NBER WORKING PAPER SERIES

# LOAN PROSPECTING AND THE LOSS OF SOFT INFORMATION

Sumit Agarwal
Itzhak Ben-David

Working Paper 19945
http://www.nber.org/papers/w19945

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2014

Previously circulated as "Do Loan Officers' Incentives Lead to Lax Lending Standards?" We are grateful to Tobias Berg, Harrison Hong, Naveen Khanna, Jose Liberti, Evgeny Lyandres, Mitchell Petersen, Rich Rosen, Kasper Roszbach, Antoinette Schoar, Amit Seru, René Stulz, Greg Udell, and Luigi Zingales for helpful comments. We wish to thank seminar participants at the University of California at Berkeley, FIRS 2012, The Fisher College of Business at The Ohio State University, the School of Public Affairs at The Ohio State University, the National University of Singapore, the NBER Behavioral Economics meeting, the NBER Risk of Financial Institutions meeting, the SIFR Conference on Real Estate and Mortgage Finance (Stockholm), the Indiana University, the University of Maryland, Tel-Aviv University Finance Conference, Dartmouth University, the University of Florida, the Wharton School of Business, New York University, Cornell University, CEPR EBC Conference, the Western Finance Association Meetings, the American Finance Association Meetings, the ABFER Conference in Singapore, the Federal Reserve Bank of New York, and the Federal Reserve Bank of Chicago for comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Loan Prospecting and the Loss of Soft Information
Sumit Agarwal and Itzhak Ben-David
NBER Working Paper No. 19945
February 2014, Revised September 2015
JEL No. G01,G21

**ABSTRACT**

We study a controlled experiment in a large U.S. commercial bank in which loan officers engaged in loan prospecting. Consequently, loan size, loan volume, and loan default increased. We show that while the bank's credit standards did not change, it put greater weight on hard information in the approval process and thus approved many applications that previously would have been rejected. Furthermore, loan officers did not source new applications but rather convinced existing applicants to borrow larger amounts. Both factors contributed to a higher default rate and to the loss of the predictive power of the bank's credit model.

Sumit Agarwal
Professor of Finance and Real Estate
NUS Business School
Mochtar Raidy Building, BIZ1
15 Kent Ridge Road
Singapore, 119245
ushakri@yahoo.com

Itzhak Ben-David
Fisher College of Business
The Ohio State University
2100 Neil Avenue
Columbus, OH 43210
and NBER
bendavid@fisher.osu.edu

## 1. Introduction

In many financial institutions, loan officers are expected to source new loans ("loan prospecting") in addition to their traditional role of screening applications. In contrast to loan screening, which is a passive role that involves analyzing the risk of existing applications, loan prospecting is an active role that requires loan officers to act as salespersons: they actively promote the bank's loan products. Banks typically reward loan officers for their efforts with a bonus that depends on the volume of originated loans (BLS 2012).

Previous studies have proposed that expanding the scope of the loan officer's job may affect a bank's loan origination process. Heider and Inderst (2012) examine this problem using a multitasking model first developed by Holmström and Milgrom (1991). In their study, they propose that an equilibrium contract is one in which loan officers are compensated according to originated volume and exert greater effort in seeking new loans. They predict that the increased competition in the credit market causes banks to weaken lending standards. Also, hard information takes greater weight in the approval decision, as the bank attempts to limit loan officers' moral hazard when reporting soft information.

In a related literature, several empirical papers have investigated the effects of variable compensation on loan officers' approval decisions. Cole, Kanz, and Klapper (2015) use an experimental setting implemented with a group of loan officers at a commercial bank in India, which allows them to study loan approval patterns in response to incentive schemes. They find that when origination volume is rewarded, loan officers are more likely to approve applications and loan quality declines. Tzioumis and Gee (2013) document that loan officers are more likely to approve residential mortgages at the end of the month (before the bonus is paid) and that end-of-month approved mortgages are of poorer quality. While these studies provide a broad view on the relation between compensation and the volume and quality of loans, we still do not have empirical evidence showing how loan prospecting affects the approval process.

In this study, we provide novel findings about how loan prospecting transforms a bank's approval process and its book of business. We analyze a controlled experiment conducted in the small business unit of one of the largest U.S. commercial banks ("the Bank"). Following competitive pressures in the industry, the Bank's management decided to expand the scope of about half of its loan officers to include loan prospecting activities, while the other half of loan officers maintained a narrower scope of screening activities only. As in Bénabou and Tirole's (2015) "bonus culture" economy, loan officers who were assigned to the loan prospecting group were compensated with bonuses that were based primarily on loan volume. Our data include detailed information on both loan applications and approved loans, which allows us to explore the approval process in great detail.

The pilot program that we study took place in 2005. For many years, loan officers in the Bank focused on screening loans, and their compensation was based on a fixed salary. With the credit expansion of the early 2000s, the Bank's management decided in 2004 to encourage loan officers to seek new business, and to compensate them according to loan volume. The pilot for the program was implemented in the following year in the Bank's New England division for about half of the loan officers. The assignment of loan officers to their groups was determined by the legacy human resources computer system to which they belonged; loan officers could not switch between systems. Although loan officers' assignment was not random, we show that there was no significant difference in any attribute of applications or approved loans in the year preceding the experiment. Our dataset contains loan details for more than 30,000 small business loan applications processed by more than 130 loan officers during the 24-month window around the change in the job scope of loan officers. We use a differences-in-differences design and within–loan officer variation to detect causal effects of loan prospecting on the approval process.

The direct effects of the loan prospecting pilot were striking. We document an increase of 28% in the number of approved applications and a 15% rise in the average loan amount in the treatment group. The processing time shortened by about a third, and the withdrawal rate of approved loans was halved. Furthermore, 17% of the originated loans in the treatment group have larger loan amounts than that originally requested by applicants (compared to 3% in the control group). Finally, the performance of loans in the treatment group has deteriorated: they were 24% more likely to default (5.2 percentage points compared to 4.2 percentage points in the control group).

The main part of our study investigates the channels through which loan prospecting affected the approval process and loan performance. A first possible explanation for the high volume that we consider is that loan officers acted according to the expectations of the Bank's management, i.e., sought new business (e.g., converting more inquiries into applications) or improved the quality of the existing pool (e.g., dissuading those with weak credit from applying). Our tests show that this channel was not important; neither the volume nor the quality of applications was different in the treated group compared to the control.

A second possible channel is a change in lending standards. If lending standards were relaxed, then the Bank would have approved more applications, and their quality would have been lower. We find that the channel had a limited effect, if any, on the experiment's outcome. In particular, the observable credit-related characteristics of approved loans in the treatment group are not statistically different from those in the control. Furthermore, we use a hedonic default model based on 2004 data and show that there no significant difference in the predicted default likelihood between the treatment and control groups in 2005. We find, however, that loan officers relaxed their approach with respect to loan amounts. Among the control group, higher default probability is associated with smaller approved loans, but this relationship does not exist in the treatment group. This change is partially compensated for by a stronger association in the treatment group between the interest rate and the predicted default probability. Overall, it appears that while there were no changes in lending standards on the extensive margin, standards were relaxed on the intensive margin. Thus, this channel can explain the increase in loan amount and potentially poor performance, but not the increase in the number of loans that were approved.

A third potential channel is a change in information usage at the Bank. We present evidence showing that the Bank put greater weight on hard information (i.e., third-party credit scores) and less emphasis on soft information (i.e., loan officers' own judgment of credit risk). By relying on hard information in the approval decision, the Bank limited the loan officers' moral hazard (as in Heider and Inderst 2012); however, this shift caused the Bank to ignore critical soft information. We show that the approval rate increased dramatically because the Bank approved many applications that looked good on paper.

We also explore the reasons for the poor performance among the Bank's loans in the treatment group. We identify two main factors. First is the Bank's aggressive loan amount policy. We find that about half of the increase in the default rate following the pilot stems from loans in which the approved amounts were larger than the amounts originally requested.

The second factor explaining poor loan performance is the loss of predictive power of the Bank's credit model. While proxies of hard information (i.e., external credit scores) was a good predictor of loans' ex post performance for the control sample, they lost their predictive power for the treatment group. In contrast, soft information (which was discounted during the approval process) appears to have better predictive power of default for the treatment group. We observe a similar phenomenon when we estimate a more elaborated predictive default model and apply it to both the control and treatment groups.

Why did ex ante credit quality variables lose their predictive power? We present evidence suggesting that these variables became obsolete since they were "fitted" over a historical range of loan variables, such as amount. We show that the predictive credit model still had good predictive power for loans with amounts that fell in the "normative" range. In contrast, the relation broke down for loans with amounts beyond this range. Because the credit model captures correlations between default and loan characteristics for a specific range, loans outside that range have different correlations not captured by the current model. This result is similar in spirit to Rajan, Seru, and Vig (2015), which presents evidence that the default models used in the residential real estate industry lost predictive power with the move toward standardized underwriting.

Overall, our results show that the loan prospecting pilot did not achieve the Bank's goals. The Bank increased its originated loan volume due to two main sources. First, the Bank overweighted hard information in order to prevent loan officers from promoting bad applications, but at the same time ignored critical soft information. As a consequence, many applications were approved that otherwise would have been rejected. Second, instead of increasing the Bank's market share by seeking new applications, loan officers increased the loan amounts offered to applicants. Both factors contributed to a higher default rate. Furthermore, since loan terms were outside the typical range for the Bank, the Bank's credit model lost its predictive power.

This study contributes to several strands of the literature. The first strand relates to incentives and moral hazard in banks. In particular, Udell (1989), Berger and Udell (2002), Inderst (2008), and Heider and Inderst (2012) argue that when information asymmetry is present, loan officers may approve too many risky loans if their incentives are misaligned with those of their employer (the lender). An agency problem arises when the lending decision depends on information collected by the loan officer that the lender can neither observe nor verify (Petersen 2004). Although the problem can theoretically be mitigated by realigning incentives (e.g., by giving loan officers an equity stake in the transaction, see Sufi 2007), in practice, such a realignment often does not occur. More broadly, the experiment we analyze is an example of how compensation for short-run performance can lead to an increase in the risk exposure of banks (Bebchuck and Spamann 2009, Acharya, Cooley, Richardson, and Walter 2010, Acharya, Litov, and Sepe 2013).

A second strand of the literature relates to information production in lending. Banks traditionally use both hard and soft information in approval decisions (Petersen 2004). As physical distance between the bank and borrower increases, banks rely more on hard information (Petersen and Rajan 2002, Agarwal and Hauswald 2010). Also, we find that lending outside the usual range led to a breakdown of the default models. This result is similar to the finding of Rajan, Seru, and Vig (2015) in the context of the subprime crisis, that default models that were calibrated in one subset of the universe of borrowers and conditional on loan terms turned out to be obsolete in other parts of the universe of loans.

