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LOAN PROSPECTING AND THE LOSS OF SOFT INFORMATION

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ABSTRACT

We study a controlled experiment in which a bank's loan officers were incentivized based on originated loan volume to encourage prospecting for new business. While treated loan officers did attract new applications, both extensive and intensive margins of loan origination expanded (+31% new loans; loan size +15%). We find that loan officers gave greater weight to hard information in approval decisions. Despite no change in the observable characteristics of approved loans, their default rate increased (+24%). Finally, the bank's imputed credit-default model lost its predictive power. Overall, loan-prospecting incentives led to unfavorable soft information being overlooked in the origination process.

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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. Loan screening is a passive role that involves analyzing the risk of existing applications. By contrast, 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 (U.S. Bureau of Labor Statistics 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) study the theoretical effects of compensation for loan prospecting. In equilibrium, the increased competition in the credit market leads banks to rely primarily on hard information when approving loans. Because critical soft information is ignored, the quantity of approved loans increases but their quality declines. In a related study, Cole, Kanz, and Klapper (2015) investigate the effects of variable compensation on loan officers' approval decisions. They 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 different incentive schemes. They find that when origination volume is rewarded, loan officers are more likely to approve applications, and loan quality declines. Although these studies provide a broad view on the relation between compensation and the volume and quality of loans, we have no empirical evidence showing how loan prospecting affects the approval process.

In this study, we provide novel empirical findings about how loan prospecting transforms the bank's use of hard and soft information and the characteristics of 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

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management decided to expand the scope of about half of its loan officers' jobs to include loan-prospecting activities, whereas the other half of the loan officers maintained a narrower scope of screening activities only. As in Bénabou and Tirole's (2016) "bonus culture" economy, loan officers who were assigned to the loan-prospecting group were compensated with bonuses that were based primarily on loan dollar volume. Our data include detailed information on both loan applications and approved loans, which allows us to study the approval process in great detail.

The pilot program 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. This compensation arrangement was a common practice in the banking industry at the time (U.S. Bureau of Labor Statistics 2012). The pilot for the program was implemented 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 no significant difference existed in any attribute of applications or approved loans in the year preceding the experiment. Our data set 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 difference-in-differences design and within-loan-officer variation to detect causal effects of loan-prospecting incentives on the approval process.

The loan-prospecting program resulted in an expansion of 31% in the extensive margin (new borrowers) and 15% in the intensive margin (larger loan amounts). We offer two hypotheses

for what led to this expansion. The first is that loan officers worked to seek new business and therefore either increased the number of applications or increased their quality. Our tests, however, detect no increase in the number of applications or any improvement in their characteristics. To the detriment of the Bank's management, loan officers did not source new applications by accessing previously untapped pools of potential borrowers.

The second hypothesis is that the Bank changed the threshold at which credit was advanced. A credit-approval decision involves two inputs: hard information (observable to the econometrician) and soft information (unobservable) (Petersen 2004). In our analysis, we examine both components. We detect no decline in the average credit quality as reflected by hard information. In addition, the average internal risk rating (credit ranking assessed by loan officers) and interest rates did not change.

We do find, however, significant evidence of a shift in the use of soft information. In particular, although we do not observe a deterioration in the expected default rates (imputed using observable information), we find the ex-post default rates of the treated group increased significantly by 24%. In other words, applications were approved if they looked good on paper (hard information), even though their soft information was not favorable. Both the expansion in the extensive and intensive margins contributed to the increase in the likelihood of default. Hence, ignoring critical soft information led to the lax credit approval.

Another important effect of the informational shift due to loan prospecting is the loss of predictive power of the Bank's imputed credit model. Whereas proxies of hard information (i.e., external credit scores) were good predictors of loans' ex-post performance for the control sample, they lost their predictive power 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 these variables became obsolete because they were "fitted" over a historical range of loan variables, such as amount. We show the imputed credit model still had good predictive power for loans with amounts that fell in the "normative" range. By contrast, the relation broke down for loans with amounts beyond this range. Because a credit model captures correlations between default and loan characteristics for a specific range, loans outside that range have different correlations the current model does not capture. This result is similar in spirit to Rajan, Seru, and Vig (2015), who present evidence that the default models used in the residential real estate industry lost predictive power with the move toward standardized underwriting.

In a final analysis, we explore the relation between loan-officer characteristics and origination outcomes. We document that applications handled by more tenured loan officers and by male loan officers were more likely to be approved. Also, conditional on approval, they were approved for significantly larger loan amounts. We attribute these results to fewer career concerns by tenured loan officers and by more competitive behavior by male loan officers. We also confirm that these correlations translate into actual compensation that these loan officers received: indeed, tenured loan officers and male loan officers receive larger compensation in the treatment group but not in the control group.

Overall, our results show the loan-prospecting pilot did not expand the Bank's reach to previously untapped pools of potential borrowers. Instead, loan approval expanded on both the extensive and intensive margins. The Bank relied more on hard information and less on soft information, which led to ignoring critical credit information and to higher default rates. The change in the information used in the approval process led also to a temporary breakdown in the imputed predictive credit model of the bank.

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 realigning incentives can theoretically mitigate the problem (e.g., by giving loan officers an equity stake in the transaction; see Sufi 2007), in practice, such 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; Tzioumis and Gee 2013).

