Do Relationships Matter? Evidence from Loan Officer Turnover

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Abstract

We study the effect of employee turnover on measures of firm performance and client retention in a firm where employees have decentralized knowledge and personal relationships with their clients. Using exogenous shocks to the relationship between borrowers and loan-officers, we document that borrowers are less likely to receive new loans from the bank and are more likely to apply for credit from other banks when their original loan officers are absent. They are also more likely to miss payments or go into default. These costs are mitigated when the bank is able to facilitate knowledge transmission from the departing loan officers to a successor. However the sharing of knowledge does not happen when turnovers are unexpected as in the case of sick leaves, or when loan officers do not have incentives to transfer information, as in the case of dismissals.

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1 Introduction

The recent management literature has documented that modern firms rely heavily on human capital-intensive technologies and flat organizational structure, which allow authority and responsibility to be pushed down further within the organization, see for example Rajan and Wulf (2006) or Guadalupe, Li, and Wulf (2013). As a result, knowledge about specific firm processes or client relationships is dispersed across employees and throughout the organization. Often this knowledge is "tacit" or relationship-specific and therefore difficult to transfer to someone else within the organization.[1] Ensuring and facilitating the transfer of this decentralized knowledge across employees, therefore, is a central management challenge for firms. The challenge of maintaining critical information and client relationships within the firm becomes especially pertinent in situations when an employee leaves the firm, either voluntarily or involuntarily.

A prominent industry, where employees have a lot of decentralized information and are key in maintaining client relationships, is commercial banking. Loan officers play a fundamental role in screening potential borrowers, making credit assessments, and monitoring the borrower over the loan cycle. These tasks are particularly challenging when lending to private firms or small businesses where information is often difficult to obtain and verify (Rajan 1992, Petersen and Rajan 1995, Berger and Udell 2002). A close and trusting relationship between the loan officer and the borrower is seen to be instrumental in obtaining "soft" information (Uzzi and Lancaster 2003) and retaining clients. The positive effect of a close relationship might be reinforced if clients develop personal loyalties with their loan officer. One could imagine that such relationships would decrease the likelihood of future problems for the organization, such as borrowers' moral hazard (Paravisini and Schoar 2012). However, on the downside, relying extensively on loan officers' personal contacts with the borrowers might make them indispensable in the lending process, creating a management challenge when a loan officer leaves. Stein (2002) and Berger, Miller, Petersen, Rajan, and Stein (2005) argue that soft information cannot easily be transferred within the bank and thus limits the organizational structure and the

[1] This idea goes back to Polyani (1966).

bank's size.

When banks are managing employee turnover, the transfer of soft information can be especially problematic if borrowers are reluctant to provide private information to a replacement loan officer. Indeed, a consistent finding in the management literature is that interpersonal ties affect the type of knowledge that economic agents are willing to share. For example, Uzzi (1996) and Uzzi and Lancaster (2003) study the extent to which information transferred in an embedded relationship is different from information transferred at arm's length, and find that information transferred in embedded relationships is more private, proprietary and tacit. Despite the important work documenting the relevance of interpersonal relationships on firms' strategies, operations, and structure, there has been little research about the costs associated to disruptions to these relationships.[2] The ability of firms to mitigate and manage the costs of turnover in situations where employees have decentralized information can have broad implications on the optimal size of the firm, the span of control, and the hierarchical structure of an organization.

In this paper, we test the impact of shocks to the relationship between loan officers and borrowers by exploiting instances where loan officers are absent from their job for long periods of time. If social relationships affect the information obtained by the loan officer and this information is difficult to transfer between employees of the bank, we expect access to credit to deteriorate when the original loan officer is absent. A replacement loan officer might initially rely more on hard information in her credit assessment and, as a result, firms with worse observable characteristics, like smaller and less profitable firms, should see the biggest effect from the switch. We use detailed transaction-level data on small business borrowers from BancoEstado, the largest lender to small businesses in Chile. These loans are issued as personal loans and therefore without limited liability. However, de facto, it is very difficult to seize any assets from these clients. Therefore, loans in this segment rely heavily on soft information. We obtain comprehensive data about the

[2]Notable examples of how information affects firms' decisions and structure are Haunschild and Beckman (1998) which finds that director interlocks affect firms' mergers and acquisitions strategies and, Hansen (1999) who shows that strong ties between the units of a firm affect the speed at which the firm can develop new products.

loan officers, their backgrounds and leaves, as well as the transaction details and repayment behavior of the clients in their portfolios.

We find that the relationship between loan officers and their clients has first-order effects on the borrowers' access to credit. If the original loan officer is absent, we observe a 19.73% drop in the unconditional probability that a client gets a new loan during that time period.[3] When decomposing this drop into the application rate of the client and the approval probability of the bank, we see that not only does the approval rate drop by more than 5%, but also the rate at which clients apply for new loans falls by about 0.91%, which represents a 13.34% reduction in the unconditional probability of applying for a new loan. At the same time, we do not observe any significant changes in credit terms after a loan officer leaves; for example, interest rates and loan maturity are, on average, unchanged. However, there is a significant increase in the probability of a client becoming delinquent or even defaulting on a loan when the original loan officer is out. For example, clients in good standing increase their probability of becoming delinquent by 21.53% compared to the average probability of becoming delinquent. Furthermore, for those borrowers who are already delinquent, the probability of default shoots up by 18.31% compared to the unconditional probability of defaulting.[4] Finally, only 11% of clients who have been rejected for a loan by the replacement loan officer are able to borrow from the outside loan market, which highlights that the credit constraints cannot be fully offset by borrowing outside the bank.

These findings suggest that disruptions to the relationship between the borrowers and the loan officers reduce the borrower access to credit. New loan officers who do not have a relationship with the client seem to rely on rationing borrowers for which hard information is poor. In addition, borrowers demonstrate less loyalty towards the bank.

Next, we test if the documented negative impact of loan officer turnover can be mitigated if there is a

[3] The change in the unconditional probability is estimated as the ratio between the absolute change (1.18% from table 3), and the unconditional probability (5.98% from table 2). We use this convention throughout the paper.

[4] A client is considered in default if he or she has late payments of more than 90 days.

possibility to transfer soft information to a replacement loan officer. For this purpose, we look at variations in (1) how well the absence of a loan officer can be planned in advance, since it should be more difficult to transfer soft information in the case of completely unplanned leaves, and (2) whether the departing loan officer has any incentives to collaborate in conveying information to a replacement loan officer. We observe four different types of leave: due to sickness, resignation, pregnancy, and dismissal. The timing of a sickness leave is difficult to plan in advance since we look at major and unexpected illnesses. Even though the officer might have incentives to convey soft information to a replacement, the severity of the disease usually prevents it. Here the replacement loan officer might not be able to access any of the soft information the previous loan officer had acquired. In comparison, a loan officer who is dismissed might have sufficient lead time but no incentives to cooperate with the replacement. In contrast, pregnancy has a nine month lead time, where the bank could ensure that the replacement loan officer be given information on the soft factors of the borrowers. Alternatively, in the months that precede the leave, a pregnant loan officer might be able to issue additional credit to compensate for the shortage in credit that is expected during the leave. In the case of resignations, loan officers give a few weeks notice before they leave, which is usually enough time to brief the replacement loan officer. If we see deterioration in the credit terms, even in the last two circumstances, it would suggest that soft information is difficult to transmit even when given enough time.

