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Do Relationships Matter? Evidence from Loan Officer Turnover

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We show that the cost of employee turnover in firms that rely on decentralized knowledge and personal relationships depends on the firms' planning horizons and the departing employees' incentives to transfer information. Using exogenous shocks to the relationship between borrowers and loan officers, we document that borrowers whose loan officers are on leave are less likely to receive new loans from the bank, are more likely to apply for credit from other banks, and are more likely to miss payments or go into default. These costs are smaller when turnover is expected, as in the case of maternity leave, or when loan officers have incentives to transfer information, as in the case of voluntary resignations.

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1. Introduction

The recent management literature has documented that modern firms rely heavily on human capital-intensive technologies and flatter organizational structures, which allows authority and responsibility to be delegated more widely in the organization (see, e.g., Rajan and Wulf 2006, Guadalupe et al. 2014). As a result, knowledge about specific firm processes or client relationships is dispersed across employees throughout the organization. Often this knowledge is "tacit" or relationship-specific and therefore difficult to transfer to someone else.[1] Ensuring the transfer of this decentralized knowledge across employees, therefore, becomes a central management challenge for firms. The task of maintaining critical information and client relationships within the firm becomes especially important in situations when an employee leaves the firm, either voluntarily or involuntarily.

A prominent industry in which employees have a lot of decentralized information and are crucial in maintaining client relationships is commercial banking. Loan officers play a key 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 may be reinforced if clients develop personal loyalties to their loan officers. Such relationships may 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 may make them indispensable in the lending process, creating a management challenge when a loan officer leaves. Stein (2002) and Berger et al. (2005) argue that soft information cannot be easily transferred within the bank, which affects the organizational structure and limits the bank's size.

In 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,

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

and they find that information transferred in embedded relationships is more private, proprietary, and tacit.

Whereas a number of papers have shown the relevance of stronger relationships on firms' outcomes and strategies, there has been little research on the costs associated with 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 for the optimal size of the firm, the span of control, and the hierarchical structure of an organization.

In this paper we use a novel strategy to study the extent to which the cost of employee turnover can be mitigated by the firm. We obtained detailed transaction-level data from BancoEstado, the largest lender to small businesses in Chile. Since these loans are issued as personal loans and are de facto uncollateralized, they rely heavily on soft information and possibly on the relationship between the borrower and the bank. In the data we identify loan officers who leave their job either permanently or temporarily, interrupting the personalized relationship between the clients and the bank. And we study how access to credit, repayment behavior, and the loyalty of the client to the bank are affected by these interruptions. This approach also allows us to compare the impact of leaves that are exogenously caused and unplanned versus those that can be anticipated by the bank.

We document 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 in 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 the rate at which clients apply for new loans also 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 with the average probability of becoming delinquent. Furthermore, for those borrowers who are already delinquent, the probability of default shoots up by 18.31% compared with 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.

The next step in the analysis is to test whether companies can mitigate the cost of employee turnover by facilitating information transmission. 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: sickness, resignation, maternity, and dismissal. In our setup, the timing of a sick leave is difficult to plan in advance because we study cases of major and unexpected illnesses.[5] 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, maternity has a nine-month lead time, during which the bank could ensure that the replacement loan officer is 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 a deterioration in credit terms, even in the last two instances, it would suggest that soft information is difficult to transmit even when given enough time.

We find that clients whose loan officers take sick leave are 19.9% less likely to get a new loan from the bank during the time of the absence compared with the average probability of getting a new loan,

[2] Notable examples of how information affects firms' decisions and structure are those of Haunschild and Beckman (1998), who find 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.

[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 this paper.

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

[5] It is possible that some of the sick leaves are planned and thus expected. However, according to the 2006 National Hospital Survey (Buie et al. 2010), only 25% of surgeries are planned. Furthermore, the most frequent planned leaves are cosmetic surgeries, which are excluded in our analysis.

which is 5.98%. This is driven by a strong decrease in the likelihood that clients apply for a loan. The approval rate also shows an economically significant reduction, but the change is not statistically significant. Furthermore, these clients show a 2.15% increase in the probability of getting a loan from another bank, which is almost 13% higher than the probability for an average client in the sample. This suggests that a significant fraction of these borrowers are a reasonable credit risk ex ante, since an outside bank is willing to lend to them. Nevertheless, 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 significantly negative impact on the access to credit and the loyalty of clients. The sick 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.

Clients of loan officers who are on maternity leave show a similar decline in their likelihood of getting 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 the approval rate. At the same time, these clients show no propensity to go 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 months before their loan officer goes on maternity leave. Whereas this effect is observable for maternity leave, it is not seen in other types of absences. 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. In addition, these clients show an increased propensity to be late on their loans and even default, which may suggest that these clients feel less loyalty to the interim loan officer.