This study also adds to the literature on information production in lending. Banks traditionally use both hard and soft information in approval decisions (Petersen 2004; Agarwal, Chomsisengphet, and Wang 2016). As physical distance between the bank and borrower increases, banks rely more on hard information (Petersen and Rajan 2002, Agarwal and Hauswald 2010).

Finally, our study relates to the literature on the financial crisis of 2008. In particular, we demonstrate the contribution of bonus-based loan-officer incentives to three phenomena that have been documented previously. First, researchers have noted that in the early 2000s, the extensive margin of mortgage lending expanded; that is, new borrowers with lower credit quality entered the residential mortgage market (e.g., Mayer and Pence 2008). Second, several studies have found the leverage ratio of mortgage borrowers increased; that is, the intensive margin expanded (e.g., Demyanyk and Van Hemert 2011). Third, researchers have proposed that during boom times,

lending criteria relax and loan officers ignore bad information, due to incentives or psychological biases (e.g., Acharya and Naqvi 2012; Gennaioli, Shleifer, and Vishny 2015; Thakor 2015). Finally, researchers have noted that in the wake of the recession, imputed default models based on historical defaults began to have poor predictive power going forward (Rajan, Seru, and Vig 2015).

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 approval process 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 loan officer, who relies on both hard and soft information, then processes the application. 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).

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[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.

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).

The local branches' credit committees, which are composed of the branch manager[3] and the loan officer(s),[4] make the credit decisions. 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 (the Bank's risk-management staff closely monitor local overrides). Upon approval by the credit committee, the loan officer prepares an offer letter for the

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

[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 and the credit committee leads to greater reliance on hard information. The hierarchy did not change during the pilot experiment explored here.

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, the Bank approved 43% of loan applications and rejected the rest. Of the 43%, only 31% were originated, because 12% were withdrawn by applicants. All originated small business loans were kept on the Bank's balance sheet; none were sold or securitized. The entire lending process, including the credit decision, typically takes several weeks from the initial loan interview.

The loan officer does not have monitoring responsibilities over the loan. During the life of the loan, the risk-management department monitors the loan. 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 2016). Other lenders in the area had initiated performance-based compensation, and the management thought introducing such a payment structure would

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[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; thus, the total obligation of the applying firms is less than $1 million and their sales are below $10 million.

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 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-evaluation formula. 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. The incentive plan came with a quality assessment. For loan officers to be eligible to participate in the incentive program, their total of unsatisfactory underwriting could not exceed 5% of total approvals, assessed in a post-approval review process.

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 had 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. The remaining 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 the two groups of loan officers received have identical expected default rates, geographic focus, portfolio-management practices, and loss outcomes prior to the modification of the compensation structure. We formally test this proposition in section 3.3.

In such an experiment, loan officers might behave strategically. For example, they could approve bad loans so that management will retract the bonus-based compensation scheme. Although this behavior is theoretically possible, we doubt 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 system because it moved them closer to the compensation scheme that was prevalent in many of the competing banks. In section 3.4, we discuss additional potential Hawthorne effects.

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 it 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 data set contains all 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, whereas 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 difference-in-differences (diff-in-diffs) 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-diffs setting, we need to ensure no confounding factors are present in the research design. In the current

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[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 geographic fixed effects.

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 from the untreated group in some ways. Our conversations with the team responsible for the program's implementation confirmed 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 and credit decisions in the two groups. Our results show no significant difference in any of the variables 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 approve loans of lower credit quality (see Keys, Mukherjee, Seru, and Vig 2010). We discussed this possibility in depth with the managers of the program and were assured no additional structural changes in the lending process occurred in parallel with the implementation of the pilot program. A different form of this concern relates to the expected default rate. The Bank's management might have decided to lower the bar and thus accept applications with higher expected default rates. We test for this possibility in Table 4 (see section 5). Our results show the imputed expected default remained unchanged.

To summarize, we conclude that the diff-in-diffs 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 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-diffs 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 (all variables are explained in Appendix A). Requested loan amounts are approximately $445,000. 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 5.8 (on a 1–10 range, where 10 = 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 substantially 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-diffs setting.

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

3.3   Validating the Diff-in-Diffs 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 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 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

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

rating are similar across groups. We intentionally omit loan-officer fixed effects from the regressions; when we add these effects, the variables of interest remain statistically insignificant.

Overall, these results show 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.

3.4   Potential Hawthorne Effects

The loan officers who participated in the pilot knew they were observed. This fact could lead to potential Hawthorne effects ("observer effects"): participants reacting in a particular way because they are being observed. Two effects are possible. First, the actions of loan officers may have been exaggerated because the pilot was salient and new. The loan officers' reactions may have decayed over time, and thus our results are only an upper bound of the true results of the experiment. To assess whether indeed there is a change in the magnitude of the effect over time, we examine Figures 1 and 2. Figure 1 shows the average of the residual likelihood of approving loans, by month.[8] Figure 2 presents the average loan size, by month. Both figures show no decay or trend in the magnitude of the effects during the first 12 months after the pilot was implemented.

The second potential effect is that loan officers could have behaved strategically to sway the management to reach conclusions in one direction or another. To assess whether our results are the effect of such behavior, we analyze the potential response of loan officers to the pilot. We assume the objective of loan officers was to minimize effort and maximize personal earnings. To do so, they would have milked the existing pool of applications in a way that (1) satisfied the

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[8] See section 5 for a complete description of the procedure generating this figure.