The paper proceeds as follows. In Section 2, we provide background information about the Bank’s approval process and specific details of the loan prospecting experiment. In Section 3, we describe the data that we use and discuss the quality of the identification. In Section 4, we describe the direct effects of loan prospecting on the Bank’s book of business: loan volume, loan amount, and loan performance. In Section 5, we explore several mechanisms that might potentially explain why loan volume and loan amount increased dramatically during the experiment. In Section 6, we explore the drivers of the poor loan performance and tie them to the origination process. Section 7 offers some concluding remarks.

## 2 The Loan Approval Process and the Loan Prospecting Experiment

### 2.1 The Loan Approval Process

To better understand the impact of loan prospecting on the loan approval process, one needs to understand the process of approval itself. The Bank’s branches offer retail services, and each branch has a small number of loan officers (typically one per branch). The loan application process begins when a client—typically a small business owner—inquires about a potential business loan. During our sample period, the Bank offered a standard product: a five-year amortizing adjustable rate mortgage. In most cases, the loan officer encourages the client to submit an application for review on which the applicant states the requested amount, the collateral offered (either business- or self-owned collateral),[1] and the purpose of the loan. The client also submits supporting information such as financial and tax information, and a list of assets owned.

The application is then processed by the loan officer, who relies on both hard and soft information. The loan officer verifies the information provided by the borrower and gathers additional data to assess the borrower's creditworthiness and probability of repayment (e.g., the borrower's and business's credit rating with an external credit agency, appraisal of the collateral). Then, the loan officer conducts an in-depth interview with the client to understand why he or she is applying for the loan as well as potential risks and prospects for the client's business. In some cases, the branch will invite the applicant to follow up on open questions, review discrepancies in credit report information, discuss the prospects of the business, and so forth. Based on this information, the loan officer determines an internal risk rating score, which summarizes his or her opinion of the potential borrower.[2] Given the internal risk rating score and additional information such as leverage and requested loan size, the computer system provides broad guidelines for the terms of the loan.

Each loan officer enjoys considerable autonomy in the assessment, approval, and pricing of loans but has to justify any deviation from bank-wide practices. The loan officer can also adjust the firm's internal score should the applicant deserve credit in the officer's opinion despite failing to meet certain credit score requirements. These subjective score revisions represent the soft information component of the Bank's internal credit assessment (see Agarwal and Hauswald 2011).

[1] Collateralized assets are typically accounts receivable (measured at their face value) or personal homes (measured using an automatic valuation model (AVM)). Loan officers have little control over these valuations. Agarwal, Ben-David, and Yao (2015) show that AVM produces less biased valuations than human appraisers do.

[2] The Bank's lending process resembles that described in Petersen (2004), Berger, Miller, Petersen, Rajan, and Stein (2005), and Agarwal and Hauswald (2010). There is a limited attempt at the Bank to code soft information, thereby transforming it into hard information.

Credit decisions are made by the local branches' credit committees, which are composed of the branch manager[3] and the loan officer(s).[4] They sketch the terms of the loan according to the Bank's lending guidelines and restrictions and can tailor those terms (including pricing) to the specific circumstances of the application (local overrides are closely monitored by the Bank's risk-management staff). Upon approval by the credit committee, the loan officer prepares an offer letter for the client with the details of the loan. Unlike residential loans, for which the lender approves or rejects the requested amount, commercial loans can be approved with an amount smaller or larger than that requested, subject to additional collateral.

Once an offer letter is received, the client may accept the loan, negotiate the terms, or withdraw the application. In 2004, 43% of loan applications made to the Bank were approved; the rest were rejected. Of the 43% approved loans, only 31% were originated, as 12% were withdrawn by applicants. All originated small business loans were kept on the Bank's balance sheet; none were sold or securitized. The whole lending process, including the credit decision, typically takes several weeks from the initial loan interview.

During the life of the loan, monitoring is done by the risk management department. On the anniversary of the loan's origination, the borrower meets with the loan officer to discuss the business's prospects and the potential need for additional financing.

## 2.2 The Loan Prospecting Pilot

In 2004, the management of the New England division of a large U.S. commercial bank,[5] motivated by competitive pressure from other lenders, decided to explore a set of incentives for small business loan officers to increase loan prospecting efforts (consistent with the "bonus culture" model of Bénabou and Tirole 2015). Other lenders in the area had initiated performance-based compensation, and the management thought that introducing such a payment

[3] The branch managers' career prospects and remuneration are not tied to the compensation of loan officers but rather depend on the success of their credit decisions.

[4] Liberti and Mian (2009) find that greater hierarchical distance between the loan officers to the credit committee leads to greater reliance on hard information. In the case of the pilot experiment explored here, there was no change in hierarchy during the pilot.

[5] During the sample period, this lender ranked among the top five commercial banks and savings institutions, according to the Federal Deposit Insurance Corporation. All loan applications fall under the definition of small- and medium-sized enterprise lending in the Basel I Accord so that the total obligation of the applying firm is less than $1 million and its sales are below $10 million.

structure would improve the profitability of the unit. The program altered the compensation scheme from a fixed salary to a commission-based system. Under the proposed program, loan officers would receive a lower fixed salary (80% of their original salary) and a bonus that increased with the originated volume and origination efficiency. The bonus was calculated every month. The Bank intended to implement the commission-based scheme for the entire portfolio of loan officers in stages to allow for evaluation of the effects of the new system. The pilot program was announced around June 2004.

The bonus system worked as follows. The loan officers were given a performance measurement system. The performance metric was based on three components: originated dollar amount (50% weight), number of loans (25% weight), and the application decision time (25% weight). Loan officers gained points on large loans, high origination volume, and quick decision turnaround. This three-pronged compensation structure forced the loan officer to generate loan volume efficiently and put more focus on larger loans.

In the first stage, beginning in January 2005, the new scheme was put into action in a subset of branches that administered their human resources through one of the Bank's legacy databases. The Bank had evolved through several mergers and acquisitions, the most recent of which took place in mid-2001. Since then the Bank still maintained two legacy computer systems that were used in administering human resources and compensation information. The incentive pilot, therefore, was implemented in one computer system (of the acquiring bank) and applied to all loan officers who were connected to that system, and the rest of the loan officers continued with their old compensation structure. Loan officers were not allowed to switch between the two systems. We call the group of branches that did not change their compensation structure Group A, and the group that experienced the compensation modification Group B.

The assignment of loan officers to each of the databases was quasi-random in the sense that it was unrelated to past performance or the prospects of loans or loan officers. Hence, the portfolio of loan applications received by the two groups of loan officers have identical underwriting standards, geographical focus, portfolio management practices, and loss outcomes prior to the modification of the compensation structure. We formally test this proposition in Section 3.1.

In such an experiment, there is a possibility that loan officers behave strategically. For example, they could approve bad loans so that management will retract the bonus-based compensation scheme. While this is a theoretical possibility, we doubt that our results stem from such behavior. First, treated loan officers were located in different branches across different localities, and therefore are not likely to have colluded. Second, during informal conversations with loan officers and management, loan officers seemed enthusiastic about the new bonus scheme because it moved them closer to the compensation scheme that was prevalent in many of the competing banks.

The complete implementation of the commission-based scheme was supposed to take place in 2006; however, the program was discontinued prematurely. The risk management division was monitoring this pilot on a monthly basis. At the beginning of 2006, the division advised the management that default rates were higher than expected and therefore recommended abolishing the incentive program. The Bank's management decided to roll back the compensation structure to a fixed salary for all loan officers, as in the pre-2005 period.

## 3 Data and Identification

Our dataset contains all of the loan applications submitted to the New England division of the Bank in 2004 and 2005. Loan officer–years that were compensated with a fixed salary are defined as the control group. This group includes loan officer–years with compensation that did not change between 2004 and 2005 (Group A), as well as loan officer–months in 2004 from the group whose pay was altered in 2005 (Group B). The treatment group consists of loan officer–years in Group B in 2005—that is, loan officer–years with pay in 2005 that was based on the volume originated. Unfortunately, we do not have access to loan applications made following the pilot in 2006.

### 3.1 Empirical Identification

In our empirical setting, the change in the scope of activities and compensation structure applied to only one group of loan officers, while the other group continued to operate as before and to be compensated at a fixed salary. The fact that the change occurred in one half of the population allows us to identify the effect of compensation using a differences-in-differences (diff-in-diff) approach. In this method, one uses time fixed effects to control for any temporal systematic shocks and loan officer fixed effects to control for loan officer average effects.[6] Then, the interaction between the treatment time (the 2005 dummy in our case) and the treatment group dummy (the group of loan officers who received incentive pay in 2005) captures the direct effect of the treatment (called the "loan prospecting" dummy in our analysis).

For the effect of the scope of activities to be properly identified based on the diff-in-diff method, we need to ensure that there are no confounding factors in the research design. In the current study, we are concerned with two issues. The first is the possibility that the assignment to treatment and control groups was not random. Perhaps the group that was assigned to the treatment was different in some ways relative to the untreated group. Our conversations with the team responsible for the program's implementation confirmed that the only active consideration in choosing the group to be treated was the ease with which the new scheme could be implemented in the computer system. Furthermore, we use the pre-experiment period (2004) to compare a host of variables related to both applications as well as credit decisions in the two groups. Our results show that there is no significant difference in any of the variables that we explore. The detailed analysis is described in Section 3.3.

Another concern is that the emphasis on prospecting is confounded with additional changes to the lending process. Specifically, the expansion in the scope of the loan officer role could be tied to a change in the underwriting model: for example, instead of the Bank holding the loans on its balance sheet, it may decide to start securitizing them. Such action might encourage loan officers to relax their underwriting standards (see Keys, Mukherjee, Seru, and Vig 2010). We discussed this possibility in-depth with the managers of the program and were assured that there were no additional structural changes in the lending process that occurred in parallel with the implementation of the pilot program. A different form of this concern relates to lending standards. It is possible that the Bank altered its lending standards for the treated group. We test this possibility in Table 4 (see Section 3.4). Our results show that the approval criteria remained unchanged.

[6] Given that we have loan officer fixed effects and that borrowers are typically from the county where the branch is located, we do not include additional geographical fixed effects.

To summarize, we conclude that the diff-in-diff identification strategy is appropriate for studying the effects of loan prospecting on the behavior of loan officers. Our identification is particularly strong because we control for loan officer fixed effects, meaning that the effects we identify are within–loan officer effects.

### 3.2 Summary Statistics

We begin our analysis by examining the summary statistics. Because of the large effects and the diff-in-diff research design, many of the effects reported in the paper can be observed directly through the summary statistics. We split the data into a two-by-two matrix: 2004 versus 2005 and Group A versus Group B. The treatment group consists of loan officers from Group B in 2005. The control group consists of loan officers from Group A in 2004 and 2005, as well as loan officers from Group B in 2004.