We find that clients whose loan officer takes a sick leave are 19.9% less likely to get a new loan from the bank during the time of the absence, compared to the average probability of getting a new loan, which is 5.98%. This is driven by a strong decrease in the likelihood that clients apply for a loan, which can be a sign that they feel less loyal to the bank. The approval rate also shows an economically significant reduction, but the change is not statistically significant. These clients also show a 2.15% increase in the probability of getting a loan outside of the bank, which is almost 13% higher than the probability for an average client in the sample. The fact that they are able to get outside financing also suggests that they are of reasonable credit risk. Furthermore, these borrowers experience a very significant increase of 0.95% in the probability of delinquency. Overall, these results suggest that the sudden leave of a loan officer has a significant impact on credit access and the loyalty of clients. The sickness leave can be interpreted as a quasi-baseline, since loan officers do not have a chance to transfer information to their replacement due to exogenous circumstances.

In comparison, the clients of loan officers who are on pregnancy leave show a similar decline in their likelihood to get a loan. However, the decline seems predominantly driven by a drop in the application rate during the loan officer's absence, not a reduction in approval. At the same time, these clients show no propensity of going to a bank outside of the current relationship. We find that one of the reasons for this outcome is that borrowers are more likely to take out a loan in the month before their loan officer goes on pregnancy leave. While this effect is observable for pregnancy leaves, it is not seen in other types of absentee spells. It appears that pregnant loan officers prepare for their absence by setting their clients up with a loan before they leave, possibly because they anticipate that the soft part of the information is difficult to transfer, and that a close relationship between the replacement loan officer and the borrowers is difficult to achieve in the short term. Moreover, during the pregnancy leave, clients show an increased propensity to be late on their loans and even default, which might underscore that these clients feel less loyalty to the interim loan officer.

In contrast, in the case of retiring loan officers (who usually retire because they have received an outside offer), conditions should be optimal to transfer information since there is enough lead time and the departing loan officer has no incentives to withhold information from the successor.[5] Interestingly, in this case we barely see a drop in the access to credit. Furthermore, these clients do not show a propensity to approach an outside bank, which underscores that their access to finance does not change much. While the likelihood of the clients missing one month of payments also increases when their loan officer is hired away, the likelihood

[5]Anecdotal evidence suggests that the incentives to transfer information are mostly explained by career concerns. Indeed, the job market of loan officers is specialized; they get a 6 month formal training plus important training in the field. The market is also small and people from different banks know each other. Therefore, when loan officers switch banks, they want to keep their reputation in the industry, which maximizes their future outside opportunities. In particular they do not want to be perceived as unloyal by stealing clients, or as poor performers if their old portfolio defaults just after they leave the bank.

of outright defaulting on a loan does not increase. This could be a sign of transitory adjustment costs rather than a situation where the portfolio is permanently deteriorating when the previous loan officer leaves.

Finally, for the portfolio of loan officers who are dismissed, we see a much stronger drop in the probability of getting a new loan compared to all other spells of absence, which is equally driven by a reduction in approval rates as well as application rates. There is also a significant increase in the probability that clients fall late on their loans and default. In fact, in the month that precedes the dismissal, we already see an increase in default. It appears that the dismissed loan officers made bad loans and, therefore, these clients do not get credit after the turnover. The new incoming loan officer has incentives to report poorly performing borrowers to start with a clean slate of clients. For a similar argument see Hertzberg, Liberti, and Paravisini (2010).

As a final step, we investigate whether the magnitude of the credit contraction varies with the characteristics of the borrowers. If relationship lending is less important in situations with more reliable hard information, we should see a smaller effect for these firms when the original loan officer leaves. We find interesting heterogeneity depending on the type of leave. For loan officers who are out due to sickness and thus did not have time to transmit any soft information to their replacement, we see a sharp decline in credit to small and low credit score clients. This reduction is even stronger for female clients since they usually have fewer assets and thus rely more on soft information lending. On the other hand there is almost no reduction in the access to credit for large borrowers and those that have high credit scores (who are usually seen as less opaque borrowers). For the portfolio of pregnant loan officers, we find qualitatively similar, but quantitatively weaker, heterogeneous treatment effects.

In contrast, the heterogeneous treatment effects on access to credit are not present for the portfolios of loan officers who either resign or are dismissed. For resigning loan officers, we see no differentiation based on observable information. Interestingly, even for the borrowers with the worst observable characteristics, we do not observe an important reduction in credit. Specifically, the credit reduction is not statistically significant, and the magnitude is more than three times smaller than the credit contraction observed during other types of leaves. This might indicate that resigning officers are able to successfully brief their replacements about the soft (and hard) information of their clients. Lastly, for clients of dismissed loan officers, we see a drastic decline in access to finance for all types of borrowers independent of observable characteristics.

Taken together, these results suggest that in situations where a loan officer lacks the time or the incentives to transmit his knowledge to his replacement (e.g. in the case of an illness, or in the case of a dismissal), the soft information disclosed by the borrower to his original loan officer is lost. As a result, access to credit for the existing clients is reduced, the credit quality of the portfolio suffers, and borrowers turn to other banks for loans. However, when given enough lead time (e.g. in the case of resignations), loan officers seem to be able to transfer information minimizing the impact on the bank and the borrowers.

2 Relationship to Prior Literature

Our paper contributes to the literature on the relevance of social relationships in information transmission. This literature highlights how personal ties facilitate information flow between and within companies (Haunschild and Beckman 1998, Hansen 1999, Argote, McEvily, and Reagans 2003, Levin and Cross 2004). Social relationships have also been documented to play a crucial role in the banking industry (Uzzi 1999, Uzzi and Lancaster 2003), and in particular in the collection of information about borrowers. For example in Uzzi and Lancaster (2003), the authors interview a sample of loan officers in Chicago, and describe how social relationships influence the type of information that borrowers are willing to disclose. They find that only embedded ties facilitate the transfer of private information which is consistent with our findings.

Our paper also contributes to the literature on relationship lending and the role of soft information in the credit process. A number of recent papers compare the effect of individualized credit evaluation via loan officers versus rule based credit scoring based on hard information. For example, Qian, Strahan, and Yang (2011) study the reform of a Chinese bank that led to a delegation of credit risk assessment to the individual loan officer. The authors find that, as a result, the predictability and performance of credit rating metrics improve. Berg, Puri, and Rocholl (2012) study a bank where loan decisions are based solely on hard information input by loan officers into a scoring system. They find that loan officers' discretion even plays a role in hard information lending, since loan officers can make a judgment on the data they collect. The authors show that loan officers use more scoring trials for loan applications that do not pass the cut-off rating in the first trial. Consequently, the number of trials positively predicts future default rates. Paravisini and Schoar (2012) find that providing loan officers with hard information based on credit scoring increases the efficiency of their decision making. The specific channel they identify is that hard information leads to more accountability and, therefore, increased incentives. On the other hand, Banerjee, Cole, and Duflo (2009) point out that one of the dangers of relationship lending is that loan officers can hide bad firm performance and evergreen loans until they are too late to save.

