee level. And 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.

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 include the score as an additional piece of information in the application file, to be used by the committees at the time of evaluation.

The score is a proxy for the expected default probability of the loan. Figure 1 plots the non-parametric relationship between scores, approved loan amounts, and default probabilities in the population of loans issued during October 2010. A loan is considered to be in default if interest or principal payments are more than 60 days overdue, and we measure default at six months after the loan is issued. There is a strong positive association between credit scores and requested loan amounts, and a negative one between scores and default probabilities.

2.3 Experimental Design

Before the full roll-out of the scores, we implemented a pilot program with a randomized control trial design in eight of their branches to evaluate the effects. The branches were chosen to be representative of the average urban branch of the bank.[6] 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, our research assistants used the last digit of the time in the research assistant's cellular phone to allocate a file to the control group or two treatment groups. The information of which group the file belonged to was available to committee members during the deliberations.

In the control group, the committee evaluates the application without the score. In the first treatment group ($T1$), the score was added to the application before the beginning of the evaluation. In the second treatment group ($T2$), the committee first evaluated the application without the score and chose an interim action. The treatment status was randomized before the committee's evaluation process and the committee could ascertain this status while deliberating the interim decision.[7] Thus, the information set under which committees made interim decisions in treatment $T2$ is the same as the information set of the control group, except for the fact that the committee had information about

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

[7] The research assistant present during the committee evaluations had the treatment status and gave it to committees upon request.

the future availability of the score. After recording the interim outcome, the research assistants disclosed the score and the committee revised its choice if necessary. We report in Appendix Table A.1 the number of control, treatment $T1$ and treatment $T2$ loans per branch in the study sample.[8]

2.4 Descriptive Statistics

We present statistics grouping all the treatment applications together, and delay until Section 4.2 the discussion regarding the distinction between treatments $T1$ and $T2$. Table 1, Panel A, shows descriptive statistics of pre-determined application characteristics for control and treatment applications. The average requested amount and the score of loan applications in the treatment and control groups are not statistically different. Figure 2 plots the cumulative distribution of scores and requested loan amounts for the treatment and control applications. The score and amount distributions are indistinguishable between the treatment and control groups in a two-sample Kolmogorov-Smirnov test for equality of distributions, with corrected p-values of 0.81 and 0.94 respectively. These findings corroborate the internal validity of the experimental design.

Table 1, Panels B through E, presents the statistics for committee and loan outcomes. Some outcomes, such as the time the committee needs to reach a decision, 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 is 4.68 minutes (std. Dev. 3.28), and committees reach a decision (accept or reject a loan) in 89% of the applications in the control group. Conditional on reaching

[8]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 detailed description of the treatments, a general explanation of the credit risk model and the scores, and a discussion about the objectives of researching the accuracy of the credit risk model in predicting client performance.

a decision, in only 0.3% of decisions the committee rejects a loan in the control group. Conditional on loan approval, the average ratio of approved to requested loan amount is 0.975, but there is substantial variance (Std. Dev. 0.419), indicating that committees often exercise discretion in how much to lend out after reviewing an application. The default rate—fraction of loans more than 30 days late in repayment measured six months after the loan was issued— is 3.3% in the control group. Comparing the raw outcomes in the treatment and controls groups in Table 1, on average committees spend more time reviewing applications in the treatment group. Committees were also more likely to reach a decision, and conditionally on making a decision, more likely to reject a loan, in treatment applications than in control ones. Loan characteristics conditional on approval are not statistically different in the treatment and control applications.

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 where 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 regional 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 do not. These statistics suggest that

We can also measure final outcomes for applications when the committee did not make a decision during the experiment by tracking the application ex post in BancaMia's information system. This allows us, for example, to measure the disbursed amount and the default rate of loans approved by the Regional Manager, or loans approved after a second round of information collection by the loan officer. These final loan outcomes differ substantially depending on the action taken by the committee. For example, the default rate is zero for loans sent by the committee to the regional manager is and 14.3% for those where the committee sent the loan officer to collect additional information.

These statistics highlight the substantial selection that takes place at the time committees are choosing whether to make a decision on a loan. When committees reach decisions, it is almost always to approve a loan, even if it involves not approving the entire requested amount. The application rejection rate by the committee is very low: committees are more likely to send an application for review to the general manager or postpone its review after collecting additional information, rather than rejecting an application in the first review. As argued before, it is difficult to ascertain whether this is the optimal decision from the banks's perspective given the heavy pre-screening of applications by the field officer, or whether the reluctance to reject reflects an agency problem inside the bank. In either case, it is likely that committees do not reach decisions on applications that are more difficult to evaluate. The statistics above indicate that the difficulty of evaluating an application is strongly positively correlated loan size, while the correlation with credit scores is weak.