Bank's credit criteria and (2) did not require much additional work. If indeed loan officers behaved strategically, we can envision two potential cases, which lead to predictable patterns.

In the first case, loan officers may have liked the new compensation scheme and therefore acted strategically so that the pilot would succeed and the program would be approved. In this case, we would expect the loan officers to exert effort to bring new business to the bank (i.e., seek new applications). Also, they would have been diligent in the approval process, so that quality would not decline.

In the second case, loan officers did not like the new compensation scheme and acted strategically so that the pilot would fail. In this case, the loan officers would have acted to show the incentives did not work and that loan volume did not increase. Thus, the treated group would have continued to act as before.

Now, let us contrast these predictions with what we observe in the data. First, we observe no significant change in the behavior of the control group. Second, the behavior of the treated group appears to be consistent with a "minimum effort and maximum compensation" strategy; that is, loan officers did not seek new applications and the quality of the approved applications declined (inconsistent with the first case above). Also, their actions *did* lead to a significant increase in loan volume (inconsistent with the second case above).

Thus, our findings seem to be inconsistent with loan officers behaving in a reasonably strategic manner. We observe that compensation levels increased with little evidence of additional effort by loan officers. Specifically, we do not find evidence that the size of the application pool increased, that is, no application sourcing from previously untapped pools. Loan officers increased loan volume by using the easiest-to-execute methods: (1) ignoring negative soft information, and (2) conditional on approval, approving larger loans.

4   Direct Effects of Loan Prospecting

We begin the analysis by diagnosing the first-order effects of loan prospecting. In particular, we are interested in how the program affected the flow of applications, extensive margin (approval rate), internal margin (loan size), and turnaround time. In all these dimensions, loan officers could have an effect given their expanded job description and pecuniary incentives. Also, the Bank's management is likely to use these dimensions to measure the program's success.

4.1   Flow of Applications

The objective of the pilot was to incentivize loan officers to seek new business; hence, they might have improved the quantity or quality of the application flow. Loan officers could have made such improvements 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, for example, by raising awareness about 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 for a difference in the quantity of applications. In Table 2, 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 and 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 the coefficients are positive 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 the quality of the applications is higher for the treatment group. 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 2, Panel B, 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 2, Panel C, which indicates no significant difference in the ex-ante likelihood of approval in the treatment group.

Overall, the findings in Table 2 indicate prospecting loan officers did not attract new applications to the Bank, nor did they improve the quality of the applications the Bank received.

4.2 Effects on the Extensive Margin

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. We examine the effects of the loan-prospecting program on the extensive margin in Table 3, Panel A, columns (1) to (4). The examined unit is loan officer–month, the dependent variable is the logged number of loans in a

month, per loan officer, and the variable of interest is the loan-prospecting dummy. The results show the number of loans approved and originated increased by about 31% in the post-period, when both calendar-month fixed effects and loan-officer fixed effects are included (columns (2) and (4)).

We also present this effect in a graphical form. 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 the observed characteristics do not explain the high approval rate in the treatment group and that the dramatic increase occurred immediately after the pilot began.

4.3   Effects on the Intensive Margin

Next, we examine the intensive margin (loan amounts). In Table 3, Panel A, columns (5) to (8), we regress the average logged loan size per loan officer–month on the loan-prospecting dummy. The regressions show that for both the approved and originated loans, loan amounts increased by about 15% (columns (6) and (8)). In fact, approved loan amounts in the treatment group were often larger than the amounts applicants requested. 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.

Figure 2 plots the average approved loan size over time. The chart shows 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.

4.4 Additional Effects: Turnaround Time and Withdrawal Rate

The Bank was also interested in shortening turnaround times to help improve the quality of service. To measure whether the program indeed improved turnaround times, 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 3, Panel B, columns (1) to (4), show turnaround time indeed declined for the treated group in 2005. For all applications, the average turnaround times declined by about three 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 3, 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 the 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 a combination of factors: a greater

effort by loan officers to convince hesitant applicants to sign on the dotted line, improvement in processing efficiency, and more aggressive loan terms.

5   Loan Prospecting and Information Processing

The fact that the pool of applications did not change in a material fashion, and yet credit provision expanded on both the extensive and intensive margins, suggests the Bank changed its risk tolerance (potentially inadvertently). One likely channel for this effect is through the information used to approve loan applications. In general, two types of information drive loan-approval decisions: hard information (which is observable) and soft information (which is unobservable) (Petersen 2004). Loan prospecting might have caused a change in how the Bank processes the different types of information.

5.1   Hard Information Used in Approving Applications

In a first set of tests, we explore whether the observable characteristics of approved applications are different across the two groups. To do so, we compare observable characteristics between the treatment and control group in the post-period, including the variables of interest: Experian business score, Experian personal score, internal risk rating, and interest rate. In the empirical specification, we restrict the sample to approved applications only and regress the variables of interest on the loan-prospecting dummy, in addition to logged approved loan amount, a personal-collateral indicator, approved LTV, and approved LTV-squared.

The results in Table 4, Panel A, show that approved applications in the control and treatment groups have statistically indistinguishable credit characteristics. Furthermore, they were

charged indistinguishable interest rates, conditional on observable risk characteristics. This finding means that, observationally, loans in the control and the treatment groups have similar characteristics.