A related strand of the literature looks at the importance of distance to the bank as a measure of how much a bank can rely on soft information. For example, Berger, Miller, Petersen, Rajan, and Stein (2005) find that larger banks lend to more distant clients compared to smaller banks, but are more likely to use credit scoring based on "hard information" tools. However, they do not find that the net access to credit is lower for firms that borrow from either of these types of lenders. Similarly, Agarwal and Hauswald (2010) find that borrowers that are closer to a bank get larger amounts, but also more expensive credit from the bank. And in turn, more distant borrowers get less credit from the bank, but the credit is cheaper. Mian (2006) finds that geographical and cultural distance reduce the ability of the banks to rely on soft information, to renegotiate, and to recover defaulted loans As a consequence, banks reduce credit to distant opaque firms. Our findings are complementary to this work since we focus on the impact of individual loan officers within a relationship lending process, rather than the difference between one credit regime and another.

Finally, two studies that examine the impact of loan officer turnovers are Hertzberg, Liberti, and Paravisini (2010) and Fisman, Paravisini, and Vig (2012). The first paper shows that after a turnover, the new loan officer has an incentive to reveal the poorly performing loans of the prior loan officer in order to start with a clean slate. The second paper analyzes the role of social and ethnic ties for the credit screening of a loan officer. The authors find that loan officers find it easier to assess the credit quality of people with whom they share a similar ethnic and religious background. In comparison, we focus on the opposite side of the turnover; by focusing on the departing loan officer, we can analyze the distortions in access to credit for the existing portfolio when client relationships are interrupted. It also allows us to analyze whether information is transferrable between loan officers. In comparison, the above papers analyze the impact of an arriving loan officer on the selection choices that they make.

3 The Setting

We analyze the credit characteristics and repayment behavior of small businesses that take loans from a large bank in Chile, BancoEstado. We obtain loan information for all of the clients that have taken loans from the micro-credit division of the bank. Only clients with yearly sales below US$ 110,000 can borrow from the micro-credit division; clients exceeding this limit must borrow through the regular lending process of the bank. The micro-credit division of the bank has 210,000 clients, of which 187,000 were borrowers (had non-zero debt) at some point during the period of this study, 2006-2008. The micro-credit division operates independently of the rest of the bank and has its own loan products, credit assessment technology, and branch personnel.

The bank has three zones: the North of Chile, the metropolitan area of Santiago, and the South of Chile. The metropolitan area consists of the capital city, Santiago, and the counties surrounding it. North of Chile consists of the counties located north of Santiago, and South of Chile consists of the rest of the counties located south of Santiago. Each zone is divided into “módulos,” a geographical subdivision that can contain one or more cities or rural counties depending on client density. There are 22 “módulos.” Each “módulo” has several branches, although not all branches offer micro-credit services.

Clients can freely choose which branch they go to, but usually select the branch that is closest to their business. In addition, clients rarely switch branches unless they relocate their home and/or business. However, some clients prefer to go to a bigger branch, even if it is located further away from their home or business. Once the client has chosen his or her branch, the allocation of new clients to loan officers works as follows: the new clients go to the branch and are allocated to the first available loan officer. This allocation of new clients to loan officers is random within branches. However, once a client has been assigned to a loan officer, they usually stay with this person for the duration of their time as a client of the bank.

Loan officer distribute their time between meeting clients, processing loan documents at the office, and conducting field work. The field work consists of visiting the businesses of clients who are applying for a loan and clients who are delinquent on their payments. Loan officers often also give financial advice or investment advice to their clients. They are even consulted by their clients about when to get a loan or how large of a loan to ask for. Loan officers are also important in the credit assessment of their clients.

The decision to extend a new loan to a client depends on two variables: the payment capacity, and the risk category of the client. The loan officer estimates the payment capacity (per month free cash flows) based on the client's business cash flows, household expenses, and nonbusiness-related income. A central risk department estimates the risk category. This category depends on demographical characteristics of the client, payment history with the bank, payment history with other banks, and the default history with formal companies in Chile. Together these two dimensions determine the size of the loan and the interest rate at offering.

Most loans are issued at the personal level and therefore, there is no limited liability. Nonetheless, seizing the personal assets of a micro-credit borrower in Chile is extremely costly and sometimes not possible. Specifically, litigation costs for this type of claim are high compared to the expected recovery. Furthermore, for this type of claim, the law system is slow and there are loopholes allowing a defaulting borrower to hide or sell valuable assets before the bank can seize them. However, defaulting on a loan is still costly for the client. A delinquent client is reported to the credit bureau, thus severely affecting the client's future ability to access the formal loan market.

Furthermore, it is important to understand the incentives for the loan officers. Loan officers have a base salary and a performance bonus that can be up to 20% of their base salary. The performance bonus depends on the volume of new loans and the default rate of the portfolio. The base salary ranges between US$ 1,000 and US$2,500 depending on the seniority of the loan officer. Anecdotal information obtained from the managers and loan officers suggests that a 20% variable bonus generates strong performance incentives. This ensures that it is in a loan officer's best interest to invest effort in the collection of soft information and use it for credit assessment. However, it might also prevent a new loan officer from blindly lending to people whose overall credit risk they cannot assess.

4 Data and Empirical Strategy

4.1 The Data

Using data from the internal records of the micro-credit division of the bank, we construct a monthly panel of all the loans that are sanctioned in a given month and the repayment history of those loans. This information is extracted directly from the bank's internal management information system and contains information on loan size, interest rate, maturity, whether there is a grace period, credit score, repayment data, and total credit amount in the formal financial market. The repayment information is divided according to the time elapsed since the payment became delinquent; these comprise delinquent payments less than 31 days old, delinquent payments between 31 and 90 days old, and delinquent payments of more than 90 days old.[6] Based on the bank records, we reconstruct the length of the relationship between the loan officer and the client that is defined as the number of months the client and the loan officer have been working together.

The panel is merged with a second database that comes from the human resources department of the

[6] In the paper we consider that a client is in default if he or she has delinquent payments of more than 90 days.

bank itself. This database contains information on temporary and permanent loan officers' leaves, including sick leaves, pregnancy leaves, layoffs, and resignations. It also contains the loan officers' starting dates as well as other demographic variables about the loan officers such as age, gender, and marital status.

The panel covers three years (2006-2008) and comprises monthly observations from 187,000 clients and 480 loan officers. In the estimations, we only include loan officers that have at least 50 active clients in their portfolio, where active clients are defined as clients having at least $10,000 Chilean pesos in debt (approximately US$ 20).

In Table 1, we present the characteristics of the loan officers and their absences. We observe that 49% of the loan officers are men, 58% are married, and their average age and years of experience at the bank is 32.6 and 3.7, respectively. The average number of clients per loan officer is 569 of which 339 are classified as active meaning they have more than US$ 20 in outstanding loans. A loan officer is considered absent if during a month he or she worked less than two weeks. We have 32 loan officers that had sick leaves, and a total of 43 sick leave episodes.[7] The average length of each sick leave is 2.12 months with a standard deviation of 1.18. We have 33 loan officers that had pregnancy leaves and 34 pregnancy leaves; the average length of a pregnancy leave is 4.64 months with a standard deviation of 1.12. It is important to mention that, by law, maternal leaves in Chile were 4.5 months long at the time of the study. We also have 26 loan officers who were dismissed and 15 loan officers that voluntarily resigned. We have anecdotal evidence that most of the people who quit their jobs received offers from other banks.