3 Results

3.1 Committee Output and Performance

We use the following reduced form equation to estimate the effect of credit scores on committee and loan outcomes:

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

where Y_i is an outcome related to loan application i (we discuss the effect of treatment $T2$ on interim decisions in Section 4.2). The variable $Score_i$ is a dummy equal to one if the loan application is in the treatment groups, i.e., if the score was available to the committee at the time of making a decision, and X_i is a vector of application characteristics that includes the applicant's credit score, the requested loan amount, a dummy if it is the first loan application of the potential borrower, and a time trend (in weeks).

For outcomes that are measured unconditionally (evaluation time or dummy for whether a decision was reached) β measures the Average Treatment Effect (ATE) of having a score as an input to the credit evaluation process. For outcomes that are measured conditionally, β represents a Local Average Treatment Effect (LATE) on loans that meet the conditioning criterion (e.g. the effect of credit scores on approved loan amount conditional on the loan being approved). The LATE and the ATE are very likely different in this setting because: 1) the conditioning variable is affected by the treatment status (scores affect the likelihood that the committee makes a decision), and 2) application where the committee reaches a decision are very different to those when the committee does not. We discuss the potential differences between the ATE and LATE magnitudes in the analysis of the results.

We present the results of specifications that include predetermined controls in Table 3 (results without controls are not significantly different, see Appendix Table A.2). The estimated effect of introducing a score on application evaluation time is 0.766 minutes, statistically significant at the 1% confidence level (column 1). This implies that committees spend 16% more time on the average application when scores are available, measured at the mean evaluation time in the control group. The increase in evaluation time comes with more decisions: the proportion of cases in which the committee makes a decision (accepts or rejects an application) increases by 4.2 percentage points, a statistically significant increase at the 5% level (column 2). This implies that when scores are added as an input in the decision process, the number of cases in which committees cannot decided is reduced by over a third of the baseline proportion of 11% in the control group.

To ascertain whether the effect comes from committees spending more time in every application or only in the marginal cases, we characterize the effect of scores on the distribution of decision time. Table 4 shows the result of estimating specification (1) using simultaneous quantile regressions for the 10th, 25th, 50th, 75th, and 90th quantiles of evaluation time. The results indicate that only percentiles at or above the median are affected by the introduction of scores (the point estimate on the 90th percentile is large but not statistically significant). 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.

If one assumes that the entire increase in evaluation time is due to the applications in which the treatment led the committee to reach a decision when it would not have done so otherwise, the estimates imply that the marginal cases require an additional 18.2 minutes to decide (0.766/0.042). Given that the average evaluation time for control group applications where committees cannot reach a decision is 5.2 minutes, this implies an almost fourfold increase in the time committees spend evaluating and making decisions on marginal cases. This back of the envelope estimate is an upper bound on the amount of time required to evaluate and reach a decision on marginal cases, and can be used to obtain an approximate estimate of the cost savings implied by the introduction of scores.

Conditional on making a decision, the probability that a committee rejects an application increases by 1.24 percentage points in the presence of scores, significant at the 5% level (Table 3, column 3). This LATE estimate implies a fourfold increase in the proportion of applications rejected by the committee relative to the baseline probability of 0.3%

in the control group. Due to the differences documented so far between the marginal and inframarginal decisions, it is unlikely that this is an estimate of the unconditional effect of scores on the likelihood of rejecting an application. Most likely, the effect is concentrated on the marginal applications where the committee made a decision due to the availability of the score (and would have not made a decision otherwise). Assuming that all the additional rejections come from these marginal decisions, the estimate implies that committees reject 22% of the marginal cases they decide on when scores are used as an input ($(1.24 - 0.3)/4.2 = 0.223$). Together with the other findings, the results suggest that more difficult applications are also those that have a higher likelihood of rejection in the first place.

Finally, conditional on the committee having approved the loan, scores do not have a significant effect on the average approved loan amount, on the likelihood that the loan is issued, on the issued loan amount, or on the probability of default of the loan (Table 3, column 4 through 7). These LATE estimates are obtained only from approved and issued loans and thus are not unbiased estimates of the ATE. The direction of the bias depends on the average size and quality of the marginal loans, those that are approved by committees due to the treatment. From the sign of the estimated coefficients on requested amount and the score in Table 3 (Columns 1 and 2), one can infer that applications for larger loans and with larger credit risk scores are less likely to be decided on and take more time to decide. It is likely then that marginal loans are larger and riskier than inframarginal ones, which would imply that the β estimates in columns 6 and 7 represent upward biased estimates of the ATE. Thus, the ATE of scores on loan size and default probability is also likely small and insignificant.

The results in this subsection 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 quality of the decisions, measured as the loan approval amounts and the ex post default rate of the loans approved, remains unaltered.

3.2 Overall Performance

Increased committee effort substitutes, in the context or our study, for other more expensive inputs to production. Namely, when committees reach decisions it reduces the need for collecting additional information or for relying on manager input to make decisions. In this subsection we can use the experimental setting to evaluate whether the introduction of scores affects overall output. That is, we can measure the effect of the introduction of scores on application outcomes without conditioning on the decision being made by the committee during the experiment. This includes outcomes that were decided in subsequent meetings by the committee after additional information was collected, or decisions made by Regional/Zonal Managers.