The summary statistics for loan applications and originated loans are presented separately. In Table 1, Panel A, we show summary statistics for loan applications (the variables featured in Table 1 and others are explained in Appendix A). Requested loan amounts are approximately $450,000. About 26% of the applicants propose using personal collateral (typically personal residence). Applicants are, on average, of high credit quality, with an average business Experian credit score of around 198 (out of a range of 100 to 250) and a personal Experian credit score around 728 (out of a range of 400 to 850). The average internal risk rating (determined by loan officers) is 5.9 (on a 1–10 range, with a 10 meaning very high risk).

The summary statistics in Table 1, Panels A and B, reveal sharp differences between the control and treatment groups in regard to approved and originated loans. First, the approval rate is 44%–51% for the control group but is 59% for the treatment group (Panel A). Second, the originated loan amount is 20% higher for the treatment group. Third, the leverage of the loans originated by treated loan officers (i.e., originated LTV) is significantly higher than that of those originated by the control group: 77% versus 75%. Fourth, even though the borrowers' average credit score is higher for the treated group, the default rate—measured as 90+ days past due within 12 months—is materially higher for the treatment groups (5.2 percentage points vs. 4.2 percentage points). In the following subsections, we investigate these patterns in a diff-in-diff setting.

Table 1, Panel C, presents summary statistics at the loan officer–month level for items in the regressions that use aggregate data (Table 2, Panel A, and Table 3, Panel A).

### 3.3 Validating the Diff-in-Diff Design

The assignment of loan officers to treatment and control in 2005 was based on their association with the legacy or new human resources system. To draw conclusions from the experiment, we need to verify that the assignment of loan officers was not associated with the quality of the applications pretreatment or with the decisions that loan officers made pretreatment.

We compare the characteristics of loan applications and originated loans of the control and treatment groups in 2004, prior to the initiation of the incentive program. Appendix B, Panel A, compares the control group and the to-be-treated group on several dimensions: the requested loan size, requested LTV, personal collateral indicator, Experian business credit score, Experian personal credit score, internal risk rating, time spent on applications, and withdrawal rate of approved applications. The panel shows that the conditional means of these variables are statistically indistinguishable between the two groups. Panel B of Appendix B displays the results of a similar test for the subset of originated loans, instead of applications, in 2004. The difference between requested and originated logged loan sizes as well as between requested and originated LTV, interest rate,[7] Experian business credit score, Experian personal credit score, and internal risk rating are similar across groups. We intentionally omit loan officer fixed effects from the regressions; when added, the variables of interest remain statistically insignificant.

Overall, these results show that there is no observable difference between the control and treatment groups in 2004; therefore, we feel confident attributing the effects in the treated group in 2005 to loan prospecting rather than to differences between the groups.

[7] All loans are adjustable-rate loans. This should not be a concern, because all regressions include month fixed effects.

## 4 Direct Effects of Loan Prospecting

We begin the analysis with a diagnosis of the first order effects of loan prospecting. In particular, we are interested in exploring the effects of the program on the flow of applications, approval rate, turnaround time, and default rate. These are all dimensions in which loan officers could have an effect given their expanded job description and pecuniary incentives. Also, these are the dimensions that the Bank's management is likely to use to measure the success of the program.

### 4.1 Approval Rate and Loan Size

The Bank's goal in proposing the loan prospecting pilot was to increase the originated volume and to compete more forcefully in the credit market. In this analysis, we examine the effects of the loan prospecting program on two aspects of volume: the number of loans and the average loan amount. In Table 2, Panel A, we compute the aggregate approved and originated loan volume (Columns (1)–(2) and (5)–(6), respectively) as well as the total number of approved and originated loans at the loan officer–month level (Columns (3)–(4) and (7)–(8), respectively). We regress these amounts on a loan prospecting dummy, in addition to loan officer and month fixed effects.

The regressions show a significant increase in loan volume and loan size. Following the loan prospecting treatment, the average dollar amount per loan of approved applications and originated loans increased by 14.9% and 14.5%, respectively (Columns (2) and (6)), and the number of approved and originated loans increased by a relative factor of 31.3% and 30.5%, respectively (Columns (4) and (8)). In fact, approved loan amounts in the treatment group are often larger than the amounts requested by applicants. Table 1, Panel B shows that in the treatment group, 17.4% of the approved amounts are larger than the amount originally requested, compared with about 3.5% in the control group.

### 4.2 Turnaround Time and Withdrawal Rate

The Bank was also interested in shortening the turnaround time as part as improving the quality of the service. To measure whether the program indeed improved the turnaround time, we measure the time from application to decision for two samples: all applications and approved applications. The dependent variable is the time from the application date to the decision date, measured in months (or month fractions). The variable of interest is an indicator for whether the application was submitted to a treated loan officer. The independent variables include the following controls: Experian business score, Experian personal score, logged requested loan amount, an indicator for whether personal collateral was used, the requested LTV, and the requested LTV squared.

The results of the analysis, presented in Table 2, Panel B, Columns (1) to (4) show that turnaround time indeed declined for the treated group in 2005. For all applications, the average turnaround time declined by about 9 days in the treated group (about 40 days in the control group, see Table 1, Panel A). The decline in turnaround time is similar for the group of approved applications.

We also explore the effect of loan prospecting on the rate of withdrawal of approved applications. In Table 2, Panel B, Columns (5) and (6) we use the sample of approved applications and regress a withdrawal indicator on the treatment indicator and the usual controls. The results show that withdrawal rate declines by 6.8% (Column (6)), relative to a rate of about 13% in the control (Table 1, Panel A). This effect is potentially due to combination of factors: a greater effort by loan officers to convince hesitating applicants to sign the dotted line, improvement in processing efficiency, and more aggressive loan terms (discussed later).

### 4.3 Loan Performance

From the Bank's perspective, the ex post quality of originated loans is an important factor in judging the success of the loan prospecting initiative. We measure loan performance as the default rate, defined as a delinquency of 90 days or more within one year of loan origination. The raw default rate in the control group is 4.2 percentage points in 2004–2005, and in the treated group in 2005, it is higher: 5.2 percentage points (Table 1, Panel B).

To test whether the univariate difference is statistically significant, we regress a default indicator on the loan prospecting dummy in addition to the loan officer, industry, and month fixed effects. The results in Table 2, Panel C, Columns (1) and (2) show that the default rate of the treated group is 1.2 percentage points higher (a 27.9% relative increase compared with the base default rate of 4.3% for the control group in 2005). In Columns (3) and (4), we also control for the interest rates charged to the loans. This control should capture the Bank's perceived ex ante risk. The coefficient on the loan prospecting dummy remains virtually unchanged with this additional control, suggesting that the increase in the default rate is not priced in the originated loans. Relative to the base default rate, the default rate is 27.9% higher for the treated group following the implementation of the loan prospecting program. The interest rates charged to loans do not appear to capture the increased default risk.

## 5 What Led to the High Approval Rate?

In the previous section, we documented that prospecting loan officers approved significantly more loans and that these loans defaulted significantly more often. The approval rate is about 8% higher in the treatment group (relative to a base rate of about 51% in the control group in 2005) (Table 1, Panel A). Figure 1 plots the residuals from a regression of an application approval dummy on controls and fixed effects for month, loan officers, and industry (see Appendix C). We estimate the regression model using the control groups in 2004 and 2005 only, and calculate the residuals for both the control and treatment groups for 2004 and 2005. The plot shows that the high approval rate in the treatment group is not explained by observed characteristics and that the dramatic increase happened immediately after the pilot began.

In this section, we explore three hypotheses to explain the high approval rate: 1) the quantity or quality of the application flow changed; 2) the lending criteria changed; or 3) the Bank altered the weight of hard information relative to soft information.

### 5.1 Application Flow

The objective of the pilot was to incentivize loan officers to seek new business; hence, it is plausible that they improved the quantity or quality of the application flow. Loan officers could have done this in several ways. For example, they could have convinced the Bank's customers to apply for loans. They could have attracted loan applicants from other banks, e.g., by raising the awareness to the Bank's products and the quality of service. Finally, they could have improved the quality of the application flow by discouraging weak potential applicants from submitting applications (to save time down the line) and by encouraging strong but hesitant potential applicants to apply.

We perform three tests that explore whether the loan prospecting experiment had an effect on the flow of applications. First, we test difference in the quantity of applications. In Table 3, Panel A, we analyze whether the application volume is statistically indistinguishable between the treatment and control groups. For each loan officer–month, we calculate the average requested loan amount across applications as well as count the number of applications. We regress the logged amount on an indicator of whether the loan officer is prospecting for loans. The results show that although there are positive coefficients for the average requested loan amount (an increase of up to 1.9%) and the number of applications (an increase of up to 0.7%), the effects are economically and statistically insignificant.

Second, we examine whether there are differences in the quality of the applications received. To do so, we regress loan characteristics (requested amount, requested LTV, personal collateral, credit scores, and internal risk rating) on the loan prospecting dummy. The results, presented in Table 3, Panel B, generally show no statistically significant difference in the quality of the applications between the two groups.

Finally, we test whether treated loan officers attracted applications that were more likely to be approved. To do so, we use pre-experiment (2004) data to estimate a model of loan approval as a function of application characteristics. Then, we predict the likelihood of approval for each application in 2005 and test whether the treated group has loans that are more likely to be approved. We present the results in Table 3, Panel C, which indicates no significant difference in the ex ante likelihood of approval in the treatment group.

Overall, the findings in Table 3 indicate that prospecting loan officers did not attract new applications to the Bank nor did they improve the quality of the applications received by the Bank.

### 5.2 Bank's Lending Standards

Another factor that may explain the change in lending patterns is the Bank's lending standards. While these standards were not supposed to change with the loan prospecting pilot, we still perform three tests to determine whether they remained consistent throughout the program.

In the first test, we explore whether the observable characteristics of approved applications are different across the two groups. The tests are presented in Table 4, Panel A. We test the difference between the groups in the Experian business score, the Experian personal score, the internal risk rating, and the interest rate. The results show that approved applications have statistically indistinguishable credit characteristics between the control and treatment groups.

In the second test, we investigate whether the ex ante credit quality for approved applications is the same in the treatment and control groups. We compute the ex ante credit quality as the likelihood of default based on a predictive regression of actual default on observable characteristics using 2004 data. In this regression, we predict default using the following characteristics: logged requested amount, a dummy for personal collateral, Experian business score, Experian personal score, requested LTV, and requested LTV squared. In addition, we control for loan officer and industry fixed effects. Next, we use the default predictions (based on the 2004 data) in the 2005 segment of the data and compare the predicted default probability of applications that were approved in the treatment and control groups in 2005. The results are presented in Table 4, Panel B. We regress the major decision outcomes of the bank on the predicted default probability. We first assess how the predicted default probability affects the likelihood of approval, interest rate, and loan size. In Column (1), we regress the approval indicator on the predicted default as well as an interaction with the treatment indicator. The results show that the likelihood of approval declines with the likelihood of default in both the control and treatment, and there is no statistically significant difference between the groups. This result, together with the findings in Panel A, demonstrates that the Bank did not relax the approval criteria following the introduction of the prospecting experiment. It did, however, relax the standards for loan size; in the treatment group, there is no longer a relation between credit quality and loan size. The bank potentially compensated for this through greater sensitivity of interest rates to loan quality.