Next, we examine the relative importance of hard information in the approval decisions of the treatment and control groups. In Table 4, Panel B, we regress the approval 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 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 the weight on hard information (i.e., external credit scores) is greater for the treatment group. Explicitly, the weight of external information is nearly double for the treatment group relative to the control group (column (6)). By contrast, the weight on soft information (proxied by 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 67% lower than that of the control group ((0.016–0.024) = –0.008 in the treatment relative to –0.024 in the control). Given that the standard error on the coefficient of the internal risk rating is in the vicinity of 0.010, this weight of soft information in the treatment group is not statistically different from zero.

We deepen the analysis and explore whether an imputed credit-default model based on observable characteristics would detect an increase in the risk the bank takes. First, we investigate whether the imputed ex-ante credit quality for approved applications is the same in the treatment and control groups. We compute the imputed 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 C. We first assess how the predicted default probability affects the likelihood of approval, loan size, and interest rate. In all regressions, the main effect of the predicted default probability is statistically significant and with the right sign: applications with a higher predicted default probability are less likely to be approved, their loan size is smaller (if approved), and their interest rate is higher (if approved). Column (1) shows the predicted default probability has the same impact on the likelihood of approval in the treatment and in the control groups. By contrast, columns (2) and (3) present evidence that, conditional on approval, the bank approved larger loan sizes to riskier borrowers, but also charged them higher interest rates.

Overall, these results indicate hard information became more important in the loan-approval process. Furthermore, we find little evidence that the imputed ex-ante credit quality of approved applications changed. Yet the loans originated under the treatment group have more aggressive terms.

5.2   Downplaying Soft Information

Soft information is by definition unobservable; however, we can study its role in the approval process by exploring the default rate and its drivers. In particular, we know hard information became a prominent factor in approving applications and that observable quality of approved applications did not deteriorate. Hence, no change occurs in soft information, we expect the ex-post default rate to stay the same. However, if the ex-post default rate increases, we can conclude soft information that was critical in screening out bad applications is no longer used.

In a first pass, we explore whether the loans treated loan officers originated defaulted more frequently than those the control group originated. We measure loan performance as the default rate, defined as a delinquency of 90 days or more within one year of loan origination. The default rate in the control group is 4.2 percentage points in 2004–2005. 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 loan-officer, industry, and month fixed effects. The results in Table 5, columns (1) and (2), show 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 imputed ex-ante risk. The coefficient on the loan-prospecting dummy remains virtually unchanged with this additional control, suggesting 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.

In the next step, we explore the determinants of the increase in default. We focus the analysis on variables that are correlated with the expansion in both the extensive and intensive margins, that is, new borrowers and aggressive lending terms.

We begin by exploring how new borrowers affect the default rate. We measure the new borrowers by estimating a residual from a regression of application approval on observable characteristics using the 2004 data (see Appendix C). A large residual from the application regression indicates a loan was not accepted based on the weights that were used to approve applications in the 2004. Table 6, 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), we regress the default indicator on the residuals from the approval regression as well as on controls and fixed effects. The regression shows that although a high approval residual is associated with a higher default rate (the main effect of the loan-approval residual), the correlation is more than doubled for loans in the treated group. Hence, this result suggests new borrowers were partly responsible for the increase in default.

Next, we explore the role of the expansion in the intensive margin (larger loan amounts) on the increase in the default rate. In Table 6, column (3), the variable of interest is the interaction between the loan-prospecting group and an indicator for whether the loan amount was larger than what the borrower originally requested. The regression shows that loans with amounts greater than requested are 2.8 percentage points more likely to default under the control (0.028 is the coefficient on the main effect) and 4.6 percentage points more likely under the treatment (= 0.028 + 0.018). In column (4), we examine a variable that reflects abnormal LTV, computed as the residual from a regression of logged LTV on loan characteristics, which is based on a sample that includes only observations from the control group (see Appendix C). The regression in column (4) shows that

loans with high residuals—that is, LTV is unusually high relative to the control group—are significantly more likely to default. The sensitivity of default to abnormal LTV is almost double that of the control sample.

Overall, these results show that under the pilot incentive program, the weight given to hard information in the approval decision increased, and soft information was discounted. The decline in the importance of soft information is asymmetrical; our results show negative soft information was ignored, leading to a higher default rate.

6   Breakdown of the Credit Model

We have shown the change in the scope of the loan officers' jobs and incentives significantly affected the origination process and the composition of the loan portfolio. Throughout the process, the Bank did not change its imputed approval criteria and credit model, but it did allow significantly larger loan amounts. Thus, an important question is how the Bank's predictive credit model fared. In other words, could the Bank have predicted the increase in default? A parallel could be drawn with 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 the imputed 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 5.1, the Bank's approval process began to rely more heavily on hard information. The combination of both types of information may have previously provided a

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good screen for borrowers, whereas relying primarily on hard information may have missed crucial details about applicants. Second, loan terms under the treatment group became significantly more aggressive. The sensitivity of performance to factors such as loan amounts and leverage might not be linear. Because the Bank was using a credit model that was fit on data with a certain range of amounts and leverages, the model may not have been applicable to loans with more aggressive terms.