In Table 2, we present the characteristics of the clients at the beginning of the sample period. We present separately the characteristics of the clients from loan officers that are never absent during the sample period and the characteristics of the clients from loan officers who have absentee episodes during the sample period. In the last column, we present the t-test for the differences in characteristics between the two groups. We note that none of the differences are significant which supports our view that the findings in the paper are

[7] Some loan officers were sick more than once during the study period. However, in the calculations we only consider the first leave as the subsequent leaves might be anticipated relapses of the first one.

not driven by ex-ante self selection. We observe that at any given month, the probability that a client gets a new loan from BancoEstado is 5.98%, and the probability that a client gets a loan outside BancoEstado is 16.92%. While the probability to get a loan outside BancoEstado is much higher, the size of the loans obtained from outside banks is significantly smaller. Loans' average monthly interest rate is 1.65% and average maturity is 24.67 months. The probability that a client misses a payment at any given month is 4.04% and the probability that a client defaults (conditional on being already delinquent for more than 60 days) is 33.26%.

4.2 Empirical Strategy

To estimate the effect of loan officer turnover on a client's credit availability and repayment behavior, we estimate a panel regression at the client level. We include a dummy variable that takes the value of one when the loan officer is absent and zero otherwise. Each panel regression includes time and client fixed effects, and it controls for the loan time to maturity and the characteristics of the loan officer.[8] To avoid biasing the comparison group, we exclude from the estimations the clients that have experienced a loan officer leave which is different from the leave being estimated. For example, if we estimate the effect of a pregnancy leave, we exclude clients who have had their loan officer leave due to sickness, dismissal, or voluntary resignation. This leads to the following specification:

$$Y_{it} = C + \beta_{leave} leave_{it} + \Sigma\beta_l Control_{l\,jt} + \mu_t + \eta_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the dependent variable for client i at time t. The $leave_{it}$ is a dummy variable that takes the value of 1 if the loan officer of client i is absent at time t, and zero otherwise. The $Control_{l\,jt}$ are control variables for loan officer j (the loan officer of client i) at time t, μ_t captures time fixed effects, η_i captures client's

[8]To control for time to maturity, we divide the loan cycle into ten intervals, one being a newly issued loan and ten being a loan that is close to expiration. We then create a dummy for each interval. This approach addresses nonlinear effects between maturity and the dependent variables.

fixed effects. Time is measured in months. Standard errors are clustered at the loan officer-level.

We also estimate how the effect of loan officer turnover changes with the characteristics of the clients that proxy for the relevance of soft information. In particular, we estimate the interaction effects between the variable *leave* and: i) the loan size of the client, ii) the credit score of the client, and iii) the gender of the client. This estimation leads to the following specification:

$$\begin{aligned} Y_{it} = C + \beta_{leave} leave_{it} + \Sigma\beta_{leave \times var_k} leave_{it} \times var_{kit} + \\ \Sigma\alpha_k var_{kit} + \Sigma\beta_l Control_{l\,jt} + \mu_t + \eta_i + \varepsilon_{it}, \end{aligned} \quad (2)$$

where all the terms are similar to equation 1, and var_{kit} is the variable that is interacted with the leave dummy: size, score, and gender for client i at time t.

5 Results

5.1 Aggregated Effect of Loan Officer Turnover

In Table 3, we present results from an aggregate specification across all types of leaves (i.e., *absent* takes the value of one if the loan officer is sick, pregnant, is dismissed, or resigns). In the first column of Table 3, we observe that loan officer absence generates a reduction of 1.18% in the probability that the client gets a new loan from the bank, which represents a 19.73% reduction as a fraction of the unconditional probability of getting a loan from the bank. In columns (2) and (3), we observe that the reduction in the probability of getting a new loan is explained by both a reduction in the application rate for new loans and a reduction in the approval rate per application. In particular, the application rate for new loans decreases by 0.91%, which represents a 13.34% decrease as a fraction of the unconditional probability of applying for a new loan. Lastly, the approval rate decreases by 5.05%, which represents a 5.76% decrease as a fraction of the unconditional approval rate. In column (5), we observe that loan-officer absence increases by 0.87% the probability that a client who is up to date with his or her payments will miss a payment, which represents a 21.53% increase as a fraction of the unconditional probability of missing a payment. And in column (6), we show that for clients that have been delinquent for more than 60 days, loan officer absentees increase by 6.09% the probability that he or she will default, which represents a 18.31% increase as a fraction of the unconditional probability of default. In columns (7) and (8), we observe that loan-officer turnover does not have a significant effect on interest rates or the maturities of newly issued loans. Finally, columns (9) and (10) show that loan officer turnover does not have a significant effect on the average loan size with BancoEstado. However, loans issued by other banks are larger on average.

5.2 Differences Across Types of Leaves

The analysis in Table 4 is similar to the analysis in Table 3 but breaks out the different types of absences separately. The first panel of this table shows the results for sickness leaves. The sequence of dependent variables follows exactly the same set up as Table 3. In columns (1) through (3), we see that the probability that the client gets a new loan from the bank drops by 1.19% when the loan officer is sick. The change in the likelihood of getting a new loan can be decomposed into two separate pieces: a change in the application rate of the client and a change in the approval probability. The application rate decreases significantly by 0.95% when the loan officer is sick. The approval probability is reduced by 3.48% but is not significant. As a result, it seems that clients whose loan officers are sick are 2.15% more likely to borrow outside of the bank. Finally, the probability that a client who is not delinquent will miss a payment increases by 0.95%. The probability of default is unaffected, however.

In comparison, clients whose loan officer goes on pregnancy leave see a 1.03% drop in their access to credit, which is mainly driven by a 0.94% reduction in applications for loans. Delinquencies go up by 0.76% when the loan officer is on pregnancy leave, and the likelihood of defaulting conditional on having already been delinquent for more than 60 days goes up by 8.54%. However, the likelihood of taking up a loan from another bank does not increase significantly.

When looking at layoffs, we see a much larger reduction, approximately 1.77%, in the likelihood of getting a new loan from BancoEstado. A large fraction of this drop is explained by a reduction in approval rates of 7.36%. However, at the same time, these clients do not see a significant increase in outside credit which might suggest that they are not perceived as acceptable credit risks by other lenders. Clients of dismissed loan officers also have a rise in the late payment rate of 0.92% and a 12.28% increase in default for clients who have been delinquent for more than 60 days.

Finally, clients of loan officers who voluntarily resign see a minimal change in the likelihood of obtaining credit from the bank. These borrowers also see no change in the probability of getting outside credit, which might be simply a function of not being constrained at all through the transition. There is however, an increase of 1.16% in 30 day late payments when the loan officer resigns. The default rate for these clients does not increase.

5.3 Are Loan Officer Absences Planned?

In Tables 5 to 6, we study how access to credit and repayment behavior change in the month that precedes the leave, where we break out the analysis for each type of leave separately. We are concerned that banks can plan the absence and issue more credit before the loan officer leaves. Additionally, clients might apply for a new loan just before the loan officer leaves if they anticipate being credit constrained by the substitute loan officer.

For sick leaves and resignations, we do not observe a change in the probability of getting a new loan in the month that precedes the leave. We also do not observe clients applying for new loans more intensively just before the loan officer leaves. This is reassuring for our hypothesis that these types of absences are not planned in advance.