In third test, we examine the lending terms for approved loans. In Columns (2) and (3) of Table 4, Panel B, we restrict the sample to applications that were approved. Column (2) substitutes the dependent variable with the logged loan size and shows that while loans in the control group with poor credit quality were smaller, credit quality did not determine loan size in the treatment group. Column (3) regresses interest rate on an interaction of the predicted default rate and the loan prospecting dummy. This regression shows that, as expected, interest rates increase with the predicted default probability and that the sensitivity of the treatment group is about double that of the control group. One way to interpret these results is that the Bank relaxed its lending standards with respect to loan amount but charged higher interest rates for riskier loans.

Overall, these results indicate that the lending standards of the Bank changed in a very specific way. The threshold of loan approval did not change. What did change was the aggressiveness of terms: loans are simply larger for the same borrower fundamentals.

### 5.3 Focusing on Hard Information and Ignoring Critical Soft Information

The third explanation to the direct effects in the Bank's lending patterns concerns the balance between hard and soft information. Banks typically use two types of information sources when evaluating loans: hard information and soft information. Given that the flow of applications did not change nor did the lending standards for application approval, it is possible that the dramatic increase in the approval rate can be explained by a change in the relative importance of hard information relative to soft information. It would not be surprising if the Bank had shifted the balance towards hard information, since this is one way that the Bank can fight the loan officers' moral hazard (e.g., manipulating the internal risk rating) (Heider and Inderst 2012).[8]

We test this hypothesis by studying the weight of hard versus soft information in the approval decisions of the treatment and control groups. In Table 5, we regress the approval

[8] This transformation is similar to what the market for residential mortgages experienced in the 2000s, as documented by Rajan, Seru, and Vig (2015). Investors in this market focused more and more over time on observable mortgage characteristics (in order to allow standardization and eliminate moral hazard). In turn, mortgage originators originated loans that fit the required observed characteristics but that potentially had poor unobserved characteristics.

indicator for all applications on interactions of loan prospecting and credit scores—both external and internal. Columns (1) and (2) present the base regressions, showing that the applications were about 8% more likely to be approved under the treatment. In Columns (3) to (6), we interact the loan prospecting dummy with both hard information measures (Experian business and personal scores) and a soft information measure (internal risk rating).

The results show that the weight on hard information (i.e., external credit scores) is higher for the treatment group. The coefficients in the regressions show that the weight of external information is nearly double for the treatment group relative to the control group. In contrast, the weight on soft information (internal risk rating) declines for the loan prospecting group (recall that the internal risk rating has high values for applications with poor credit quality). The weight of the internal risk ratings in the treatment group is 70% lower than that of the control group (–0.038/0.054). Given that the standard error on the internal risk rating is in the vicinity of 0.020, this weight of soft information in the treatment group is not statistically different from zero.

These results show that hard information became much more important in the approval decision. With the focus being primarily on hard information, many applications with favorable hard information features were approved, where before they had been rejected based on negative soft information.

## 6 What Led to the Poor Performance?

In this section, we investigate what led loans in the treatment groups to underperform relative to those in the control group. We focus on two related aspects of the loan origination process: loan amount and the informational content of loan characteristics.

### 6.1 Large Loan Amounts

Approved loans in the treatment group are significantly larger than those in the control group, in terms of both average loan amount (+14%, relative to the control) and the fraction of loans with approved amounts greater than those requested by borrowers (an increase from 3% to 17% of loans). Thus, it appears that loan officers took an active role in convincing borrowers to take loans larger than they originally planned. Figure 2 plots the average approved loan size over time. The chart shows that the average loan size increased around the beginning of 2005 in the treatment group and remained constant throughout the year, supporting the idea that the change in loan size is a direct effect of loan prospecting.

To test the importance of loan size for loan performance, we explore the relation between loan default and loan size. In Table 6, we use a sample of originated loans and regress the 12-month default dummy on measures of abnormal loan size and controls. Column (1) shows the base regression with the usual controls and fixed effects: loan officer, industry, and month. As seen before, the treatment group's default rate is 1.3 percentage points higher. In Column (2), the variable of interest is the interaction of the loan prospecting group and an indicator for whether the loan amount was larger than what the borrower originally requested. The regression shows loans with amounts greater than requested are more likely to default by 2.8 percentage points under the control (0.028 is coefficient on the main effect), and by 4.6 percentage points under the treatment (= 0.028 + 0.018).

We examine two additional measures of loan size. In Column (3), the variable of interest is an interaction of the treatment dummy with a variable that reflects abnormal loan size. This variable is a residual from a regression of logged loan amount on loan characteristics, which is based on a sample that includes only observations from the control group (see Appendix C). The regression in Column (3) shows that loans with high residuals, i.e., loan size is unusually high relative to the control group, are significantly more likely to default. The sensitivity of default to abnormal loan size is almost double that of the control sample.

In a similar fashion, we test the role of unusually high leverage. Again, we use a residual of LTV from a model based on characteristics in the control sample. In Column (4), we interact the treatment dummy with the residual from the LTV leverage. The regression shows that this variable is also important in explaining default. Here the sensitivity of the abnormal originated LTV is one-third larger in the treatment group than in the control group.

## 6.2 Breakdown of the Credit Model

We have shown that the change in the scope of the loan officers' job and incentives significantly affected the origination process and the composition of the loan portfolio. Throughout the process, the Bank did not change its approval criteria and credit model (see Section 5.2), but did allow significantly larger loan amounts. Thus, an important question is how the Bank's predictive credit model fared. In other words, could the increase in default be predicted by the Bank? A parallel could be drawn to the residential mortgage market during the early 2000s. There, old predictive credit models were applied to a new population (subprime borrowers) with more aggressive lending terms. Rajan, Seru, and Vig (2015) show that the predictive credit models that had been fitted to borrowers with prime credit lost their predictive power once they were applied to the subprime population.

The Bank's old credit model may have become obsolete due to a combination of two factors. First, as shown in Section 5.3, the Bank's approval process shifted the weight from soft information to hard information. The combination of both types of information may have previously formed a good screen for borrowers, whereas relying primarily on hard information may miss crucial details about applicants. Second, loan terms under the treatment group became significantly more aggressive. It is plausible that the sensitivity of performance to factors like loan amounts and leverage are not linear. Because the Bank was using a credit model that was fit on data with a certain range of amounts and leverages, it may not have been applicable to loans with more aggressive terms.

To test the proposition that the Bank's predictive model became defunct, we conduct two tests. In the first, presented in Table 7, Panel A, we regress a default dummy on an interaction of the treatment dummy and the different types of information (hard vs. soft) as well as controls and fixed effects. We find that loan default is explained well by both hard and soft information variables. In contrast, the sensitivity of loan default to hard information variables in the treatment group is significantly lower, bringing the overall effect of hard information on default to zero. The effect of soft information, proxied by the internal risk rating, is about double in the treatment group compared to the control group. Ironically, the Bank began putting significantly lower weight on this type of information (see Section 5.3). Overall, these results show that raw information variables have different sensitivity to default in the control and treatment groups.

The second test explores the relation between actual default and predicted default in the control and treatment groups. The purpose is to use a predicted default regression model, in an effort to emulate the credit default model that the Bank uses. As in Table 4, we use 2004 originated loans data to estimate a default model (using the following covariates: logged approved amount, personal collateral dummy, approved LTV, approved LTV squared, Experian business score, Experian personal score, and internal risk rating). Then, for each originated loan in 2005, we compute the predicted default likelihood.

The results are presented in Table 7, Panel B. Column (1) uses the control sample of originated loans in 2005. It regresses the actual default dummy on the predicted default variable as well as on the internal risk rating and interest rates. The analysis shows that all three variables explain actual default well, meaning that loans with ex ante low credit quality were more likely to default. In addition, loan officers' opinion about loans (as captured in the internal risk rating) and interest rates identified poor loan quality at origination.

We find the converse result for the loan prospecting group. In Column (2), we repeat the regression for the treatment sample but find no relation between actual default and predicted default. Furthermore, loan officers' opinions are unrelated to actual default. Finally, the sensitivity of actual default to interest rates is about half the magnitude of that in the control sample. Column (3) shows these effects in a combined sample of the control and treatment groups.

In a final analysis, we examine why the Bank's predictive model stopped working. In particular, we test whether it was effective on a subset of loans with terms that are not normative within the treatment group. In other words, we observed before that many loans in the treatment group received terms that were aggressive relative to the Bank's standard origination criteria. Since these loans are outside the historical normal range of underwriting for the Bank, it is likely that the predictive model underperformed for loans with non-normative terms.

In Table 7, Panel C, we repeat the regressions of actual default on the predicted default probability. We split the data in two ways, both of which attempt to approximate the aggressiveness of loan terms. The first split is by whether loan officers approved loans larger than the amounts requested by applicants.[9] Column (1) shows the subset of loans equal to or below the original requested amount. The regression indicates that the interaction between the loan prospecting dummy and the predicted default likelihood is statistically indistinguishable from zero. In contrast, for the subset of aggressive loans (Column (2); loan amount is greater than requested), the interaction is negative and statistically significant. The magnitude of the coefficient is as large as that in the main effect, suggesting that default is not predictable for this subset of loans based on the history of loans that the Bank made in 2004.

In the second test, we split the sample by abnormal loan amount. We estimate which loans have abnormal loan amounts by regressing the logged loan amount on observable fundamentals (using 2004 data). We use the residual as a measure of abnormal loan size. Then, we categorize the 2005 originated loans as either less aggressive (Column (3); residual is smaller than one standard deviation) or more aggressive (Column (4); residual is greater than one standard deviation). Again, we repeat the regression specification from Panel B. The results in Column (3) show that the coefficient on the interaction of the loan prospecting indicator and the predicted default likelihood is indistinguishable from zero, meaning that the default of loans with less aggressive terms is predictable using 2004 data. Conversely, the interaction in Column (4) is negative and statistically significant, indicating that the performance of loans with aggressive amounts cannot be predicted using 2004 performance data.

Overall, our results show that the Bank's original credit model was fragile. Furthermore, it appears that the loans whose performance is the least predictable are those whose amounts are outside the normative range of the Bank. Thus, changes in the approval process caused the credit model to lose its predictive power.

## 7 Conclusion

In this paper, we present evidence that when a large commercial U.S. bank expanded the role of the loan officer from traditional loan screening to include a loan prospecting component, it resulted in dramatic changes to the origination process. In the corporate pilot program that we study, the Bank provided incentives to loan officers to bring new business to the Bank ("loan

[9] As reported earlier, in the treatment sample, the fraction of originated loans with amounts greater than requested is 17%, relative to a mere 3% in the control sample.

prospecting”). The approval standards were not altered, yet granted loan amounts rose. At a first glance, it appears that the pilot had some success: the Bank expanded its book of business: a greater number of approved loans at larger amounts. A caveat is this apparent success was the high default rate.