In the case of resigning loan officers (who usually resign 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.[6] Interestingly, in these cases, we do not see a drop in access to financing. Furthermore, these clients do not approach an outside bank, which confirms that their access to financing does not change much. Although the likelihood of the clients missing one month of payments also increases when their loan officer is hired away, the likelihood of outright default on a loan does not increase. This could be a sign of transitory adjustment costs rather than a situation in which the portfolio permanently deteriorates when the previous loan officer leaves.

Finally, in the case of the portfolio of loan officers who are dismissed, we see a much stronger drop in the probability of getting a new loan compared with all other kinds of absences; this is driven equally by a reduction in approval rates and application rates. There is also a significant increase in the probability that clients are late on their loans and default. In fact, in the month preceding the dismissal, we already see an increase in defaults. It appears that the dismissed loan officers make bad loans, and these clients do not get credit after the turnover. The new incoming loan officer therefore has incentives to report poorly performing borrowers to start with a clean slate of clients. For a similar argument, see Hertzberg et al. (2010).

Overall, these findings suggest that disruptions to the relationship between the borrowers and the loan officers reduce the availability of soft information and the loyalty of the borrowers to the bank. An alternative explanation would be that loan officers provide credit to friends and family at favorable terms, and when the loan officer leaves, they are not able to renew their loans, and thus they stop paying. The key difference between the two hypotheses is that under the first, the loan officer–client relationship is beneficial to the bank, whereas under the second, it hurts the bank. Although we cannot fully reject this alternative, the evidence suggests that lending to family and friends at favorable terms is uncommon. First, under the alternative explanation, family and friends in financial distress would get credit from the original loan officer, but not from his replacement; thus the proportion of new loans issued to borrowers in default should decrease when the loan officer leaves. In contrast, we find that the proportion of borrowers in default who get a new loan only decreases when a loan officer is dismissed, which supports the idea that, for the most part, loan officers do not lend to friends and family in financial distress. Similarly, when a loan officer leaves unexpectedly due to sickness, there is deterioration in payment behavior in the portfolio, but the clients are still able to access outside credit, suggesting that these clients are creditworthy. We also interviewed a number of bank managers who confirmed that loan officers do not behave improperly.

As a final step, we investigate whether the impact of loan officer absences varies with the characteristics of

[6] Anecdotal evidence suggests that the incentives to transfer information are mostly explained by career concerns. Indeed, the loan officer job market is highly specialized, with a six-month formal training course plus important training in the field. In addition, the market is small, and people from different banks know each other. Therefore, when loan officers change banks, they want to keep their reputation in the industry to maximize their future outside opportunities. In particular, they do not want to be perceived as disloyal by stealing clients or considered poor performers if their old portfolio defaults just after they leave the bank.

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 clients and clients with low credit scores. 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, these heterogeneous treatment effects do not seem to be important for loan officers who 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 see a reduction in credit. This might indicate that resigning officers are able to successfully brief their replacements about the soft (and hard) information of their clients. Finaly, for clients of dismissed loan officers, we see a drastic decline in access to financing for all types of borrowers, independent of observable characteristics. Furthermore, the reduction in the approval rate is particularly strong for clients with long relationships with the loan officer. We think that low-quality loan officers try to hide their bad past lending decisions by renewing loans to their underperforming old clients. Once the low-quality loan officers are dismissed, these clients are less likely to get a new loan.

Taken together, the results suggest that the impact of employee turnover is less severe if there is sufficient lead time before the transition and if the affected employees have incentives to transmit information to their successors (as is the case of maternity leaves or voluntary resignations). However, in situations in which a loan officer lacks the time or the incentives to transmit knowledge to his replacement, the relationship between the bank and the client suffers: important soft information between the loan officer and the client is lost, and the loyalty of the client to the bank decreases.

2. Literature Review

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 et al. 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 particularly 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 et al. (2014) 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 et al. (2013) 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 judgments on the data they collect. The authors show that loan officers use more scoring trials for loan applications that do not pass the cutoff 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 et al. (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 et al. (2005) find that larger banks lend to more distant clients compared with smaller banks, but they 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 loan 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 reduces 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 complement 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 those by Hertzberg et al. (2010) and Fisman et al. (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 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 creditworthiness 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 microcredit division of the bank. Only clients with yearly sales below US$110,000 can borrow from the microcredit division; clients exceeding this limit must borrow through the regular lending process of the bank. The microcredit division of the bank has 210,000 clients, of which 187,000 were borrowers (had nonzero debt) at some point during the period of this study, 2006–2008. The microcredit 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. Northern Chile consists of the counties located north of Santiago, and southern 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 microcredit services.

Clients can choose freely which branch they go to, but usually they 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 farther 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 assigned to a loan officer, the client usually stays with this person for the duration of time that he or she is a client of the bank.