To do so, we estimate specification 1 using as the dependent variable a dummy for whether the loan was issued, the amount of the loan issued, and a dummy if the loan defaulted after 6 months (see Table 5). All point estimates are close to zero, and not statistically significant at the standard levels. These results imply that scores shift the decision making to the committee, without altering either the quantity or quality of the overall loan approval process. The results confirm, for example, that committees reject more loans in the treatment group that would have been rejected anyway either by a Regional/Zonal Manager or by the same committee in a later evaluation in the control.

Because the estimated effect on the likelihood that the loan is issued does not condition on endogenous decisions made by the committee, the estimates represent an ATE of scores on the overall likelihood that a loan application will turn into an actual loan. Because the effect of treatment on this extensive margin is not significant, the LATE estimates for loan amount and default that condition on the loan being issued are likely unbiased estimates of the ATE. Taken together, the results confirm that scores increase committee productivity without affecting the overall performance of the decision making process of the bank.

The introduction of scores may affect overall bank performance in a manner that cannot be captured by the experimental design: by changing the pool of applications that reaches the committee. For example, in anticipation of the availability of scores in the committee stage of the evaluation process loan officers may have changed their information gathering effort, manipulated the entry of data into the system to affect the score of an applicant, influenced the borrower to change the requested loan amount in the application, or postponed certain types of applications to the committee until the pilot implementation in the branch ended. Because the randomization occurs at the committee level, once the information in an application is already collected, we cannot use the experimental design to evaluate this effect. Moreover, all the documented effects are measured conditional on potential application composition changes.

We can perform a non-experimental test to evaluate whether scores affected the application pool characteristics. We compare outcomes of the experimental branches during the weeks of experimentation relative to other weeks, and relative to propensity score-matched non-experimental branches of the bank during the same weeks, using the following specification:

$$Y_i = \gamma \cdot ExperimentWeek_i + Z_i' \cdot \psi + \varepsilon_i, \quad (2)$$

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 controls that includes a full set of branch and week dummies, and branch-specific trends.

We present the results in Table 6 estimated on two subsamples. Panel A shows the estimates using experimental branches only, using all the loans approved starting four weeks before the experiment began on the first branch (week 41 of 2010), and four weeks after the experiment ended (week 26 of 2011). Panel B shows the estimates using experimental branches and the same number of propensity-score matched branches during the same period. Branches were matched based on size (number and total amount of loans approved), average approved loan size and borrower score during the month prior to the beginning of the experiment.

We find no statistically significant change in the score, loan amount, or default probability of approved loans during experimental weeks across all specifications in Table 6. These results imply that the introduction of scores either did not affect the applicant pool, or that it affected the application pool in a way that exactly offset the effect of introducing scores on loan outcomes. Either way, the results reinforce the conclusion that the introduction of scores changed the composition of inputs in the evaluation of loans, with little impact on total output. The empirical setting only allows us to evaluate the short run effects on total output, however. 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 on total output.

4 Identifying the Channel and Mechanism

This section explores the channel through which scores improve the productivity of committees in the loan evaluation process, and attempts to unpack the economic mechanism behind the effect. To evaluate the channel, we document which margins of non-decisions are affected by the introduction of scores. To explore the mechanism, we exploit the experimental design of the second treatment ($T2$) to evaluate whether scores affect productivity keeping the information set of the committees constant.

4.1 Information Collection versus Problem Solving

The data allows identifying two distinct margins through which scores increase committee productivity: 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 use the following multinomial logistic specification to model committee choice between between making a decision, collecting additional information, or sending the application to a manager in a higher hierarchical level to make the decision:

$$\ln \frac{P\left(D_i = m\right)}{P\left(D_i = 1\right)} = \beta_m \cdot Score_i + X_i' \cdot \chi_m + \varepsilon_{mi}, \tag{3}$$

where D_i represents the committee choice. We use the committee's choice to make a decision (approve or reject application), $D_i = 1$, 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 the choice to collect more information and one for the choice to send the application to the manager. A positive estimate for β_m implies that committees are more likely to take action m than to make a decision (accept or reject) in the treatment group relative to the control group.

The results are presented in Table 7. The β_m estimate is negative for, both, the choice to collect more information and to send the decision to the manager.[9] This implies scores reduce both non-decision margins significantly. To evaluate the economic significance of the effects, we report on the bottom rows of Table 7 the implied marginal effect of

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

treatment on the probability of each choice. Observing a score decreases the probability of sending the decision up to the manager by 2.1 percentage points, and the probability of sending the loan officer to collect additional information by 1.6 percentage points. The declines are economically significant: they represent 44% and 25% reductions in the baseline probability that an application is sent to the boss and postponed for additional information collection, respectively.