To test the proposition that the Bank's predictive model became defunct, and to explore the reasons why, we conduct three tests. We have seen the Bank began to rely more heavily on hard information in the approval decision. The first test (Table 7, Panel A), therefore, examines how well observable information predicts ex-post default in the treatment versus the control groups. The table shows the different types of information (Experian business and personal information, as well as the internal risk rating) predict default for the entire sample. However, for the treatment, these variables lose their predictive ability.

The second test offers a more elaborated specification of a default predictor. As in Table 4, we use the predicted default (based on the 2004 data) to explain ex-post default of loans originated in 2005. For each originated loan in 2005, we compute the predicted default likelihood. We regress the actual default dummy on the predicted default variable as well as on the internal risk rating and interest rate. Table 7, Panel B, column (1), includes only the control sample in 2005. It shows that for this sample, all three variables explain actual default well; in particular, the predicted default predicts current ex-post default. The converse happens when we examine the treatment sample in 2005 (column (2)). For this sample, we find no relation between actual default and predicted default. Furthermore, loan officers' opinions (internal risk raking) 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) presents these effects in a combined sample of the control and treatment groups in 2005.

In a final analysis, we explore why the Bank's imputed predictive model stopped working. Our hypothesis is that the fitted model is doing a good job for originated loans that are similar to the loans in the sample in which it was estimated. However, we expect the fitted model to have poor predictive power 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 the interaction between the loan-prospecting dummy and the predicted default likelihood is statistically indistinguishable from zero. By 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 default is not predictable for this subset of loans based on the history of loans originated by the Bank 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; see Appendix C). 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. For less aggressive loan

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[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.

terms (column (3)) the coefficient on the interaction of the loan-prospecting indicator and the predicted default likelihood is indistinguishable from zero, meaning the default of loans with less aggressive terms is predictable using 2004 data. Conversely, for more aggressive terms (column (4)), the performance of loans with aggressive amounts cannot be predicted using a predictor based on 2004 performance data.

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

7   Loan-Officer Characteristics

Our final analysis examines loan-officer characteristics and outcomes of the loan-origination process. We focus on two main characteristics: loan-officer tenure and gender. Loan officers who have been on the job longer have greater familiarity with the loan-origination process, as well as fewer career concerns. Hence, we expect loan officers who have been with the Bank for longer periods to exhibit higher approval rates than other loan officers following the loan-prospecting experiment. We test this hypothesis in Table 8, Panel A. Using the sample of all applications, we regress the approval indicator on an interaction of the treatment dummy with a dummy for whether the loan officer has above-median tenure at the Bank. The results show that longer-tenured loan officers have approval rates that are 2.5 percentage points higher than those of their peers (compared with a 51.2% approval rate in the control group in 2005). In column (6), we test the relation between logged loan amount and loan officers' tenure for the sample of

approved loans. After controlling for application characteristics, we find that loans originated by tenured loan officers are 5 percentage points larger than those handled by less tenured peers.

We are also interested in the effect of loan officers' gender on loan outcome. Male loan officers may exhibit stronger competitive behavior (Gneezy, Niederle, and Rustichini 2003; Gneezy and Rustichini 2004) and may therefore be more willing to push loans more aggressively through the system. We test this hypothesis in column (3). Indeed, we find that applications handled by male loan officers in the treatment group are 2.0 percentage points more likely to be approved. Also, column (7) shows that applications handled by treated male loan officers have loan amounts that are 7.0 percentage points larger than loans originated by treated female loan officers.

Finally, we confirm that loan-officer characteristics indeed translate to larger salaries. We use a data set of loan officer–months to test this proposition. In Table 8, Panel B, we regress logged compensation on the treatment dummy interacted with loan-officer characteristics. The panel presents evidence that tenured loan officers and male loan officers earn higher salaries relative to their peers in the treatment group, but not in the control group.

Overall, our findings indicate tenure within the organization (potentially indicating lower career concerns) and gender may amplify the effects of loan prospecting.

8   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, the expansion resulted in dramatic changes to the origination process. In the corporate pilot

program we study, the Bank provided incentives to loan officers to bring new business to the Bank ("loan prospecting"). The expected default of approved applications did not change, yet granted loan amounts rose. At a first glance, the pilot appears to have had some success: the Bank expanded its book of business through a greater number of approved loans at larger amounts. A caveat to this apparent success is the high default rate.

Our analysis shows the move to loan prospecting led to several striking changes in the loan-origination process. Despite the fact that loan officers did not bring new business to the Bank as expected, loan origination expanded on both the extensive margin (new borrowers) and the intensive margin (larger loan amounts). The bank relied more heavily on hard information in the approval process and discounted negative soft information. These policy changes led to material changes in the composition of borrower and loan characteristics. We show that due to these changes, the Bank's imputed credit model broke down and lost its predictive power.

These results highlight 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.