Our analysis shows that the move to loan prospecting led to several dramatic changes in the loan origination process. Loan officers did not bring new business to the Bank; instead, they offered more aggressive loan terms to borrowers. The Bank, presumably in an attempt to reduce the opportunity for moral hazard, relied more on hard information and discounted soft information (loan officers’ input). Both of these policy shifts led to material changes in the composition of borrower and loan characteristics. We show that due to these changes the Bank’s credit model broke down and lost its predictive power.

The study stresses the importance of unintended consequences of changing business models. The management’s effort to refocus loan officers to generate new business and compete better in the marketplace resulted in the dramatic loss of critical soft information, larger loans, and poor credit quality. In other words, the incentives to loan officers created a chain reaction that eventually led to a riskier loan portfolio.

## References


Acharya, Viral V., Thomas Cooley, Matthew Richardson, and Ingo Walter, 2010, Manufacturing Tail Risk: A Perspective on the Financial Crisis of 2007-2009, *Foundations and Trends* 4(4), 247-325.

Acharya, Viral V., Lubomir V. Litov, and Simone M. Sepe, 2013, Non-Executive Incentives and Bank Risk-Taking, Working Paper, New-York University.

Agarwal, Sumit, Itzhak Ben-David, and Vincent Yao, 2015, Collateral Valuation and Institutional Pressures: Evidence from the Residential Real-Estate Market, *Management Science*, forthcoming.

Agarwal, Sumit, and Robert Hauswald, 2010, Distance and Private Information in Lending, *Review of Financial Studies* 23(7), 2757-2788.

Agarwal, Sumit, and Robert Hauswald, 2011, Authority and Information, Working Paper, Chicago Federal Reserve Bank.

Bebchuck, Lucian A., and Holger Spamann, 2009, Regulating Bankers' Pay, *Georgetown Law Journal* 98(2), 247-287.

Bénabou, Roland, and Jean Tirole, 2015, Bonus Culture: Competitive Pay, Screening, and Multitasking, *Journal of Political Economy*, forthcoming.

Berger, Allen N., and Gregory F. Udell, 2002, Small Business Credit Availability and Relationship Lending: The Importance of Bank Organizational Structure, *Economic Journal* 112, 32-53.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein, 2005, Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks, *Journal of Financial Economics* 76, 237-269.

Bureau of Labor Statistics, 2012, Loan Officers, in *Occupational Outlook Handbook*, 2012-13 Edition, U.S. Department of Labor, http://www.bls.gov/ooh/Business-and-Financial/Loan-officers.htm.

Cole, Shawn, Martin Kanz, and Leora Klapper, 2015, Incentivizing Calculated Risk Taking: Evidence from an Experiment with Commercial Bank Loan Officers, *Journal of Finance* 70(2), 537-575.

Heider, Florian, and Roman Inderst, 2012, Loan Prospecting, *Review of Financial Studies* 25(8), 2381-2415.

Holmström, Bengt, and Paul Milgrom, 1991, Multitask Principal Agent Analyses: Incentive Contracts, Asset Ownership and Job Design, *Journal of Law, Economics, and Organizations* 7 (Special issue), 24-52.

Inderst, Roman, 2008, Loan Origination under Soft- and Hard-Information Lending, Working Paper, University of Frankfurt.

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig, 2010, Did Securitization Lead to Lax Screening? Evidence from Subprime Loans, *Quarterly Journal of Economics* 125(1), 307-362.

Liberti, Jose M., and Atif Mian, 2009, Estimating the Impact of Hierarchies on Information Use, *Review of Financial Studies* 22(10), 4057-4090.

Petersen, Mitchell A., 2004, Information: Hard and Soft, Working Paper, Northwestern University.

Petersen, Mitchell A., and Raghuram G. Rajan, 2002, Does Distance Still Matter? The Information Revolution in Small Business Lending, *Journal of Finance* 57(6), 2533-2570.

Rajan, Uday, Amit Seru, and Vikrant Vig, 2015, The Failure of Models that Predict Failure: Distance, Incentives and Defaults, *Journal of Financial Economics* 115(2), 237-260.

Sufi, Amir, 2007, Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans, *Journal of Finance* 62(2), 629-668.

Tzioumis, Konstantinos, and Matthew Gee, 2013, Nonlinear Incentives and Mortgage Officers' Decisions, *Journal of Financial Economics* 107(2), 436-453.

Udell, Gregory F., 1989, Loan Quality, Commercial Loan Review and Loan Officer Contracting, *Journal of Banking and Finance* 13(3), 367-382.

## Appendix A. Variable Definitions

| Variable | Description |
|---|---|
| *Requested amount* | The dollar amount requested by the loan applicant. |
| *Originated amount* | The dollar amount that was originated by the Bank. |
| *Personal collateral* | An indicator variable as to whether the loan applicant proposes to collateralize a personal asset (=1) or a business asset (=0). |
| *Loan-to-value (LTV)* | The loan amount divided by the value of the collateral. |
| *Experian business score* | Applicant's Experian business credit score. Scores range from 100 to 250. A higher score means higher credit quality. |
| *Experian personal score* | Applicant's Experian personal credit score. Scores range from 400 to 850. A higher score means higher credit quality. |
| *Time spent* | Time interval between application submission and decision. Measured in months. |
| *Internal risk rating* | Applicant's risk rating as computed by the loan officer. Scores range from 1 to 10. Unlike Experian scores, a low internal risk rating reflects higher credit quality. |
| *Withdrawn* | An indicator of whether a loan application was withdrawn before or after a decision was made by the Bank. |
| *Commission-based compensation* | An indicator of whether 1) the loan application was handled by a loan officer who is part of Group B (treated with commission-based compensation in 2005) and 2) the year of the loan application is 2005. |
| *Interest rate* | The interest rate paid on the loan. |
| *Default within 12 months* | An indicator of whether the loan became delinquent (90 days or more past due) within 12 months of origination. |
| *Loan originated* | An indicator of whether a loan application was originated by the Bank. |
| *Residual from loan originating regression* | Residual from a regression of the loan originated variable on loan characteristics (see Appendix C). |
| *Residual from internal risk rating regression* | Residual from a regression of the internal risk rating variable on loan characteristics (see Appendix C). |
| *Residual from LTV regression* | Residual from a regression of the LTV variable on loan characteristics (see Appendix C). |
| *Residual from log(Originated amount) regression* | Residual from a regression of the log(originated amount) variable on loan characteristics (see Appendix C). |

## Appendix B. Comparing Groups A and B in 2004

The table compares the characteristics of applications and originated loans of Groups A and B in 2004. Panel A tests whether loan applications received by Group A (control) and Group B (to be treated in 2005) are different in the pretreatment period (2004). Panel B tests does the same for originated loans. All regressions are ordinary least squares (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

## Panel A: Loan Applications in Groups A and B in 2004

| Dependent variable: | log(Req'd amount) | Personal collateral | Requested LTV | Experian business score | Experian personal score | Internal risk rating | Time spent | Application withdrawn | Loan officer salary ($k) |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Group B (to be treated in 2005) (0/1) | -0.035 | -0.041 | 0.001 | -3.169 | -4.176 | 0.004 | 0.001 | 0.003 | 0.343 |
| | (0.050) | (0.125) | (0.014) | (3.298) | (5.623) | (0.007) | (0.048) | (0.009) | (0.579) |
| log(Requested amount) | | | 0.036*** | -0.013 | -0.006 | 0.004 | 0.007 | 0.135 | 0.773 |
| | | | (0.011) | (0.010) | (0.014) | (0.018) | (0.026) | (0.057) | (0.818) |
| Personal collateral (0/1) | 0.046 | 0.022 | -0.027 | 0.033 | 0.021 | -0.007 | -0.009 | 0.030* | 0.260 |
| | (0.046) | (0.075) | (0.026) | (0.022) | (0.028) | (0.041) | (0.055) | (0.015) | (0.176) |
| Requested LTV | | | 0.018*** | 0.037 | 0.001** | 0.002 | 0.002 | 0.070*** | 0.028 |
| | | | (0.006) | (0.037) | (0.000) | (0.008) | (0.010) | (0.019) | (0.021) |
| Requested $LTV^2$ | | | 0.038*** | -0.043** | -0.004*** | 0.004 | 0.005 | 0.0407* | 0.008 |
| | | | (0.005) | (0.021) | (0.001) | (0.038) | (0.055) | (0.021) | (0.007) |
| Experian business score | 0.028*** | 0.047*** | -0.064*** | | 0.030*** | -0.007*** | -0.005 | -0.141*** | 0.265 |
| | (0.008) | (0.008) | (0.015) | | (0.008) | (0.003) | (0.003) | (0.050) | (0.420) |
| Experian personal score | 0.0368 | 0.057*** | -0.020 | 0.029* | | -0.035*** | -0.045*** | -0.091* | 0.182 |
| | (0.058) | (0.018) | (0.034) | (0.017) | | (0.004) | (0.004) | (0.048) | (0.136) |
| Loan officer fixed effects | No | No | No | No | No | No | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,916 | 14,916 | 14,916 | 14,916 | 14,916 | 14,916 | 14,916 | 14,916 | 14,916 |
| Adj. $R^2$ | 0.05 | 0.07 | 0.19 | 0.11 | 0.10 | 0.73 | 0.20 | 0.07 | 0.06 |

## Appendix B. Comparing Groups A and B in 2004 (Cont.)

## Panel B: Originated Loans in Groups A and B in 2004

| Dependent variable: | log(Originated amount) -log(Requested amount) | Personal collateral | Originated LTV -Requested LTV (%) | Interest rate | Experian business score | Experian personal score | Internal risk rating |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Group B (to be treated in 2005) (0/1) | -0.020 | 0.325 | -0.038 | 0.001 | 1.070 | 1.586 | 0.003 |
| | (0.050) | (0.568) | (0.061) | (0.016) | (2.204) | (2.431) | (0.009) |
| log(Requested amount) | | 0.481 | | 0.034*** | -0.010 | -0.006 | 0.003 |
| | | (0.439) | | (0.010) | (0.009) | (0.012) | (0.015) |
| Personal collateral | 0.053 | | 0.042 | -0.023 | 0.032 | 0.018 | -0.006 |
| | (0.045) | | (0.065) | (0.021) | (0.021) | (0.019) | (0.037) |
| Requested LTV | | 0.024 | | 0.016*** | 0.033 | 0.001** | 0.002 |
| | | (0.021) | | (0.005) | (0.035) | (0.000) | (0.007) |
| Requested $LTV^2$ | | 0.006 | | 0.037*** | -0.035*** | -0.004*** | 0.004 |
| | | (0.004) | | (0.005) | (0.022) | (0.001) | (0.032) |
| Experian business score | 0.024*** | 0.198 | 0.034*** | -0.055*** | | 0.024*** | -0.006*** |
| | (0.008) | (0.242) | (0.008) | (0.012) | | (0.007) | (0.002) |
| Experian personal score | 0.041 | 0.167* | 0.037*** | -0.018 | 0.022* | | -0.032*** |
| | (0.087) | (0.089) | (0.007) | (0.029) | (0.013) | | (0.004) |
| Loan officer fixed effects | No | No | No | No | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,740 | 4,740 | 4,740 | 4,740 | 4,740 | 4,740 | 4,740 |
| Adj. $R^2$ | 0.07 | 0.05 | 0.11 | 0.21 | 0.12 | 0.10 | 0.69 |