The results suggest that scores increase committee decision making ability by reducing, both, the degree to which they rely on managers in upper levels of the hierarchy to solve problems and on the collection of additional costly information. One potential economic mechanism through which scores affect these decision margins is by providing an additional signal about applicant creditworthiness. This additional signal substitutes for the manager's expertise in solving the 'problem' of making the decision regarding a loan application, as in Garicano (2000) . The signal also substitutes for the signal provided by an additional information collection round by the loan officer.

In this purely informational interpretation, the source of the signal in scores is not idiosyncratic information about the borrower, because all the borrower-specific information collected by the officer is in the application folder. Moreover, since the loan officer that collects the information in the field and has direct contact with the applicant is present in the committee, it is likely that the committee has more soft, borrower-specific, information than that contained in the score. The additional signal of the scores comes from the additional precision of the mapping of the applicant's characteristics to loan performance in the population, rather than the mapping based on the small sample that is drawn from the personal experience of committee members. This additional precision may be purely statistical and due to the larger sample size, or it may be the result of cognitive limitations of committee members in mapping complex and multi-dimensional variables (borrower characteristics) into a single predicted outcome (default). In either case, under this informational interpretation scores make committees aware or relationships between borrower characteristics and expected borrower performance that would otherwise be unavailable, or would require the expertise of the manager to ascertain.

There are other potential mechanisms through which scores may affect committee effort and output. A salient one is by reducing information asymmetries between committee members and management. As mentioned in Section 2 committee member compensation is not sensitive to the cost of the decision making process. In particular, it is not sensitive to whether the decision to issue the loan is made by the manager or whether making the decision required an additional round of information collection. Since committees are better are likely better informed about the difficulty of assessing an evaluation than the managers, committees may resort to these choices too much, in the sense that the cost to the bank of the marginal choices is larger than the private savings to the committee.

Scores may reduce the asymmetric information problem by providing an additional signal of the borrower's creditworthiness to the manager, and an additional signal of the difficulty of the committee's task to evaluate the loan and make a decision. Together with implicit incentives (job retention, promotions), scores may reduce the likelihood that committees take wasteful actions, as in Hubbard (2000). For example, once the score makes the difficulty of evaluating an application observable, the probability of being fired may increase and the probability of a promotion may decrease if the committee seems incapable of making decisions on marginal applications.

In the next subsection we attempt disentangle the information and the agency mechanisms by analyzing separately the two treatments described in Section 2.

4.2 Information Versus Agency

The results presented so far are obtained using the final choices by the committee. 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 (e.g. with the same information set as the control applications). The committees had available the information about which treatment group the application belongs to during the deliberations of the interim choice, and thus, about whether the score would be ultimately available in the loan application or not.

In theory, we can use this treatment to evaluate how ratings affect committee decision-making holding the information set of the committee constant, and to isolate the effect of the pure information channel on committee output. For example, if scores have no effect on interim choices then the agency mechanism described in the previous subsection is unlikely to be a first order determinant of the overall effect of scores on committee behavior.

One caveat of measuring the effect in interim committee choices is that committees may have weak incentives to perform a thorough interim evaluation when they know that they can revise the decision after observing the score. In this case scores would have a negative effect on interim output and the results will be difficult to interpret. Although study participants were explicitly asked to perform a thorough evaluation of the application regardless of the treatment status of the application, we interpret any observed effect on interim decisions bearing the potential weakened incentives to exert effort in mind.

We estimate the OLS equation (1) and the multinomial logit model (3) with interim committee decisions as the left-hand side variable, and using for estimation only the control and $T2$ subsamples. 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 8 the results. The effect of the score on the probability of making an interim decision estimated using the linear model 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 effect on final decisions but not statistically different. The interim choice effects of scores on the probability of rejecting an application (column 2), of sending the loan officer to collect more information (column 5) and of sending the application to the manager (column 6), also have the same sign and similar magnitude than the effects estimated using final committee decisions.

These findings indicate that scores have an effect on committee output even when one holds constant the information that the committee has about the applicant. This implies that scores have an effect on committee productivity above and beyond the pure information effect, and the results are consistent with scores solving agency problems inside the bank.

The point estimates of the effect on interim behavior are smaller than those on final, behavior, although the precision of the estimates does not allow to plausibly distinguish the difference in these specifications. To evaluate the pure information effect we can adopt a different approach: compare how committees revise their interim decisions in treatment $T2$ applications after observing the score. Table 9 presents in matrix form the transitions between interim and final decisions for all the applications in treatment $T2$. There is a large concentration of the observations on the diagonal indicating that observing the score does not have a first order effect on the interim decisions made by committees.

Committees revise an interim decision in eight out of the of the over five hundred applications in treatment $T2$, or 1.5%. In every instance in which the committee changes its decision, the change is between accepting the loan and sending the application up to the manager, and vice versa. In seven out of the eight changes, the committee amends the decision from sending up to the manager to accepting the loan. Thus, observing the score does not change in any instance an interim decision to reject an application. The net effect of observing the scores is a 1.1% increase in the probability of making a decision once the score is available. Added to the effect on interim decisions, it comes up roughly to the estimated overall effect of scores on decisions estimated in the previous section.