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Appendix A. Variable Definitions

Variable	Description
Default within 12 months	An indicator of whether the loan became delinquent (90 days or more past due) within 12 months of origination.
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.
Interest rate	The interest rate paid on the loan.
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.
Loan originated	An indicator of whether a loan application was originated by the Bank.
Loan prospecting	An indicator of whether (1) the loan application was handled by a loan officer who is part of Group B (loan prospecting treatment in 2005) and (2) the year of the loan application is 2005.
Loan-to-value (LTV)	The loan amount divided by the value of the collateral.
Originated amount	The dollar amount originated by the Bank.
Personal collateral	An indicator variable as to whether the loan applicant proposes collateralizing a personal asset (=1) or a business asset (=0).
Requested amount	The dollar amount requested by the loan applicant.
Residual from internal risk-rating regression	Residual from a regression of the internal risk-rating variable on loan characteristics (see Appendix C).
Residual from loan-originating regression	Residual from a regression of the loan-originated 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).
Residual from LTV regression	Residual from a regression of the LTV variable on loan characteristics (see Appendix C).
Time spent	Time interval between application submission and decision. Measured in months.
Withdrawn	An indicator of whether a loan application was withdrawn before or after the Bank made a decision.

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 pre-treatment period (2004). Panel B does the same for originated loans. All regressions are ordinary least squares 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

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 approved 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 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)	
# Applications:	6,920		7,996		7,564		7,788	
	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
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)	
# Originated loans:	2,192		2,548		2,744		3,680	
	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
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)	
# Loan officers:	68		65		65		65	
	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
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 ($k))	5.281	5.394	5.299	5.307	5.294	5.374	5.551	5.446
log(# Applications)	3.794	1.885	3.795	1.884	3.799	1.865	3.812	1.842
log(# Approved loans)	3.378	1.858	3.399	1.878	3.381	1.840	3.705	1.819
log(# Originated loans)	3.373	1.861	3.396	1.861	3.391	1.834	3.816	1.840
Salary ($)	43,292	32,941	43,023	32,114	43,139	32,327	47,305	32,672
log(Salary ($))	4.567	4.555	4.583	4.544	4.608	4.601	4.660	4.521
Tenure (years)	3.1	2.6	3.1	2.6	3.0	2.6	3.1	2.6
Male (%)	62.9		68.0		64.5		66.9	

N(loan officer-month) = 3,192

Table 2. 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 engaged in loan prospecting. 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 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 2. 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 3. 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 regressions. Variables are defined in Appendix A. Standard errors, reported in parentheses, are clustered at the month level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effects on the Extensive and Intensive Margins of Loan Approval and Origination

Dependent variable:	log(#Loans)				log(Avg amount ($))			
Sample:	Approved		Originated		Approved		Originated	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan prospecting (0/1)	0.282***	0.313***	0.276***	0.305***	0.147***	0.149***	0.144***	0.145***
	(0.058)	(0.051)	(0.046)	(0.038)	(0.048)	(0.040)	(0.046)	(0.043)
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	0.15	0.17	0.19	0.20	0.13	0.15	0.16	0.17

Table 3. Direct Effects of Loan Prospecting (Cont.)

Panel B: Turnaround Time and Withdrawal Rate

Dependent variable:	#Months between application and decision				I(Application withdrawn)	
Sample:	Applications		Approved loans		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 4. Did the Bank Approve Applications of Lower Observed Credit Quality?

The table presents regressions testing whether the lending standards of the Bank changed along with the change in the scope of loan-officer activities. Panel A tests whether a significant difference exists in the credit quality of loans that were approved in the treatment and control groups. Panel A uses only 2005 data, because the calculation of expected default uses 2004 data. Panel B presents an analysis of the effects of loan prospecting on the approval of loans with respect to credit quality. Panel C tests whether a difference exists in the imputed expected default likelihood of loans that were approved by the treatment and control groups. *Imputed predicted default probability* is the predicted value from a regression of the default indicator on observable characteristics using the 2004 applications data. Panels B and C use a sample of all applications. All regressions are ordinary least square regressions. Variables are defined in Appendix A. Standard errors, reported in parentheses, are clustered at the loan-officer level. ***, **, 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 the Bank Approve Applications of Lower Observed Credit Quality? (Cont.)

Panel B: Focusing on Hard Information

Sample:	All applications					
Dependent variable:	Application approved (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Loan prospecting (0/1)	0.074***	0.084***	0.049***	0.038**	0.037**	0.040**
	(0.019)	(0.019)	(0.018)	(0.016)	(0.017)	(0.019)
× Experian business score			0.019***	0.015***	0.014***	0.013**
			(0.003)	(0.001)	(0.005)	(0.005)
× Experian personal score			0.005	0.008**	0.004***	0.008
			(0.003)	(0.003)	(0.001)	(0.005)
× Internal risk rating			0.016	0.015	0.016	0.016
			(0.014)	(0.011)	(0.012)	(0.011)
Experian business score					0.003	0.016***
					(0.010)	(0.006)
Experian personal score					0.006**	0.013***
					(0.003)	(0.003)
Internal risk rating					-0.026***	-0.024***
					(0.006)	(0.005)
log(Requested amount)					0.005***	0.004
					(0.001)	(0.004)
Personal collateral (0/1)					0.011	0.008
					(0.037)	(0.015)
Requested LTV					-0.008***	-0.002
					(0.000)	(0.002)
Requested LTV^2					-0.032***	-0.018***
					(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 4. Did the Bank Approve Applications of Lower Observed Credit Quality? (Cont.)