A different story emerges for maternity leaves. In the month that precedes the leave, there is a significant increase in the application rate for new loans with BancoEstado and a reduction in the probability of taking a loan from another bank. This confirms that, in particular, pregnancies are planned leaves and loan officers seem to provide their clients with sufficient access to finance in anticipation of the time that they are going to be out of the office.

For clients of dismissed loan officers, we observe an economically large reduction in the probability of getting a new loan in the month before the leave. While this result is not statistically significant, it might still be an indication that the bank limits credit to borrowers of poor performing loan officers even before dismissing them.

5.4 Interactions With Client Characteristics

In Tables 7 and 8 we look at heterogeneous treatment effects for borrowers with larger loans and borrowers with higher credit scores. The idea is that these are observable characteristics we could obtain from the bank and that are usually associated with less opaque credit risk assessment. We also look at heterogeneous treatment effects for female borrowers, since they usually have fewer assets and thus rely more on soft information lending. As before, we break out the analysis by type of leave.

Within the portfolio of loan officers who are on a sick leave, we see very strong heterogeneous treatment effects. The negative effects of sickness leaves on access to credit and repayments are particularly strong for small, low credit score, and female borrowers. In contrast, the interaction terms of the absence dummy with the client characteristics show that the effects are much more muted for larger and high credit score borrowers. More specifically, the effect is reduced by more than half for these sets of borrowers. For example, the direct effect of *leave* on the probability of getting a new loan is negative 2.38% and the interaction term of the *leave* dummy with the firm size dummy is positive 1.38% and highly significant. Similarly, looking at whether clients access outside loans, we see that the direct effect of *leave* on the smaller and lower credit score borrowers increases by 5.7%, which represents an increase of 33.69% as a fraction of the unconditional probability of borrowing outside of the bank. This effect is even more pronounced for clients with a good credit score. They experience a 7.04% increase in the probability of borrowing outside of the bank, which represents a 41.61% increase as a fraction of the unconditional probability. On the other hand, large clients do not experience an increase in the probability of borrowing outside of the bank. The interaction with the firm size dummy is negative and equal in magnitude to the direct effect (the coefficient is 6.07% and significant at the 1% level), which suggests that these large borrowers are not constrained in their access to finance and thus do not need to borrow outside. Finally, columns (5) and (6) of Table 7 show that the late payment rate and default rate vary significantly for borrowers with larger loans and higher credit scores.

In the second panel of Table 7 we look at the impact of pregnancy leaves on different client types. The results are weaker than for sick leave but go in a similar direction. Loan renewals are less negatively affected for larger borrowers and those with better credit scores. As a result, large clients seem to be less likely to seek a loan from an outside bank. As before, we see in this case that delinquency rates and default rates do not increase for good credit score borrowers. While large borrowers still have an increased probability of missing payments, they are not likely to default more often when their loan officer is absent.

Interestingly, when looking at the credit constraints for clients of dismissed loan officers (in the first panel of Table 8) we find very limited differentiation by borrower characteristics. As before, we see that access to finance for clients drops significantly for these clients, but there is no differential effect in obtaining a loan for borrowers that are larger or have better credit scores. In column (2), we do see that large firms are more likely to apply for a loan than small firms; however, the rejection rate is similar. In addition, these larger firms are less likely to receive a loan from other banks outside of BancoEstado. It might be another indication that in the case of dismissed loan officers, clients were receiving too much leverage previously, and once a new loan officer comes in, the portfolio is consolidated to a reasonable risk level.

Finally in Panel 2 of Table 8, we do not see heterogeneous treatment effects for the access to credit of borrowers from loan officers who resign. Neither their ability to get a new loan from the bank nor the likelihood of accessing outside loans changes. This result confirms the idea that in the case of resignations, loan officers are able to pass on information about all borrowers to their replacement. As a result, even borrowers with bad observable characteristics do not suffer an important reduction in their access to finance.

6 Discussion and Conclusion

In this paper, we show that the sudden leave of a loan officer leads to a significant reduction in the likelihood that his clients receive a new loan from the bank. This decrease is the result of a drop in the probability that the borrowers apply for a new loan and a reduction in the likelihood that the bank approves the applications. These results suggest that the leave of the loan officer reduces the availability of soft information, making it difficult to asses the creditworthiness of the clients, but also reduces the loyalty of the clients who seem less likely to approach the bank for credit. The reduction in loyalty also seems to make clients more prone to fall behind on their payments with the original bank and apply for credit at other banks.

We expect the magnitude of these effects to depend on the extent to which soft information can be transmitted within the bank (i.e. passed from one loan officer to the other). In line with this interpretation, the observed outcomes strongly depend on the type of leave. We see that the negative effects are strongest in the cases of unplanned leaves such as sickness. Here, the outgoing loan officer usually does not have time to transfer any soft information to the replacement since we focus on serious and unexpected illnesses. As a result, the existing clients see a strong drop in their likelihood of receiving new loans and instead borrow from outside sources. They also show an increased probability of becoming delinquent on their loans. We also find evidence suggesting that in these cases, hard information (observable borrower characteristics such as size, gender or credit score) becomes more important in the credit decision, which is consistent with soft information being less available.

We find a much weaker effect in the case of anticipated leaves, which can be planned for in advance, such as resignations. These are cases where the loan officer is hired away but usually has enough time to brief the successor loan officer about the soft information aspects of the clients before he leaves. Consequently, we find minimal disruption in the lending relationship. Pregnancy related absences are somewhere in the middle: while the loan officer has a long lead time in which she could prepare the replacement officer, she can also reduce the costs for the borrowers by providing them with loans *prior* to leaving for maternity leave, which is what we find in the data. Finally, in the case of dismissals, we see a strong drop in credit access and a spike in defaults. We think that this is not only driven by differences in soft information but also by an effort of the bank to reduce its exposure to the portfolio of high risk clients that the dismissed loan officer had built up.

The results highlight that in an environment wherein employees have difficult to transfer tacit knowledge (for example soft information about their clients), managing employee turnover becomes centrally important for the performance of the firm. Loan officers who leave, not only need to have the time to communicate their tacit knowledge to a colleague, but our results also underscore that the employees need to have the *incentives* to transfer this knowledge. Therefore, transition processes should be set up to facilitate and encourage this transfer. The firm might want to set incentives for employees to train their replacement and transmit any soft information to the new person. In situations where the departing employee does not have the incentives to help in the transfer of knowledge, the firm might need to develop backup systems to reduce the dependence on individual employees.

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Tables

Table 1: The Summary Statistics for Loan Officers

In this table, we present the summary statistics for the loan officers and the different sources of turnover. The gender variable takes the value of one for men and zero for female. The married variable takes the value of one for married loan officers and zero for single loan officers. The city variable takes the value of one for loan officers working in urban areas and zero for loan officers working in rural areas.