Two conclusions can be drawn from these results. First, taking the magnitudes of the point estimates at face value, they imply that over 75% of the effect of scores on decisions occurs before the actual score is observed by the committee $(0.039/(0.039+0.011))$. Thus, the bulk of the effect of scores on committee output is unlikely driven by information that the score provides to the committee about the prospective borrower's creditworthiness. This non-information effect is consistent with an agency mechanism and leads committees to make more decisions.

Second, this non-information effect explains the entire increase in the probability that the committee rejects a marginal application. In other words, committees know which loans ought to be rejected even before observing the score, and observing the score leads to little update along the rejection margin. This suggests an agency agency problem in which officers are reluctant to reject loans themselves: postponing the rejection of the loan, at a cost to the organization, has an option value to the loan officer and the committee. There are multiple potential sources for this agency problem. For example, committees might try the loan to get approved by the manager because its members do not does not pay reputation cost of a defaulting loan that was approved by boss. Alternatively, the loan officer that brought the application in might push the case too hard because having the application rejected outright tarnishes his reputation as a good screener. Again, under these interpretations, scores may reduce the agency problem by lowering the cost to managers and other committee members to judge the merits of the application.

We can also explore the pure information effect on the intensive margin of lending by comparing the loan amounts approved in the interim and final decision for the applications in treatment $T2$. The scatterplot of the two decisions, shown in Figure 3, indicates that although most of the amounts remain the same after observing the score (77.2%), in 16.2% of the cases the approved amount is revised downwards, and in 6.6% revised upwards, after observing the score. This result indicates that although the effect of scores through the pure information channel seems to be secondary in the extensive margin of decisions made by committees, it seems to have a substantial effect in the intensive margin of lending. The result also highlights how the information effect through the intensive margin can pass undetected with the typical estimation of ATEs: scores may lead to substantial upwards and downwards revisions to approved amounts, but the effect on average lending can be trivial even if these effects cancel out.

5 Conclusions

Information technology that make agents' problems 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)) and have private information about the productivity of their actions (Prat (2005)), IT innovations may under certain circumstances reduce performance.

The present paper uses a randomized controlled trial to identify the incentive effect of an information technology innovation in the context of a micro-finance institution. We measure the effect of including in a credit application file a unidimensional metric of a borrower's credit repayment probability based on her observable characteristics —a credit score— on the output and efficiency of credit evaluation committee. To distinguish the incentive effect, we use a treatment in which committees make decisions in anticipation that the score will be available in the application, but before observing the actual score.

We find that credit committees are more likely to make credit decisions —accept or reject an application— as opposed to passing the decision up to a superior in the hierarchy or engaging in additional information gathering activities, when a credit score of the borrower is available, even holding the information set of the committee constant. The results imply that credit scores affect the committee productivity mainly by reducing agency conflicts inside the lending institution.

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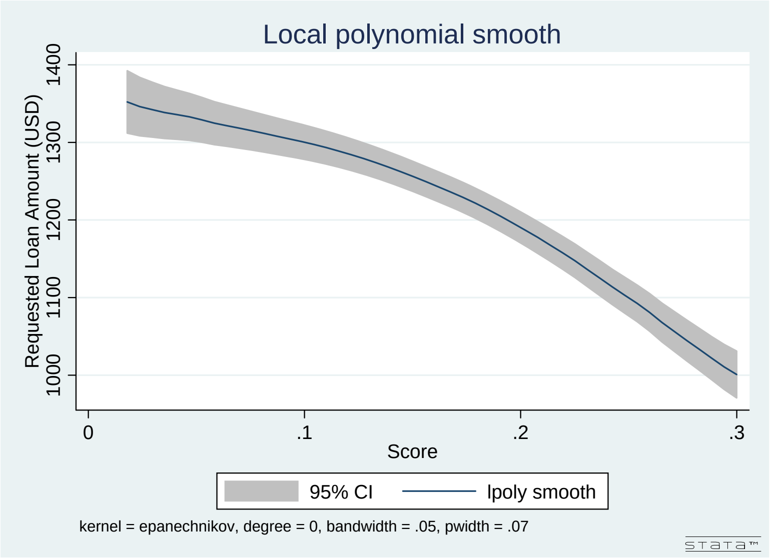
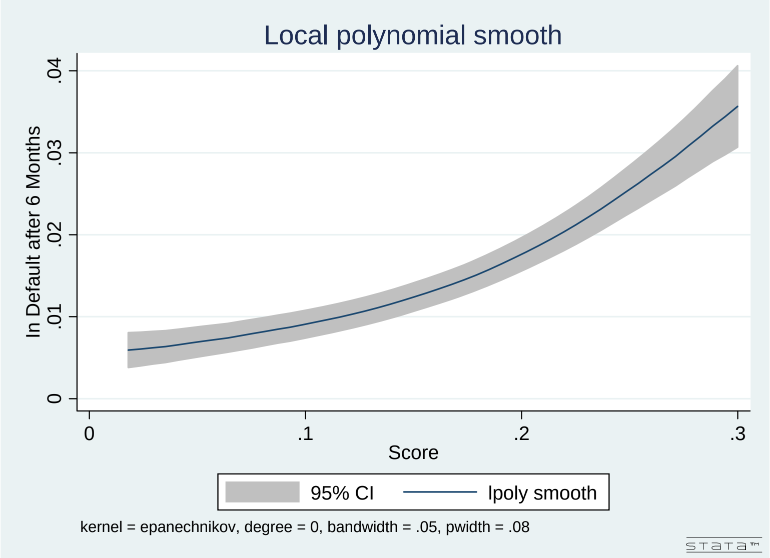
Figure 1: Population Credit Risk Scores and Loan Characteristics, Before Experiment