Panel C: 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)
Imputed 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. Default Rates

The table presents an analysis of the default rates following the loan-prospecting experiment. All regressions are ordinary least squares regressions. Variables are defined in Appendix A. Standard errors, reported in parentheses, are clustered at the month level. ***, **, 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)	0.012***	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 6. Default Drivers: Extensive and Intensive Margins

The table explores the relation between loan amount and loan performance. All regressions are ordinary least square regressions. Variables are defined in Appendix A. Standard errors, reported in parentheses, are clustered at the loan-officer level. ***, **, 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)	(5)
Loan prospecting (0/1)	0.013***	0.067***	0.055***	0.066***	0.030***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
$\times$ Loan approved (residual)		0.040***			0.036***
		(0.015)			(0.014)
$\times$ I(Amount approved > Amount requested)			0.038***		0.034***
			(0.010)		(0.011)
$\times$ Originated LTV (residual)				0.034**	0.034**
				(0.013)	(0.015)
Loan approved (residual)		0.027**			0.026*
		(0.014)			(0.015)
I(Amount approved > Amount requested)			0.028**		0.026**
			(0.012)		(0.012)
Originated LTV (residual)				0.037**	0.035**
				(0.015)	(0.014)
log(Originated loan amount)	0.077***	0.082***	0.029	0.078***	0.007
	(0.022)	(0.027)	(0.022)	(0.025)	(0.019)
Personal collateral (0/1)	-0.038	-0.059	-0.055	-0.045	-0.043
	(0.033)	(0.043)	(0.034)	(0.035)	(0.028)
Experian business score	-0.001	-0.001*	-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)	(0.001)	(0.001)
Originated LTV	0.014**	0.013**	0.016**		0.012***
	(0.006)	(0.006)	(0.007)		(0.004)
Originated LTV^2	0.035***	0.036***	0.033***		0.031***
	(0.002)	(0.002)	(0.002)		(0.002)
Interest rate (%)	0.038***	0.051***	0.048***	0.039***	0.044***
	(0.013)	(0.012)	(0.014)	(0.012)	(0.019)
Loan officer fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	11,164	11,164	11,164	11,164	11,164
Adj. R^2	0.21	0.23	0.21	0.23	0.26

Table 7. Performance Driver: Breakdown of the Credit Model

The table tests the hypothesis that the Bank's credit model 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 regressions. Variables are defined in Appendix A. Standard errors, reported in parentheses, are clustered at the loan-officer level. ***, **, 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			-0.020	-0.018	-0.020	-0.019
			(0.015)	(0.014)	(0.016)	(0.014)
Experian personal score			-0.016**	-0.017*	-0.017**	-0.018*
			(0.008)	(0.010)	(0.008)	(0.010)
Internal risk rating			0.037***	0.032	0.039***	0.033
			(0.014)	(0.020)	(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. Performance Driver: 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	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
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)	≤ 1 StDev (Less aggressive)	> 1 StDev (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	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	5,525	899	3,195	3,229
Adj. R^2	0.09	0.07	0.07	0.06

Table 8. Loan-Officer Characteristics and Loan Origination

The table tests the relation between loan-officer characteristics (tenure, gender) and the loan-origination process. Panel A tests the relation between the likelihood of loan approval and loan-officer characteristics (columns (1) to (4)), and the relation between loan amounts and loan-officer characteristics (columns (5) to (8)). Panel B tests the relation between loan officers' compensation and loan-officer characteristics. All regressions are ordinary least square regressions. Variables are defined in Appendix A. Standard errors, reported in parentheses, are clustered at the loan-officer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### Panel A: Loan-Officer Characteristics and Decision-Making

Dependent variable:	Approved loan (0/1)				log(Loan amount)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan prospecting (0/1)	0.054***	0.033***	0.041***	0.052***	0.103***	0.058***	0.032***	0.023**
	(0.018)	(0.006)	(0.002)	(0.006)	(0.010)	(0.010)	(0.011)	(0.010)
× Tenure above median (0/1)		0.025**		0.005*		0.051**		0.054***
		(0.009)		(0.003)		(0.025)		(0.017)
× Male (0/1)			0.020***	0.003			0.070***	0.050**
			(0.001)	(0.003)			(0.023)	(0.018)
Tenure above median (0/1)		0.003		0.004		0.002		0.003
		(0.002)		(0.013)		(0.012)		(0.002)
Male (0/1)			0.002	0.005**			0.005**	0.001
			(0.002)	(0.002)			(0.002)	(0.004)
Experian business score	0.003	0.003	0.004	0.006***	0.001	0.002	0.004	0.007***
	(0.002)	(0.005)	(0.004)	(0.002)	(0.002)	(0.003)	(0.009)	(0.000)
Experian personal score	0.005***	0.008***	0.010***	0.008***	0.003***	0.001	0.004**	0.006***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)
Internal risk rating	0.008***	0.004	0.005	0.003	0.006	0.004***	0.002	0.001
	(0.000)	(0.008)	(0.008)	(0.007)	(0.007)	(0.000)	(0.009)	(0.002)
log(Requested amount)	0.000	0.001	0.001	0.001	0.877***	0.857***	0.878***	0.860***
	(0.000)	(0.004)	(0.001)	(0.004)	(0.123)	(0.122)	(0.121)	(0.120)
Personal collateral (0/1)	0.002	0.005	0.001	0.005	0.010	0.005	0.007	0.002
	(0.026)	(0.004)	(0.025)	(0.014)	(0.018)	(0.008)	(0.028)	(0.001)
Requested LTV	-0.000	-0.002	-0.001***	-0.002***	-0.006***	-0.000*	-0.005***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Requested LTV^2	-0.001	-0.006***	-0.003	-0.008***	-0.002***	-0.003	-0.004**	-0.001
	(0.002)	(0.002)	(0.004)	(0.002)	(0.000)	(0.003)	(0.002)	(0.001)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,268	30,268	30,268	30,268	14,916	14,916	14,916	14,916
Adj. R^2	0.28	0.28	0.29	0.29	0.41	0.41	0.42	0.42

Table 8. Loan-Officer Characteristics and Loan Origination (Cont.)