	Loan-Officer Characteristics			
	N	mean	sd	median
Gender %	370	49	50	
Age	370	32.6	4.7	31.8
Married %	370	58	49	
Number of children	370	0.77	0.9	1
Years of experience	370	3.7	2.6	3.2
City %	293	64	48	
Number of clients	480	339	112	341
	Absentee Episodes			
	number of officers that were absent	number of episodes	average length (in months)	sd length
Sick leave	32	43	2.12	1.18
Pregnancy	33	34	4.64	1.12
Layoff	26	26		
Resignation	15	15		

Table 2: The Summary Statistics for Clients

In this table, we present the characteristics of the borrowers at the beginning of the sample period. The probability of missing one payment is estimated for clients without late payments, and the probability of default is estimated for clients who have been delinquent on their loans for more than two months. The interest rate is expressed in percentages per month and is denominated in nominal currency, and maturity is expressed in months. Probabilities are expressed in percentages.

	clients from non absent loan officers	clients from absent loan officers	difference (s.e. difference)
Renewal probability	5.98	6.08	-0.10
			(0.33)
Application probability	6.82	7.04	-0.22
			(0.35)
Approval probability	87.66	86.40	1.26
			(1.71)
Probability new outside loan	16.92	16.45	0.464
			(0.38)
Log loan size	14.28	14.38	-0.10
			(0.07)
Log loan outside bank	12.48	12.48	0.00
			(0.06)
Interest rate	1.65	1.64	0.02
			(0.02)
Maturity	24.67	25.66	-0.99
			(0.92)
Delinquent 1^{st} month	4.04	4.08	-0.04
			(0.28)
Default rate conditional on being	33.26	35.19	-1.93
already delinquent for more than 60 days			(4.82)

Table 3: The Effect of Turnover on Credit Availability, Credit Characteristics, and Repayment Behavior

We present the effect of all the sources of turnover. Each column represents one regression, and the columns are organized as follows: i) renewal probability, ii) application probability, iii) approval probability, iv) probability of getting credit from other banks, v) probability of missing one payment, vi) probability of default for clients who have been delinquent on their loans for more than 60 days, vii) monthly nominal interest rate, viii) maturity, ix) log loan size at the bank, and x) log loan size outside the bank. Estimations in columns vii to ix are restricted to clients that get a new loan at the bank, and estimation in column x is restricted to clients that get a new loan outside the bank. All the estimations are controlled for time to maturity, client fixed effects, and time fixed effects. Probabilities are expressed in percentages. Standard errors in parentheses are clustered at the loan officer level.

	(1) renewal prob.	(2) applic. prob.	(3) approval prob.	(4) outside loan	(5) delinquent 1^{st} month	(6) default	(7) interest rate	(8) maturity	(9) loan size	(10) out loan size
Leave	-1.18***	-0.91***	-5.05***	0.25	0.87***	6.09**	0.02	0.35	0.03	0.08**
	(0.21)	(0.23)	(1.51)	(0.40)	(0.18)	(3.08)	(0.02)	(0.62)	(0.03)	(0.04)
L.o. experience	-0.00	-0.01**	0.09***	0.00	-0.01**	-0.03	0.00**	-0.00	-0.00	-0.00***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.06)	(0.00)	(0.01)	(0.00)	(0.00)
L.o. gender	-0.14	-0.08	-0.64	0.14	0.09	0.08	0.02**	0.04	0.00	-0.02
	(0.10)	(0.12)	(0.67)	(0.12)	(0.11)	(1.21)	(0.01)	(0.23)	(0.01)	(0.02)
Rel. length	0.01*	0.01	0.02	0.00	0.05***	0.25***	-0.00	0.03*	0.00***	0.01***
	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.08)	(0.00)	(0.02)	(0.00)	(0.00)
N	2471578	2471578	191774	2471578	2217262	216418	135545	135545	135545	403459
Adj-r^2	0.081	0.084	0.090	0.200	0.185	0.325	0.668	0.401	0.812	0.655

Table 4: The Effect of Sickness Leaves, Pregnancy Leaves, Terminations, and Resignations on Credit Availability, Credit Characteristics, and Repayment Behavior

We present the effect of different sources of turnover. Each column represents one regression, and the columns are organized as follows: i) renewal probability, ii) application probability, iii) approval probability, iv) probability of getting credit from other banks, v) probability of missing one payment, vi) probability of default for clients who have been delinquent on their loans for more than 60 days, vii) monthly nominal interest rate, viii) maturity, ix) log loan size at the bank, and x) log loan size outside the bank. Estimations in columns vii to ix are restricted to clients that get a new loan at the bank, and estimation in column x is restricted to clients that get a new loan outside the bank. All the estimations are controlled for time to maturity, client fixed effects, and time fixed effects. Probabilities are expressed in percentages. Standard errors in parentheses are clustered at the loan officer level.

	(1) renewal prob.	(2) applic. prob.	(3) approval prob.	(4) outside loan	(5) delinquent 1^{st} month	(6) default	(7) interest rate	(8) maturity	(9) loan size	(10) out loan size
Sick	-1.19***	-0.95**	-3.48	2.15**	0.95***	-1.18	-0.00	0.53	0.06	0.08
	(0.38)	(0.37)	(2.67)	(0.94)	(0.28)	(5.52)	(0.03)	(1.02)	(0.05)	(0.06)
Pregnancy	-1.03***	-0.94**	-1.72	0.21	0.76**	8.54**	0.03	0.53	0.02	0.11
	(0.34)	(0.43)	(2.39)	(0.32)	(0.34)	(3.80)	(0.04)	(1.18)	(0.05)	(0.07)
Dismissed	-1.77***	-1.23***	-7.36***	-1.13	0.92**	12.28***	0.05	0.25	0.04	0.00
	(0.40)	(0.46)	(2.78)	(0.82)	(0.38)	(4.27)	(0.04)	(0.94)	(0.05)	(0.03)
Resigned	-0.67*	-0.62	-4.22	-0.30	1.16***	-2.75	0.02	-0.06	0.02	0.15
	(0.41)	(0.39)	(2.95)	(0.90)	(0.35)	(6.57)	(0.05)	(1.65)	(0.05)	(0.11)

Table 5: The Effect of Sickness, and Pregnancy Absentees in the Month that Precedes the Leave, and in the Month that Follows the Leave

We present the effect of sickness, and pregnancy absentees on the credit characteristics and credit behavior of the borrowers. The effects are presented for the month after the absence, for the months of absence and for the month prior to the absence. Each column represents one regression, and the columns are organized as follows: i) renewal probability, ii) application probability, iii) approval probability, iv) probability of getting credit from other banks, v) probability of missing one payment, vi) probability of default for clients who have been delinquent on their loans for more than 60 days, vii) monthly nominal interest rate, viii) maturity, ix) log loan size at the bank, and x) log loan size outside the bank. Estimations in columns vii to ix are restricted to clients that get a new loan at the bank, and estimation in column x is restricted to clients that get a new loan outside the bank. All the estimations are controlled for time to maturity, client fixed effects, and time fixed effects. Probabilities are expressed in percentages. Standard errors in parentheses are clustered at the loan officer level.