(a) Requested Loan Amount, by Score



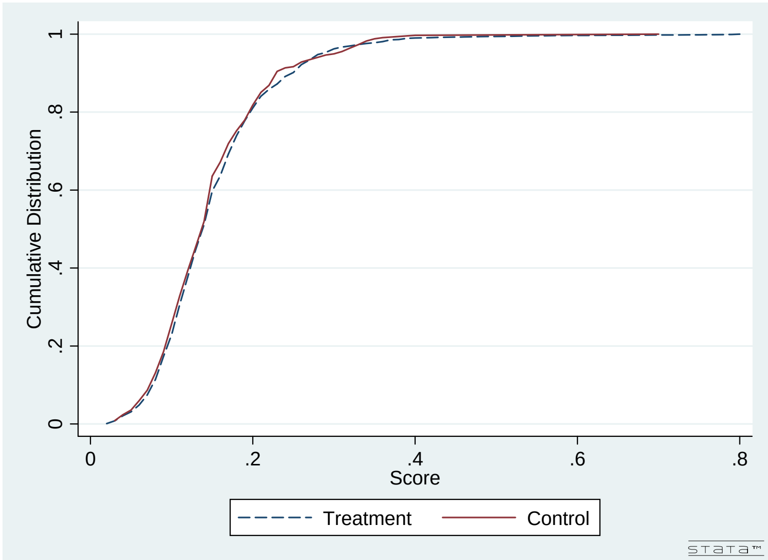
(b) Default Probability, by Score



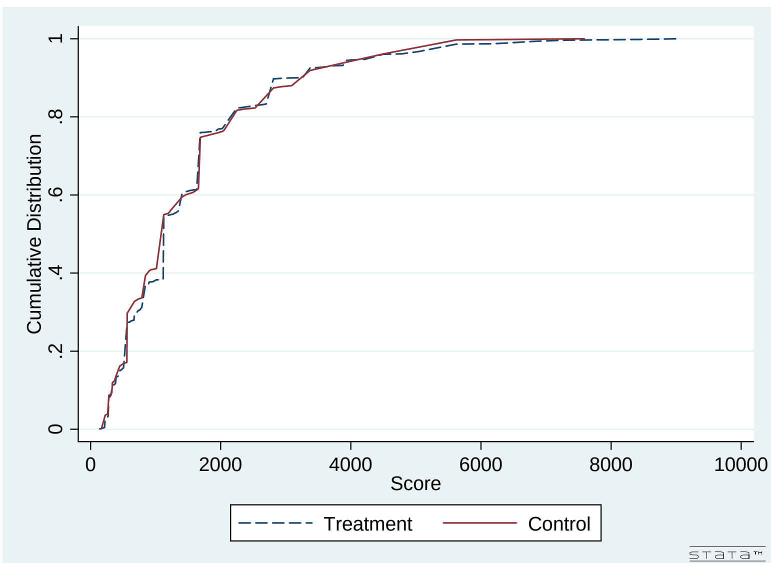
Non-parametric relationship between the score assigned by the credit risk model and requested loan amount (a) and default probability (b) estimated on the sample of *all* loans approved by BancaMia during October 2010, one month before the roll out of the randomized pilot program.