## Appendix C. Calculating Residuals

The table presents analysis used to calculate abnormal application approval, as well as abnormal leverage and loan amount. The sample contains only applications (Column (1)) and originated loans (Columns (2) and (3)) from the control group: Group A in 2004 and 2005, and Group B in 2004. All regressions are ordinary least squares (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| Sample: | Applications (Control only) | Approved loans (Control only) | |
|---|---|---|---|
| Dependent variable: | Loan approved (0/1) | LTV | log(Loan amount) |
| | (1) | (2) | (3) |
| log(Requested amount) | -0.3007** | 0.0256 | -0.0164 |
| | (0.0700) | (0.0224) | (0.0122) |
| Personal collateral (0/1) | 0.0215*** | -0.0395*** | 0.0818** |
| | (0.0077) | (0.0070) | (0.0344) |
| Experian business score | -0.1397*** | -0.0063*** | 0.0032*** |
| | (0.0481) | (0.0004) | (0.0008) |
| Experian personal score | -0.1295*** | -0.0052*** | 0.0093*** |
| | (0.0391) | (0.0012) | (0.0003) |
| LTV (Requested) | 0.0471*** | -0.6075*** | -0.8142*** |
| | (0.0139) | (0.0838) | (0.2224) |
| $LTV^2$ (Requested) | -0.0796*** | -0.7031*** | 0.6948*** |
| | (0.0162) | (0.0774) | (0.1485) |
| Loan officer fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes |
| Observations | 22,480 | 10,470 | 10,470 |
| Adj. $R^2$ | 0.17 | 0.14 | 0.10 |

## Table 1. Summary Statistics

The table presents summary statistics for the data used in the study. Panel A presents summary statistics for loan applications. Panel B presents summary statistics for the originated loans. Panel C presents summary statistics for data aggregated at the loan officer–month level. Variables are defined in Appendix A.

### Panel A: Loan Applications

| | 2004 | | | | 2005 | | | |
|---|---|---|---|---|---|---|---|---|
| | Group A (Control) | | Group B (Control) | | Group A (Control) | | Group B (Treatment) | |
| | Mean | St Dev | Mean | St Dev | Mean | St Dev | Mean | St Dev |
| # Applications | 6,920 | | 7,996 | | 7,564 | | 7,788 | |
| Requested amount ($) | 455,240 | 336,805 | 426,480 | 378,698 | 454,141 | 369,635 | 444,137 | 381,829 |
| Personal collateral (0/1) | 0.255 | 0.436 | 0.261 | 0.439 | 0.280 | 0.449 | 0.239 | 0.427 |
| Requested LTV (%) | 61.283 | 43.001 | 65.301 | 44.029 | 65.161 | 46.873 | 63.049 | 43.483 |
| Experian business score (100-250) | 200.863 | 72.228 | 195.884 | 75.868 | 195.988 | 75.273 | 200.359 | 68.471 |
| Experian personal score (400-850) | 731.847 | 70.305 | 725.405 | 68.063 | 725.908 | 74.394 | 728.057 | 76.723 |
| Internal risk rating (1-10) | 5.819 | 1.734 | 5.813 | 1.537 | 5.940 | 1.313 | 5.958 | 1.470 |
| Time spent (months) | 1.380 | 0.850 | 1.350 | 0.700 | 1.320 | 0.750 | 1.060 | 0.530 |
| Application approved (0/1) | 0.449 | 0.497 | 0.436 | 0.496 | 0.512 | 0.500 | 0.592 | 0.491 |
| Withdrawn after being approved (0/1) | 0.132 | 0.338 | 0.118 | 0.322 | 0.150 | 0.357 | 0.119 | 0.324 |

### Panel B: Originated Loans

| | 2004 | | | | 2005 | | | |
|---|---|---|---|---|---|---|---|---|
| | Group A (Control) | | Group B (Control) | | Group A (Control) | | Group B (Treatment) | |
| | Mean | St Dev | Mean | St Dev | Mean | St Dev | Mean | St Dev |
| # Originated loans | 2,192 | | 2,548 | | 2,744 | | 3,680 | |
| Loan originated (0/1) | 0.306 | 0.461 | 0.322 | 0.467 | 0.357 | 0.499 | 0.466 | 0.476 |
| Requested amount ($) | 302,074 | 305,891 | 302,966 | 301,933 | 303,082 | 306,939 | 302,224 | 317,073 |
| Originated amount ($) | 224,614 | 279,361 | 216,048 | 229,403 | 253,219 | 257,801 | 301,004 | 299,013 |
| I(Amount approved > Amount requested) | 0.035 | 0.025 | 0.032 | 0.028 | 0.032 | 0.027 | 0.174 | 0.073 |
| Personal collateral (originated) (0/1) | 0.270 | 0.409 | 0.280 | 0.403 | 0.300 | 0.420 | 0.250 | 0.404 |
| Requested LTV (%) | 79.060 | 20.930 | 78.440 | 19.280 | 79.030 | 17.040 | 78.520 | 18.400 |
| Originated LTV (%) | 72.986 | 31.477 | 76.237 | 30.899 | 74.901 | 33.105 | 77.033 | 26.049 |
| Experian business score (100-250) | 184.870 | 68.946 | 186.115 | 78.924 | 185.500 | 93.091 | 196.095 | 87.015 |
| Experian personal score (400-850) | 716.692 | 87.439 | 718.897 | 88.580 | 719.537 | 98.245 | 725.765 | 66.510 |
| Time spent (months) | 1.270 | 0.880 | 1.282 | 0.858 | 1.275 | 0.799 | 1.020 | 0.540 |
| Internal risk rating (1-10) | 5.230 | 1.840 | 5.380 | 1.520 | 5.440 | 1.300 | 4.930 | 1.530 |
| Interest rate (%) | 9.910 | 5.020 | 9.850 | 4.890 | 9.580 | 4.880 | 9.650 | 4.930 |
| # Defaults | 91 | | 107 | | 119 | | 192 | |
| Defaulted within 12 months (0/1) | 0.042 | 0.199 | 0.042 | 0.201 | 0.043 | 0.204 | 0.052 | 0.222 |
| log(Originated amount)-log(Requested amount) | -0.129 | -0.039 | -0.146 | -0.117 | -0.077 | -0.075 | 0.014 | 0.104 |
| Originated LTV-Requested LTV | -0.060 | 0.104 | -0.022 | 0.116 | -0.041 | 0.158 | 0.007 | 0.080 |
| Residual from leverage regression | 0.003 | 0.034 | 0.003 | 0.033 | 0.004 | 0.032 | 0.007 | 0.032 |
| Residual from loan size regression | 0.004 | 0.038 | 0.003 | 0.040 | 0.004 | 0.042 | 0.071 | 0.039 |

## Table 1. Summary Statistics (Cont.)

## Panel C: Loan Officer-Month Data

| | 2004 | | | | 2005 | | | |
|---|---|---|---|---|---|---|---|---|
| | Group A (Control) | | Group B (Control) | | Group A (Control) | | Group B (Treatment) | |
| | Mean | St Dev | Mean | St Dev | Mean | St Dev | Mean | St Dev |
| N(loan officer-month) = 3,192 | | | | | | | | |
| # Loan officers | 68 | | 65 | | 65 | | 65 | |
| log(Application avg amount ($k)) | 5.582 | 5.336 | 5.382 | 5.352 | 5.587 | 5.349 | 5.399 | 5.534 |
| log(Approved avg amount ($k)) | 5.293 | 5.562 | 5.296 | 5.485 | 5.290 | 5.433 | 5.525 | 5.661 |
| log(Originated avg amount ($k)) | 5.281 | 5.394 | 5.299 | 5.307 | 5.294 | 5.374 | 5.551 | 5.446 |
| log(# Applications) | 3.794 | 1.885 | 3.795 | 1.884 | 3.799 | 1.865 | 3.812 | 1.842 |
| log(# Approved loans) | 3.378 | 1.858 | 3.399 | 1.878 | 3.381 | 1.840 | 3.705 | 1.819 |
| log(# Originated loans) | 3.373 | 1.861 | 3.396 | 1.861 | 3.391 | 1.834 | 3.816 | 1.840 |

## Table 2. Direct Effects of Loan Prospecting

The table presents an analysis of the effects of loan prospecting: loan approval and origination rates, and average loan size (Panel A), turnaround time and withdrawal rate (Panel B), and default rate (Panel C). All regressions are ordinary least squares (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the month level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### Panel A: Approval and Origination Rates and Average Loan Size

| Sample: | Approved applications (loan officer-month) | | | | Originated loans (loan officer-month) | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: | log(Avg amount ($)) | | log(#Approved loans) | | log(Avg amount ($)) | | log(#Originated loans) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Loan prospecting (0/1) | 0.147*** | 0.149*** | 0.282*** | 0.313*** | 0.144*** | 0.145*** | 0.276*** | 0.305*** |
| | (0.048) | (0.040) | (0.058) | (0.051) | (0.046) | (0.043) | (0.046) | (0.038) |
| Loan officer fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 3,192 | 3,192 | 3,192 | 3,192 | 3,192 | 3,192 | 3,192 | 3,192 |
| Adj. $R^2$ | 0.13 | 0.15 | 0.15 | 0.17 | 0.16 | 0.17 | 0.19 | 0.20 |