Panel B: Loan-Officer Characteristics and Compensation

| Dependent variable:	log(Compensation ($))			
	(1)	(2)	(3)	(4)
Loan prospecting (0/1)	0.082***	0.075***	0.066***	0.060***
	(0.020)	(0.014)	(0.016)	(0.015)
× Tenure above median (0/1)		0.025**		0.021**
		(0.011)		(0.011)
× Male (0/1)			0.036***	0.038***
			(0.011)	(0.010)
Tenure above median (0/1)		0.006		0.005
		(0.014)		(0.014)
Male (0/1)			0.007	0.006
			(0.012)	(0.011)
Month fixed effects	Yes	Yes	Yes	Yes
Observations	3,192	3,192	3,192	3,192
Adj. R^2	0.54	0.57	0.69	0.70

Figure 1. Approval Rate (Residual) over Time and across Groups
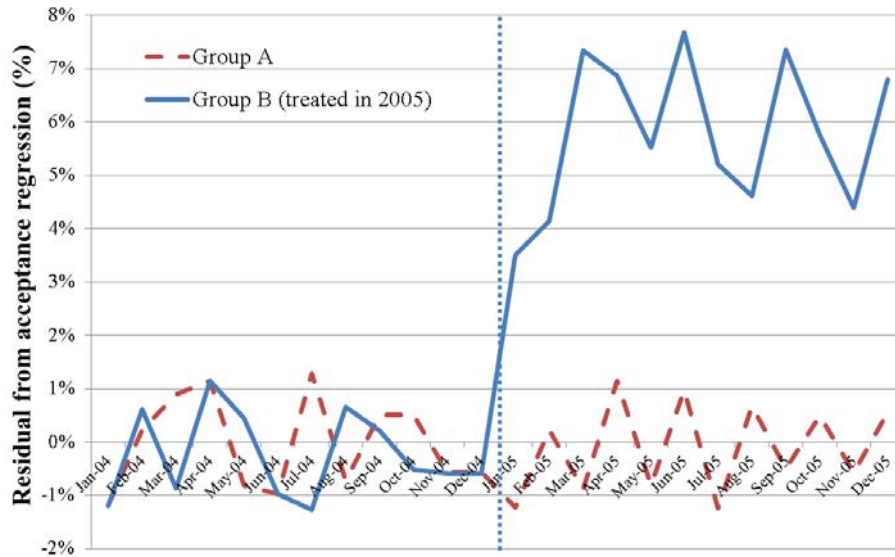
The chart shows the average residual from the approval regression (see Appendix C). The residuals are averaged within group (Groups A and B) and month. Note that whereas the regression uses only the control sample, the residuals are calculated for the entire sample and therefore do not have a mean of zero.

Figure 2. Average Originated Loan Amount over Time and across Groups
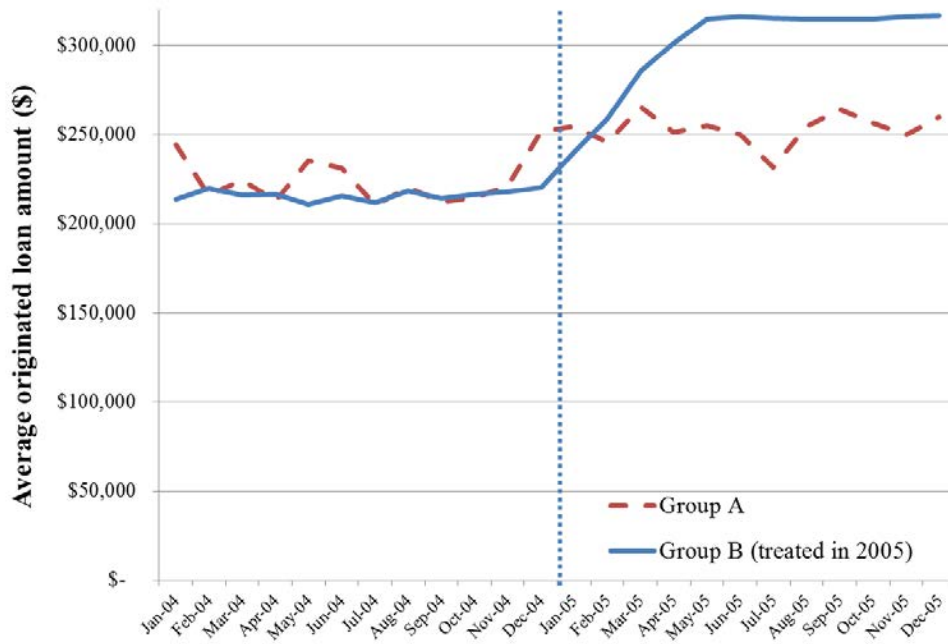
The chart shows the average loan size. Loan sizes are averaged within group (Groups A and B) and month.