Figure 2: Cumulative Distributions, by Treatment Group

(a) Scores

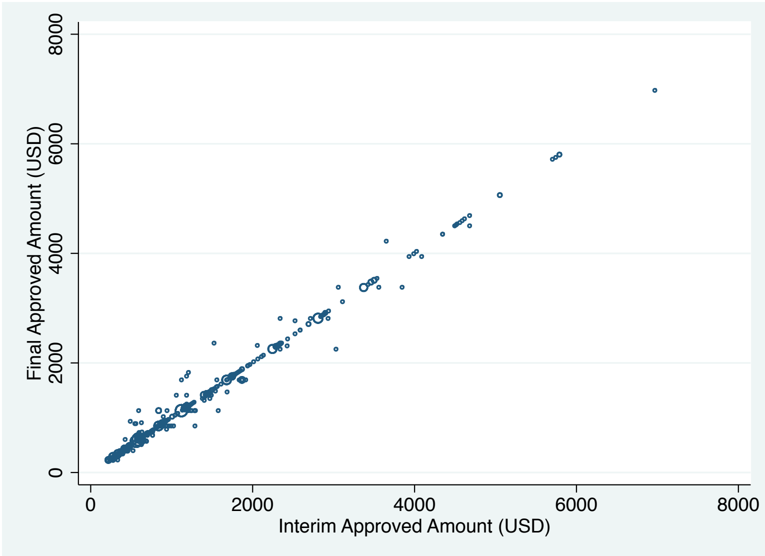


(b) Requested Loan Amounts



Cumulative Distribution of the scores and requested loan amounts of the loan applications in the randomized pilot program. In the treatment applications, the credit review committee received the score before making final decisions. Scores and requested amounts are pre-determined at the time of the randomization.

Figure 3: Approved Loan Amounts before and after Observing Scores (Treatment $T2$)



Plots interim and final approved loan amounts in the subsample of applications in treatment $T2$, in which officers made an interim decision before observing the score and then revised the decision after observing the score.

Table 1: Loan Application Characteristics, Committee Decisions, and Approved Loan Performance, by Treatment Group

	(1) Control (n = 335)		(2) Treatments (T1, T2) (n = 1,086)		(3) p-value
	Mean	SD	Mean	SD	(1) = (2)
Panel A. Ex Ante Loan Characteristics					
Requested Amount (USD)	1,551.5	1,321.4	1,552.7	1,335.5	0.978
Credit Risk Score	0.151	0.068	0.156	0.077	0.253
First Application (Dummy)	0.146		0.153		0.774
Panel B. Committee Outcomes					
Evalutation Time (minutes)	4.68	3.28	5.27	5.29	**0.052**
Committee Approves/Rejects (Dummy)	0.890		0.940		**0.002**
Panel C. Committee Outcomes, Conditional on Reaching decision					
Loan Approved (Dummy)	0.997		0.985		0.116
Panel D. Committee Outcomes, Conditional on Approval					
Approved Amount/Requested Amount	0.975	0.419	0.969	0.312	0.773
Loan Issued (Dummy)	0.754		0.772		0.515
Panel E. Final Outcomes, Conditional on Loan Issued					
Disbursed Amount/Requested Amount	0.959	0.382	0.969	0.436	0.738
In Default after 6 Months (Dummy)	0.0329		0.0398		0.627

The last column presents the p-value of a t test of equality of means between the treatment and control applications. 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 the credit risk model estimated using BancaMia's historical data on borrower characteristics and repayment performance. 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 Info (n = 21) (3)	
	mean	sd	mean	sd	mean	sd
Requested Amount (US$)	1,443	1,170	2,480	2,126	2,476	1,994
Credit Risk Score	0.152	0.069	0.155	0.060	0.137	0.047
First Loan (Dummy)	0.154		0.125		0.048	
Time to decision (minutes)	4.608	3.188	5.438	3.405	5.105	4.508
Loan Issued (Dummy)	0.752	0.433	0.750	0.447	0.333	0.483
Disbursed Amount/Requested Amount	0.945	0.272	0.950	0.227	1.486	1.807
In Default after 6 Months (Dummy)	0.031	0.174	0.000	0.000	0.143	0.378

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: Effect of Scores on Committee Output – OLS

Sample Conditioning:	None		Committee Decides	Committee Approves		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	0.7663***	0.0419**	-0.0124**	-0.0000	0.0022	0.0135	0.0034
	(0.231)	(0.018)	(0.005)	(0.020)	(0.029)	(0.023)	(0.014)
ln(Requested Amount)	1.0137***	-0.0455***	0.0025	0.8752***	-0.0363**	0.8229***	-0.0055
	(0.168)	(0.009)	(0.004)	(0.010)	(0.015)	(0.016)	(0.007)
Credit Risk Score	-1.0063	-0.1368	-0.1122	-0.5721***	0.0533	-0.5941***	0.4092***
	(1.429)	(0.112)	(0.084)	(0.128)	(0.152)	(0.170)	(0.104)
First Application	0.7074*	0.0063	-0.0030	-0.0003	0.0254	0.0231	0.0089
	(0.389)	(0.018)	(0.009)	(0.024)	(0.032)	(0.028)	(0.018)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,405	1,414	1,319	1,315	1,303	1,001	1,001
R-squared	0.045	0.039	0.010	0.840	0.019	0.777	0.031

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 4: Effect of Scores on the Distribution of Decision Time – Quantile Regressions