### Panel B: Turnaround Time and Withdrawal Rate

| Dependent variable: | #Months between application and decision | | | | I(Application withdrawn) | |
|---|---|---|---|---|---|---|
| Sample: | All applications | | All approved loans | | All approved loans | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Loan prospecting (0/1) | -0.104* | -0.100** | -0.157** | 0.166*** | -0.057** | -0.068** |
| | (0.056) | (0.050) | (0.062) | (0.064) | (0.028) | (0.031) |
| Experian business score | -0.048*** | -0.042*** | -0.051*** | -0.049*** | 0.048*** | 0.039** |
| | (0.017) | (0.016) | (0.019) | (0.017) | (0.016) | (0.016) |
| Experian personal score | -0.042*** | -0.037** | -0.046*** | -0.043*** | 0.039*** | 0.028** |
| | (0.014) | (0.014) | (0.016) | (0.014) | (0.011) | (0.014) |
| log(Requested amount) | 0.019*** | 0.017*** | 0.021*** | 0.020*** | -0.017*** | -0.020*** |
| | (0.007) | (0.006) | (0.007) | (0.007) | (0.005) | (0.004) |
| Personal collateral (0/1) | -0.032 | -0.030 | -0.038 | -0.034 | 0.031 | 0.025 |
| | (0.063) | (0.060) | (0.066) | (0.065) | (0.062) | (0.057) |
| Requested LTV | 0.016*** | 0.016*** | 0.019*** | 0.017*** | -0.014*** | -0.014*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) |
| Requested $LTV^2$ | 0.068*** | 0.068*** | 0.079*** | 0.070*** | -0.062*** | -0.042*** |
| | (0.016) | (0.014) | (0.016) | (0.016) | (0.013) | (0.014) |
| Loan officer fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | No | Yes | No | Yes | No | Yes |
| Observations | 30,268 | 30,268 | 14,359 | 14,359 | 14,359 | 14,359 |
| Adj. $R^2$ | 0.18 | 0.19 | 0.21 | 0.22 | 0.07 | 0.09 |

## Table 2. Analysis of the Effects of Prospecting on Approved and Originated Volume (Cont.)

### Panel C: Default Rate

| Sample: | All originated loans | | | |
|---|---|---|---|---|
| Dependent variable: | Defaulted within 12 months (0/1) | | | |
| | (1) | (2) | (3) | (4) |
| Loan prospecting (0/1) | 0.012*** | 0.012*** | 0.012*** | 0.011*** |
| | (0.003) | (0.003) | (0.004) | (0.003) |
| Interest rate (%) | | | 0.039*** | 0.035** |
| | | | (0.014) | (0.014) |
| Loan officer fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | No | Yes | No | Yes |
| Month fixed effects | No | Yes | No | Yes |
| Observations | 11,164 | 11,164 | 11,164 | 11,164 |
| Adj. $R^2$ | 0.21 | 0.21 | 0.23 | 0.23 |

## Table 3. Volume and Quality of Applications

The table presents an analysis of the loan application volume and characteristics. Panel A uses a sample at the loan officer–month level and explores whether the dollar volume and the number of applications are different for applications made to loan officers who receive commission-based compensation. Panel B tests whether the characteristics of loan applications are different for applications made to loan officers who engage in loan prospecting. Panel C tests whether loan applications received by the loan prospecting group were more likely to be approved based on characteristics. All regressions are ordinary least squares (OLS) regressions. Variables are defined in Appendix A. In Panel A, standard errors are clustered at the month level. In Panels B and C, standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### Panel A: Loan Application Volume in Treated and Control Groups

| Dependent variable: | All applications (loan officer-month) | | | |
|---|---|---|---|---|
| Denoted in: | log(Avg requested amount ($)) | | log(# Applications) | |
| | (1) | (2) | (3) | (4) |
| Loan prospecting (0/1) | 0.019 | 0.013 | 0.001 | 0.007 |
| | (0.029) | (0.030) | (0.013) | (0.025) |
| Loan officer fixed effects | No | No | No | No |
| Month fixed effects | No | Yes | No | Yes |
| Observations | 3,192 | 3,192 | 3,192 | 3,192 |
| Adj. $R^2$ | 0.07 | 0.13 | 0.06 | 0.08 |

### Panel B: Characteristics of Loan Applications

| Dependent variable: | log(Requested amount) | Requested LTV | Personal collateral | Experian business score | Experian personal score | Internal risk rating |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Loan prospecting (0/1) | 0.016 | 0.026 | 0.014 | 7.146 | 3.976 | 0.043 |
| | (0.064) | (0.183) | (0.056) | (5.871) | (5.068) | (0.138) |
| Loan officer fixed effects | No | No | No | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 30,268 | 30,268 | 30,268 | 30,268 | 30,268 | 30,268 |
| Adj. $R^2$ | 0.07 | 0.06 | 0.09 | 0.06 | 0.05 | 0.07 |

**Table 3. Volume and Quality of Applications (Cont.)**

**Panel C: Are Loan Applications in the Treated Group More Likely to Be Approved?**

| Sample: | 2005 Applications | | | |
|---|---|---|---|---|
| Dependent variable: | Application ex ante probability of apporval | | | |
| | (1) | (2) | (3) | (4) |
| Loan prospecting (0/1) | 0.008 | -0.007 | 0.004 | 0.001 |
| | (0.018) | (0.019) | (0.019) | (0.019) |
| Experian business score | | | 0.071*** | 0.076*** |
| | | | (0.019) | (0.020) |
| Experian personal score | | | 0.063*** | 0.094*** |
| | | | (0.016) | (0.016) |
| Internal risk rating | | | -0.103** | -0.084** |
| | | | (0.026) | (0.025) |
| log(Requested amount) | | | -0.049*** | -0.030*** |
| | | | (0.008) | (0.008) |
| Personal collateral (0/1) | | | 0.070 | 0.050 |
| | | | (0.086) | (0.087) |
| Requested LTV | | | -0.026*** | -0.028*** |
| | | | (0.003) | (0.004) |
| Requested LTV$^2$ | | | -0.120*** | -0.117*** |
| | | | (0.019) | (0.018) |
| Loan officer fixed effects | No | Yes | No | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes |
| Observations | 15,352 | 15,352 | 15,352 | 15,352 |
| Adj. $R^2$ | 0.14 | 0.17 | 0.15 | 0.17 |

## Table 4. Did Lending Standards Change?

The table presents regressions testing whether the lending standards of the Bank changed together with the change in the scope of loan officer activities. Panel A tests whether there is a significant difference in the credit quality of loans that were approved in the treatment and in the control groups. Panel B tests whether there is a difference in the expected default likelihood of loans that were approved by the treatment and control groups. Panel A uses only 2005 data, as the calculation of expected default uses 2004 data. All regressions are ordinary least squares (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### Panel A: Characteristics of Approved Applications in the Treatment and Control Groups

| Sample: | All approved applications | | | |
|---|---|---|---|---|
| Dependent variable: | Experian business score | Experian personal score | Internal risk rating | Interest rate |
| | (1) | (2) | (3) | (4) |
| Loan prospecting (0/1) | 5.333 | 3.129 | 0.045 | 0.007 |
| | (5.880) | (5.286) | (0.139) | (0.047) |
| log(Approved amount) | 0.041** | 0.045** | 0.041*** | 0.049*** |
| | (0.016) | (0.020) | (0.016) | (0.019) |
| Personal collateral (0/1) | 0.018*** | 0.020*** | 0.014*** | 0.022*** |
| | (0.006) | (0.006) | (0.005) | (0.007) |
| Approved LTV | 0.037*** | 0.040*** | 0.029** | 0.041** |
| | (0.012) | (0.015) | (0.012) | (0.016) |
| Approved $LTV^2$ | 0.007*** | 0.008*** | 0.006*** | 0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Loan officer fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,359 | 14,359 | 14,359 | 14,359 |
| Adj. $R^2$ | 0.36 | 0.28 | 0.27 | 0.18 |

**Table 4. Did Lending Standards Change? (Cont.)**

**Panel B: Predicted Default Probability in the Treatment and Control Groups in 2005**

| Sample: | All 2005 applications | All 2005 approved loans | |
|---|---|---|---|
| Dependent variable: | Application approved (0/1) | log(Loan amount) | Interest rate |
| | (1) | (2) | (3) |
| Predicted default likelihood | -0.024** | -0.027** | 0.047** |
| | (0.011) | (0.011) | (0.022) |
| × Loan prospecting (0/1) | 0.003 | 0.056** | 0.054** |
| | (0.009) | (0.025) | (0.025) |
| Loan prospecting (0/1) | 0.027** | 0.017 | 0.037* |
| | (0.012) | (0.013) | (0.023) |
| Loan officer fixed effects | No | No | No |
| Industry fixed effects | Yes | Yes | Yes |
| Month fixed effects | No | No | No |
| Observations | 15,352 | 8,485 | 8,485 |
| Adj. $R^2$ | 0.21 | 0.07 | 0.14 |

## Table 5. Focusing on Hard Information

The table presents an analysis of the effects of commission-based compensation on the characteristics of approved loans. The table uses a sample of all applications. All regressions are ordinary least square (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| Sample: | All applications | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: | Application approved (0/1) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Loan prospecting (0/1) | 0.007*** | 0.009*** | 0.005** | 0.004** | 0.032*** | 0.004** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) |
| × Experian business score | | | 0.019*** | 0.016*** | 0.015*** | 0.014* |
| | | | (0.003) | (0.001) | (0.006) | (0.006) |
| × Experian personal score | | | 0.005 | 0.009*** | 0.004* | 0.008 |
| | | | (0.003) | (0.003) | (0.001) | (0.006) |
| × Internal risk rating | | | 0.005*** | 0.004** | 0.004*** | 0.006*** |
| | | | (0.001) | (0.002) | (0.002) | (0.002) |
| Experian business score | | | | | 0.003 | 0.017 |
| | | | | | (0.010) | (0.006) |
| Experian personal score | | | | | 0.007** | 0.014* |
| | | | | | (0.003) | (0.004) |
| Internal risk rating | | | | | 0.012*** | 0.029 |
| | | | | | (0.010) | (0.009) |
| log(Requested amount) | | | | | 0.005*** | 0.004*** |
| | | | | | (0.001) | (0.004) |
| Personal collateral (0/1) | | | | | 0.011 | 0.009 |
| | | | | | (0.038) | (0.015) |
| Requested LTV | | | | | -0.009*** | -0.002*** |
| | | | | | (0.000) | (0.002) |
| Requested $LTV^2$ | | | | | -0.034*** | -0.019*** |
| | | | | | (0.005) | (0.003) |
| Loan officer fixed effects | No | Yes | No | Yes | No | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 30,268 | 30,268 | 30,268 | 30,268 | 30,268 | 30,268 |
| Adj. $R^2$ | 0.14 | 0.14 | 0.15 | 0.15 | 0.15 | 0.15 |