	(1) renewal prob.	(2) applic. prob.	(3) approval prob.	(4) outside loan	(5) delinquent 1^{st} month	(6) default	(7) interest rate	(8) maturity	(9) loan size	(10) out loan size
	sick									
Leave	-1.16***	-0.91**	-4.93*	2.17**	0.90***	-5.72	-0.00	0.54	0.06	0.05
	(0.43)	(0.43)	(2.68)	(0.92)	(0.28)	(4.85)	(0.03)	(1.08)	(0.05)	(0.07)
Lead1	-0.22	0.10	-3.99	0.79	0.41	-2.34	-0.01	1.29	-0.01	0.07
	(0.56)	(0.58)	(3.82)	(1.32)	(0.35)	(4.77)	(0.06)	(1.47)	(0.07)	(0.13)
Lag1	-0.33	-0.36	0.76	1.55*	1.06**	4.95	0.09*	-0.37	0.11	0.08
	(0.56)	(0.56)	(4.82)	(0.81)	(0.45)	(4.50)	(0.05)	(1.69)	(0.08)	(0.05)
	pregnancy									
Leave	-0.85**	-0.67	-2.86	-0.32	0.73**	7.07	0.05	-0.00	0.01	0.08
	(0.36)	(0.43)	(2.45)	(0.43)	(0.36)	(4.79)	(0.04)	(1.13)	(0.04)	(0.07)
Lead1	0.58	0.84*	-2.82	-3.07**	0.31	9.35	0.06	1.50	0.07	0.03
	(0.40)	(0.47)	(4.09)	(1.53)	(0.44)	(6.31)	(0.04)	(2.23)	(0.06)	(0.09)
Lag1	-0.72	-0.36	-3.29	-1.05	1.14**	20.92***	0.04	1.35	0.10	0.07
	(0.54)	(0.65)	(3.62)	(0.86)	(0.48)	(6.19)	(0.07)	(1.36)	(0.07)	(0.08)

Table 6: The Effect of Terminations and Resignations in the Month that Precedes the Leave.

We present the effect of termination and resignation on the credit characteristics and credit behavior of the borrowers. The effects are presented for the months of the absence, and for the month prior to the absence. Each column represents one regression, and the columns are organized as follows: i) renewal probability, ii) application probability, iii) approval probability, iv) probability of getting credit from other banks, v) probability of missing one payment, vi) probability of default for clients who have been delinquent on their loans for more than 60 days, vii) monthly nominal interest rate, viii) maturity, ix) log loan size at the bank, and x) log loan size outside the bank. Estimations in columns vii to ix are restricted to clients that get a new loan at the bank, and estimation in column x is restricted to clients that get a new loan outside the bank. All the estimations are controlled for time to maturity, client fixed effects, and time fixed effects. Probabilities are expressed in percentages. Standard errors in parentheses are clustered at the loan officer level.

	(1) renewal prob.	(2) applic. prob.	(3) approval prob.	(4) outside loan	(5) delinquent 1^{st} month	(6) default	(7) interest rate	(8) maturity	(9) loan size	(10) out loan size
	dismissal									
Leave	-1.87***	-1.25***	-7.71***	-1.21	1.02**	14.35***	0.05	0.32	0.04	0.06
	(0.40)	(0.47)	(2.91)	(0.77)	(0.43)	(4.98)	(0.04)	(0.91)	(0.06)	(0.04)
Lead1	-0.24	0.29	-4.33	-2.59	0.23	6.75	0.00	1.08	0.08	0.29*
	(0.58)	(0.61)	(3.70)	(1.70)	(0.32)	(5.43)	(0.04)	(1.61)	(0.08)	(0.15)
	resignation									
Leave	-0.92*	-0.73	-4.56	-0.52	1.18***	-6.53	0.03	-0.13	0.02	0.20
	(0.49)	(0.46)	(3.33)	(0.83)	(0.42)	(6.50)	(0.06)	(1.89)	(0.06)	(0.12)
Lead1	-1.05	-0.89	4.33	0.29	-0.30	-5.55	0.08	-2.24	0.02	0.25*
	(0.67)	(0.67)	(5.53)	(0.86)	(0.47)	(10.28)	(0.11)	(3.22)	(0.10)	(0.13)

Table 7: The Effect of Sick Leaves, and Pregnancy Leaves Interacted with Client Gender, Client Size, and Credit Score

In this table, we show how the effects of turnover change with different characteristics of the borrower. Each column represents one regression, and the columns are organized as follows: i) renewal probability, ii) application probability, iii) approval probability, iv) probability of getting credit from other banks, v) probability of missing one payment, vi) probability of default for clients who have been delinquent on their loans for more than 60 days, vii) monthly nominal interest rate, viii) maturity, ix) log loan size at the bank, and x) log loan size outside the bank. Estimations in columns vii to ix are restricted to clients that get a new loan at the bank, and estimation in column x is restricted to clients that get a new loan outside the bank. All the estimations present the interaction effects with the borrowers' gender, size, and credit score. All the estimations are controlled for time to maturity, client fixed effects, and time fixed effects. Probabilities are expressed in percentages. Standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	renewal prob.	applic. prob.	approval prob.	outside loan	delinquent 1^{st} month	default	interest rate	maturity	loan size	out loan size
	sick									
Leave	-2.38***	-2.44***	-1.17	5.70***	2.61***	9.55	0.03	1.79	-0.07	-0.02
	(0.61)	(0.55)	(5.79)	(1.68)	(0.80)	(8.96)	(0.07)	(1.76)	(0.12)	(0.08)
LeaveXgender	-0.88*	-1.13**	1.96	-0.32	1.33**	2.51	0.08	-2.46	0.02	-0.04
	(0.49)	(0.48)	(5.56)	(1.02)	(0.65)	(7.05)	(0.10)	(1.77)	(0.09)	(0.06)
LeaveXsize	1.38***	2.04***	-5.75	-6.07***	0.19	-17.20***	-0.09**	0.61	0.23*	0.12
	(0.43)	(0.58)	(4.75)	(2.04)	(0.61)	(6.24)	(0.03)	(1.86)	(0.12)	(0.10)
LeaveXscore	1.52***	1.43***	3.99	1.34*	-5.02***	-2.68	-0.01	-1.77	-0.13*	0.07
	(0.44)	(0.49)	(4.82)	(0.81)	(0.70)	(10.66)	(0.06)	(2.05)	(0.08)	(0.06)
	pregnancy									
Leave	-1.67***	-1.44**	-6.61	0.78	3.09***	8.69*	0.04	0.49	-0.21**	0.11
	(0.54)	(0.63)	(4.29)	(0.65)	(0.70)	(5.11)	(0.08)	(1.71)	(0.10)	(0.12)
LeaveXgender	-0.97**	-1.13**	-3.05	0.21	0.75**	6.33	0.04	0.94	0.05	-0.02
	(0.41)	(0.46)	(3.35)	(0.55)	(0.34)	(7.73)	(0.06)	(1.96)	(0.09)	(0.07)
LeaveXsize	0.94*	0.84	7.33	-1.80**	-0.64	-3.97	-0.05	0.73	0.32***	0.05
	(0.52)	(0.65)	(4.90)	(0.87)	(0.57)	(4.48)	(0.06)	(1.55)	(0.09)	(0.12)
LeaveXscore	0.82*	0.81	0.27	1.49	-4.64***	-8.84	0.06	-2.50*	-0.15**	-0.08
	(0.46)	(0.50)	(4.37)	(1.04)	(0.60)	(14.89)	(0.06)	(1.50)	(0.06)	(0.06)

Table 8: The Effect of Termination, and Resignation Interacted with Client Gender, Client Size, and Credit Score