Dependent Variable:	Evaluation Time				
Percentile	10th	25th	50th	75th	90th
Score Dummy	0.0748	0.1197	0.4866***	0.5777***	0.9196
	(0.184)	(0.190)	(0.152)	(0.219)	(0.734)
ln(Requested Amount)	0.3632***	0.4279***	0.5724***	0.7721***	1.7921***
	(0.121)	(0.107)	(0.074)	(0.142)	(0.355)
Credit Risk Score	-1.0897	-0.8108	-1.4674	-1.7307	3.4497
	(0.886)	(0.777)	(0.956)	(1.420)	(3.432)
First Application	0.4373**	0.4798**	0.5043***	0.7519	0.9737
	(0.189)	(0.208)	(0.186)	(0.515)	(0.810)
Trend	Yes	Yes	Yes	Yes	Yes
Observations	1,405	1,405	1,405	1,405	1,405

Bootstrapped standard errors (500 repetitions) estimated via simultaneous quantile regressions 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	Defaults
Percentile	Issued	Amount)	
	(1)	(2)	(3)
Score Dummy	0.0179	0.0198	0.0050
	(0.028)	(0.026)	(0.013)
ln(Requested Amount)	-0.0423***	0.8199***	-0.0055
	(0.015)	(0.016)	(0.006)
Credit Risk Score	-0.0733	-0.5710***	0.3953***
	(0.159)	(0.165)	(0.099)
First Application	0.0345	0.0249	0.0130
	(0.032)	(0.028)	(0.018)
Trend	Yes	Yes	Yes
Observations	1,414	1,046	1,046
R-squared	0.007	0.771	0.025

OLS estimates of the effect of treatment on overall outcomes regarding loan applications, 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 Zonal/Regional Manager. Column (1) is estimated on all applications, and columns (2) and (3) 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: Aggregate Effects on Branch Outcomes

	(1) Score	(2) Loan Amount	(3) In Default after 6 months
Panel A. Experiment Branches Only			
Experiment Week	0.0023	-0.0370	-0.0011
	(0.002)	(0.024)	(0.005)
Branch Dummies	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes
Branch Trends	Yes	Yes	Yes
Observations	9,607	9,607	9,591
R-squared	0.029	0.017	0.012
Panel B. Experiment and Propensity Score Matched Branches			
Experiment Week	-0.0014	0.0026	-0.0014
	(0.002)	(0.020)	(0.004)
Branch Dummies	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes
Branch Trends	Yes	Yes	Yes
Observations	18,327	18,327	18,296
R-squared	0.026	0.019	0.010

OLS regression of committee outcomes 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, and 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). Panel A: sample includes only loans approved in the eight pilot BancaMia branches. Panel B: sample includes eight BancaMia branches and eight propensity-score matched branches. The matching was based on branch size (number and total amount of loans approved), average approved loan size and borrower score during October 2010. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 7: Information Collection and Problem Solving

Choice:	Committee Decides (Omitted) (1)	More Information (2)	Send to Manager (3)
Score Dummy		-0.4651*	-0.8270**
		(0.271)	(0.395)
ln(Requested Amount)		0.7670***	0.8379***
		(0.291)	(0.262)
Credit Risk Score		0.7713	3.4760
		(1.622)	(2.391)
First Application		-0.4909	0.2415
		(0.329)	(0.533)
Trend	Yes		
Observations	1,413		
Pseudo R-squared	0.0754		
Fraction in Control Subsample	0.8896	0.0627	0.0478
Marginal Effects:			
Treatment	0.0363***	-0.01550*	-0.0208**
	(0.0162)	(0.0094)	(0.0116)

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. 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 8: Information and Incentives

Estimation	OLS			Multinomial Logit		
	Committee Decides	Committee Approves	ln(Approved Amount)	Decide (Omitted)	More Information	Send to Manager
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment $T2$	0.0388**	-0.0151**	-0.0105		-0.4485	-0.7284*
	(0.019)	(0.007)	(0.023)		(0.338)	(0.400)
ln(Requested Amount)	-0.0488***	0.0033	0.8572***		0.8817***	0.6285*
	(0.013)	(0.005)	(0.014)		(0.273)	(0.323)
Credit Risk Score	-0.1070	-0.2181*	-0.8223***		1.1933	2.3407
	(0.135)	(0.130)	(0.177)		(1.621)	(3.024)
First Application	0.0400*	-0.0019	-0.0123		-1.0022	-0.5921
	(0.021)	(0.010)	(0.033)		(0.637)	(0.658)
Trend	Yes	Yes	Yes		Yes	Yes
Observations	854	789	784	853		
R-squared	0.042	0.028	0.819			
Pseudo R-squared				0.075		
Fraction in Control Subsample				0.8896	0.0627	0.0478
Marginal Effects:						
Treatment 1				0.0377**	-0.0158	-0.0218*
				(0.0177)	(0.0131)	(0.0129)

Estimated effect of treatment on interim committee decisions, before observing the score. Columns (1) through (3) are estimated with OLS and columns (4) through (6) are estimated with a Multinomial Logistic Regression. Robust standard errors in parenthesis. ***, **, and * indicate significance at the 1%, 5% and 10% levels.

Table 9: Interim and Final Decisions in Treatment $T2$

	Final Decision (after Observing Score):				
	Accept Loan	Reject Loan	Obtain More Information	Send Decision to Manager	Total
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.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.