## Table 6. Loan Performance: Loan Amount

The table explores the relation between loan amount and loan performance. All regressions are ordinary least square (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| Sample: | All originated loans | | | |
|---|---|---|---|---|
| Dependent variable: | Defaulted within 12 months (0/1) | | | |
| | (1) | (2) | (3) | (4) |
| Loan prospecting (0/1) | 0.013*** | 0.006*** | 0.005* | 0.007*** |
| | (0.004) | (0.002) | (0.003) | (0.002) |
| × I(Amount approved > Amount requested) | | 0.018*** | | |
| | | (0.005) | | |
| × log(Originated loan amount) (residual) | | | 0.013** | |
| | | | (0.005) | |
| × Originated LTV (residual) | | | | 0.013*** |
| | | | | (0.005) |
| I(Amount approved > Amount requested) | | 0.028** | | |
| | | (0.012) | | |
| log(Originated loan amount) (residual) | | | 0.016* | |
| | | | (0.008) | |
| Originated LTV (residual) | | | | 0.036** |
| | | | | (0.014) |
| log(Originated loan amount) | 0.077*** | 0.028 | | 0.075*** |
| | (0.022) | (0.021) | | (0.025) |
| Personal collateral (0/1) | -0.038 | -0.054 | -0.056 | -0.043 |
| | (0.033) | (0.034) | (0.034) | (0.034) |
| Experian business score | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Experian personal score | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Originated LTV | 0.014** | 0.015** | 0.015** | |
| | (0.006) | (0.007) | (0.007) | |
| Originated LTV$^2$ | 0.035*** | 0.032*** | 0.030*** | |
| | (0.002) | (0.002) | (0.002) | |
| Interest rate (%) | 0.038*** | 0.047*** | 0.046*** | 0.037*** |
| | (0.013) | (0.014) | (0.014) | (0.012) |
| Loan officer fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,164 | 11,164 | 11,164 | 11,164 |
| Adj. $R^2$ | 0.21 | 0.21 | 0.22 | 0.23 |

## Table 7. Loan Performance: Breakdown of the Credit Model

The table tests the hypothesis that the credit model that the Bank used broke down during the loan prospecting experiment. Panel A tests whether default is correlated with different information types. Panel B tests whether default is correlated with predicted default in the control and in the treatment groups. All regressions are ordinary least square (OLS) regressions. Variables are defined in Appendix A. Standard errors are clustered at the loan officer level. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### Panel A: Information Types and Default

| Sample: | All originated loans | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: | Defaulted within 12 months (0/1) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Loan prospecting (0/1) | 0.014*** | 0.012*** | 0.012** | 0.012** | 0.049*** | 0.006** |
| | (0.004) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| × Experian business score | | | 0.030*** | 0.021*** | 0.029*** | 0.017* |
| | | | (0.004) | (0.006) | (0.006) | (0.010) |
| × Experian personal score | | | 0.011 | 0.014*** | 0.009* | 0.011 |
| | | | (0.008) | (0.005) | (0.005) | (0.009) |
| × Internal risk rating | | | 0.026*** | 0.019** | 0.031*** | 0.032*** |
| | | | (0.006) | (0.009) | (0.009) | (0.009) |
| Experian business score | | | -0.0198 | -0.0180 | -0.020 | -0.019 |
| | | | 0.0155 | 0.0138 | (0.016) | (0.014) |
| Experian personal score | | | -0.0164 | -0.0170 | -0.017** | -0.018* |
| | | | 0.0081 | 0.0098 | (0.008) | (0.010) |
| Internal risk rating | | | 0.0374 | 0.0316 | 0.039*** | 0.033 |
| | | | 0.0139 | 0.0203 | (0.014) | (0.021) |
| log(Requested amount) | | | | | 0.014*** | 0.016*** |
| | | | | | (0.003) | (0.005) |
| Personal collateral (0/1) | | | | | -0.021 | -0.024 |
| | | | | | (0.048) | (0.042) |
| Requested LTV | | | | | 0.010*** | 0.010*** |
| | | | | | (0.002) | (0.002) |
| Requested LTV$^2$ | | | | | 0.050*** | 0.047*** |
| | | | | | (0.009) | (0.008) |
| Loan officer fixed effects | No | Yes | No | Yes | No | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11,164 | 11,164 | 11,164 | 11,164 | 11,164 | 11,164 |
| Adj. $R^2$ | 0.21 | 0.21 | 0.23 | 0.25 | 0.26 | 0.27 |

## Table 7. Breakdown of the Credit Model (Cont.)

### Panel B: Predicted Default Likelihood and Actual Default

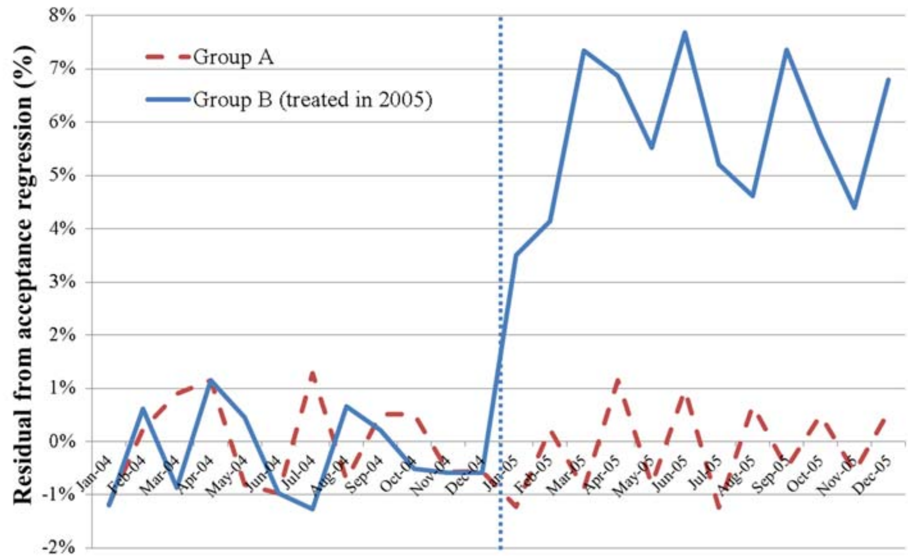
| Sample: | 2005 Originated loans (Group A) | 2005 Originated loans (Group B) | All 2005 Originated loans |
|---|---|---|---|
| Dependent variable: | Default (0/1) | Default (0/1) | Default (0/1) |
| | (1) | (2) | (3) |
| Loan prospecting (0/1) | | | 0.010*** |
| | | | (0.004) |
| × Predicted default likelihood | | | -0.015*** |
| | | | (0.006) |
| × Internal risk rating | | | 0.010** |
| | | | (0.005) |
| × Interest rate | | | -0.019*** |
| | | | (0.003) |
| Predicted default likelihood | 0.022** | 0.003 | 0.022** |
| | (0.009) | (0.006) | (0.009) |
| Internal risk rating | -0.015* | -0.002 | -0.014* |
| | (0.008) | (0.005) | (0.008) |
| Interest rate | 0.043*** | 0.024*** | 0.046*** |
| | (0.004) | (0.004) | (0.003) |
| Loan officer fixed effects | No | No | No |
| Industry fixed effects | Yes | Yes | Yes |
| Month fixed effects | No | No | No |
| Observations | 2,744 | 3,680 | 6,424 |
| Adj. $R^2$ | 0.09 | 0.09 | 0.10 |

## Table 7. Breakdown of the Credit Model (Cont.)

### Panel C: Predicted Default Likelihood and Non-"Normative" Lending

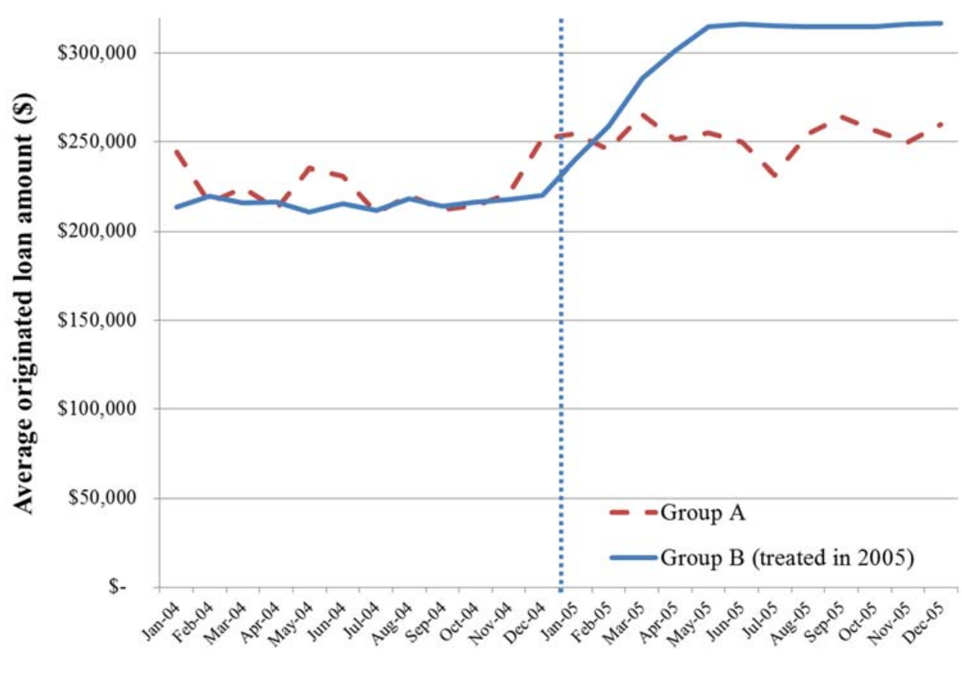
| Sample: | 2005 Originated loans, where… | | | |
|---|---|---|---|---|
| | | | residual(log(loan amount)) | |
| | I($ Approved ≤ $ Requested) (Less aggressive) | I($ Approved > $ Requested) (Aggressive) | ≤ 1SD (Less aggressive) | > 1SD (Aggressive) |
| Dependent variable: | Default (0/1) | Default (0/1) | Default (0/1) | Default (0/1) |
| | (1) | (2) | (3) | (4) |
| Loan prospecting (0/1) | 0.010** | 0.008 | 0.009 | 0.012 |
| | (0.005) | (0.007) | (0.006) | (0.008) |
| × Predicted default likelihood | -0.007 | -0.016** | -0.004 | -0.015** |
| | (0.005) | (0.008) | (0.006) | (0.007) |
| × Internal risk rating | 0.007 | 0.008 | 0.004 | 0.008 |
| | (0.010) | (0.009) | (0.008) | (0.013) |
| × Interest rate | -0.014 | -0.013 | -0.008 | -0.019* |
| | (0.019) | (0.017) | (0.019) | (0.011) |
| Predicted default likelihood | 0.019** | 0.015* | 0.015** | 0.018*** |
| | (0.009) | (0.008) | (0.006) | (0.005) |
| Internal risk rating | -0.013* | -0.015** | -0.009 | -0.016** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Interest rate | 0.046*** | 0.038*** | 0.035*** | 0.045*** |
| | (0.003) | (0.008) | (0.003) | (0.003) |
| Loan officer fixed effects | No | No | No | No |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | No | No | No | No |
| Observations | 5,525 | 899 | 3,195 | 3,229 |
| Adj. $R^2$ | 0.09 | 0.07 | 0.07 | 0.06 |

**Figure 1. Approval Rate (Residual) over Time and across Groups**




The chart shows the average residual from the approval regression (see Appendix C). The residuals are averaged within group (Groups A and B) and month. Note that while the regression uses only the control sample, the residuals are calculated for the entire sample and therefore do not have a mean of zero.

**Figure 2. Average Originated Loan Amount over Time and across Groups**




The chart shows the average loan size. Loan sizes are averaged within group (Groups A and B) and month.