In this table, we show how the effects of absence change with different characteristics of the borrower. Each column represents one regression, and the columns are organized as follows: i) renewal probability, ii) application probability, iii) approval probability, iv) probability of getting credit from other banks, v) probability of missing one payment, vi) probability of default for clients who have been delinquent on their loans for more than 60 days, vii) monthly nominal interest rate, viii) maturity, ix) log loan size at the bank, and x) log loan size outside the bank. Estimations in columns vii to ix are restricted to clients that get a new loan at the bank, and estimation in column x is restricted to clients that get a new loan outside the bank. All the estimations present the interaction effects with the borrowers' gender, size, and credit score. All the estimations are controlled for time to maturity, client fixed effects, and time fixed effects. Probabilities are expressed in percentages. Standard errors in parentheses are clustered at the loan officer level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	renewal prob.	applic. prob.	approval prob.	outside loan	delinquent 1^{st} month	default	interest rate	maturity	loan size	out loan size
	termination									
Leave	-2.68***	-2.11***	-14.03*	0.50	3.00***	12.36	0.08	-1.38	0.02	0.18*
	(0.51)	(0.46)	(7.32)	(1.29)	(0.87)	(7.81)	(0.09)	(1.71)	(0.09)	(0.10)
LeaveXgender	0.36	0.13	7.24	-1.10	1.35***	15.92**	-0.03	-0.13	-0.03	-0.19***
	(0.46)	(0.72)	(6.56)	(1.33)	(0.39)	(6.62)	(0.08)	(1.72)	(0.06)	(0.05)
LeaveXsize	0.68	1.20***	2.40	-2.17**	-0.57	-8.77	-0.06	1.26	0.08	-0.02
	(0.45)	(0.40)	(6.01)	(0.88)	(0.56)	(8.47)	(0.06)	(1.56)	(0.09)	(0.08)
LeaveXscore	0.64	0.06	3.65	0.67	-4.36***	-0.53	0.07	1.73	-0.07	-0.17**
	(0.57)	(0.56)	(6.08)	(0.89)	(0.71)	(13.10)	(0.08)	(1.76)	(0.09)	(0.07)
	resignation									
Leave	-0.71	-1.29*	6.92	-1.14	3.89***	7.69	-0.01	-0.54	-0.10	0.20
	(0.66)	(0.75)	(7.21)	(1.95)	(0.78)	(7.89)	(0.12)	(2.54)	(0.12)	(0.14)
LeaveXgender	-0.18	0.20	-8.00	-1.47	0.32	-5.13	0.07	1.26	-0.07	-0.09
	(0.70)	(0.70)	(6.55)	(1.20)	(0.48)	(10.99)	(0.07)	(1.33)	(0.10)	(0.10)
LeaveXsize	-0.21	0.33	-8.09	1.28	-1.43**	-17.11*	-0.02	0.50	0.19	0.11
	(0.56)	(0.58)	(7.78)	(2.46)	(0.56)	(9.83)	(0.08)	(1.53)	(0.13)	(0.10)
LeaveXscore	0.55	0.78	-4.12	1.22	-3.89***	12.42	0.04	-1.17	0.01	-0.21
	(0.79)	(0.84)	(4.27)	(1.04)	(0.78)	(30.74)	(0.06)	(3.26)	(0.10)	(0.15)

Appendices

Table 9: Predictive Power of Observable Characteristics of the Client

In this table, we estimate the application probability, the approval probability, and the probability of paying late as a linear function of the observable characteristics about the client. The estimations are presented separately for when the loan officer is absent and for when he is present. We also test if the predictive power of observable characteristics (measured as the r-squared of the estimation) depends on the loan officers' being present or absent (following Cramer (1946) we test the difference in r-squared using the asymptotic distribution $\sqrt{n}[\widetilde{r^2} - r^2] \sim N(0,(1-r^2)^2)$, where $\widetilde{r^2}$ is the estimated r-squared and r^2 is the real r-squared.). All the estimations are controlled for time fixed effect, firm industry, and borrower educational level. We present the standard errors in parentheses. "Leverage bank" is the client's current loan outstanding at the bank divided by his maximum loan outstanding during the sample period. "Leverage out" is the client's current loan outstanding outside the bank divided by his maximum loan outstanding during the sample period. Bounced checks take the value of 1 if the client does not have cash to cover his checks, and zero otherwise.

	application			approval			missed payment		
	absent	present	Δ	absent	present	Δ	absent	present	Δ
Constant	50.69***	60.78***	-10.09	137.02***	89.57***	47.45**	21.38***	25.99***	-4.61
	(5.73)	(4.26)	(7.14)	(18.61)	(9.06)	(20.69)	(4.1)	(2.35)	(4.72)
Gender	-0.41	-0.74***	0.32	-1.26	0.41	-1.67	-0.01	0.24	-0.26
	(0.34)	(0.24)	(0.41)	(1.38)	(0.68)	(1.54)	(0.3)	(0.16)	(0.34)
Marital status	0.26	-0.12	0.38	1.34	-0.65	1.99	0.34	-0.32**	0.66*
	(0.3)	(0.21)	(0.36)	(1.74)	(0.54)	(1.82)	(0.34)	(0.14)	(0.36)
Log age	-0.89	-1.32***	0.43	-1.37	1.84	-3.21	-6.24***	-5.74***	-0.5
	(0.66)	(0.42)	(0.78)	(4.16)	(1.12)	(4.31)	(0.91)	(0.47)	(1.03)
Savings	-0.35	-0.14	-0.21	-1.49	-0.61	-0.88	-0.39	-0.98***	0.59
	(0.34)	(0.16)	(0.37)	(1.64)	(0.64)	(1.76)	(0.33)	(0.14)	(0.36)
Log size	1.07***	1.09***	-0.02	-2.17**	-0.99***	-1.18	-0.09	-0.2**	0.11
	(0.23)	(0.14)	(0.27)	(0.89)	(0.31)	(0.94)	(0.12)	(0.08)	(0.15)
Leverage bank	-46.43***	-43.57***	-2.86	-19.58***	-8.43***	-11.15***	8.23***	4.81***	3.42**
	(3.89)	(2.47)	(4.61)	(3.14)	(1.58)	(3.52)	(1.48)	(0.62)	(1.6)
Leverage out	-0.13	1.25***	-1.37*	2.25	3.25***	-1	2.91***	3.11***	-0.19
	(0.7)	(0.35)	(0.78)	(2.28)	(1.08)	(2.53)	(0.44)	(0.25)	(0.5)
Delinquent 1 months	1.48**	0.57	0.91	-7.59**	-3.96**	-3.64			
	(0.64)	(0.49)	(0.81)	(3.37)	(1.64)	(3.75)			
Delinquent 2 months	-1.59	-3.55***	1.96	5.57	-2.44	8.01			
	(1.74)	(1.09)	(2.06)	(7.25)	(3.76)	(8.17)			
Delinquent 3 months	-11.9***	-13.32***	1.43	-37.63	-7.21	-30.42			
	(3.61)	(1.77)	(4.02)	(25.57)	(11.04)	(27.85)			
Bounced checks	-4.54***	-5***	0.46	-10.1***	-8.5***	-1.6	8.63***	7.46***	1.17
	(0.52)	(0.27)	(0.59)	(3.76)	(1.6)	(4.09)	(0.89)	(0.39)	(0.97)
R-squared	0.0883***	0.0889***	-0.0006	0.1788***	0.0687***	0.1101***	0.0415***	0.0379***	0.0036
	(0.0058)	(0.0027)	(0.0064)	(0.0197)	(0.0091)	(0.0217)	(0.0061)	(0.0028)	(0.0067)
N	29700	137152		2406	12077		26537	125308	