Loan officers divide their time between meeting clients, processing loan documents at the office, and conducting fieldwork. In the field, loan officers visit clients who are delinquent in their payments to assess their financial situation, and they visit the businesses of clients who are applying for a loan to estimate the clients payment capacity (per month free cash flow). 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 a loan to ask for.

The lending decision depends on two variables: the payment capacity and the risk category of the client. The loan officer estimates the payment capacity based on the client's business cash flow, household expenses, and non-business-related income. Many of these variables are not formally recorded, and therefore the value reported to the bank is at the discretion of the loan officer, which increases his decision-making power. The risk category is estimated by a central risk department based on hard information and therefore cannot be modified by the loan officer. 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 microcredit borrower in Chile is extremely costly and sometimes not possible. Specifically, litigation costs for this type of claim are high compared with the expected recovery. Furthermore, for this type of claim, the legal system is slow, and there are loopholes that allow 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.

In addition, 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. In addition, it may also prevent a new loan officer from blindly lending to people whose overall credit risk he cannot assess.

4. Data and Empirical Strategy

4.1. The Data

Using data from the internal records of the microcredit 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, grace period availability, 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 more than 90 days old. Based on the bank's records, we reconstruct the length of the relationship between the loan officer and the client—that is, 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 bank itself. This database contains information on temporary and permanent loan officers' leaves, including sick leave, maternity leave, 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 47% of the loan officers are men, 62% are married, and their average age and years of experience at the bank are 33 and 4.1, respectively. The average number of active clients per loan officer is 339, where an active client is defined as a borrower with 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 leave 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 maternity leave and 34 maternity leaves; the average length of a maternity leave is 4.64 months, with a standard deviation of 1.12. It is important to mention that, by law, maternity leave in Chile was 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.

Table 1 Summary Statistics for Loan Officers

	Loan officer characteristics			
	N	Mean	SD	Median
Gender (%)	551	47		
Age	551	33	5	32
Married (%)	551	62		
Number of children	370	0.8	0.9	1
Years of experience	551	4.1	2.8	3.8
City (%)	293	64		
Number of clients	480	339	112	341

	Absentee episodes			
	No. of officers that were absent	No. of episodes	Average length (in months)	SD length
Sick leave	32	43	2.12	1.18
Maternity leave	33	34	4.64	1.12
Layoff	26	26		
Resignation	15	15		

Notes. In this table, we present the summary statistics for the loan officers and the different sources of turnover. The values are estimated using demographic characteristics of the loan officers working at the bank during the time frame considered for the study. The *Gender* variable takes a value of 1 for male loan officers and 0 for female loan officers, and therefore its mean indicates the proportion of male loan officers as a fraction of the total number of loan officers. *Age* is expressed in years. The *Married* variable takes a value of 1 if the loan officer is married according to the Chile civil registry and 0 otherwise, and therefore its mean indicates the proportion of loan officers in the sample who are married. The *City* variable takes a value of 1 if the loan officer works in urban areas and 0 if the loan officer works in rural areas, and therefore its mean indicates the proportion of loan officers in the sample who work in urban areas.

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 of loan officers that were never absent during the sample period and the characteristics of the clients from loan officers who had 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 is significant, which

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

Table 2 Summary Statistics for Clients

	Clients from nonabsent loan officers	Clients from absent loan officers	Difference (SE 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 1st month	4.04	4.08	−0.04 (0.28)
Default rate conditional on being already delinquent for more than 60 days	33.26	35.19	−1.93 (4.82)
Relationship length	11.12	11.26	−0.133 (0.07)

	Summary statistics at the end of the sample period	
	Mean	SD
Length of the relationship between the borrower and its most recent loan officer	21.85	16.72
Length of the relationship between the borrower and its most habitual loan officer	33.76	14.41

Notes. 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; maturity and relationship length are expressed in months. Probabilities are expressed in percentages. We only observe two years of history before the sample period; therefore the relationship length in the first part of the table is biased toward zero. To address this problem, in the second part of the table we present information about the length of the relationship between the borrower and its most recent loan officer and between the borrower and its most habitual loan officer. In the regression we use a binary variable to capture relationship length. This binary variable takes a value of 1 if the borrower–loan officer relationship is longer than the median relationship length and 0 otherwise.

supports our view that the findings in this paper are not driven by ex ante self-selection. We observe that in 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%. Although the probability of getting a loan outside BancoEstado is much higher, the size of the loans obtained from outside banks is significantly smaller. The loan's average monthly interest rate is 1.65% and average maturity is 24.67 months. The probability that a client misses a payment in any given month is 4.04%, and the probability that a client defaults (conditional on already being delinquent for more than 60 days) is 33.26%. The average relationship length between the borrower and the loan officer, measured at the beginning of the sample, is 11.1 months. However, this measure is biased downward because we only observed two years of data at that time. To reduce the bias, in the last two rows of Table 2 we include summary statistics of the relationship length observed at the end of the sample period. At that time, we observed 60 months of historical information, and the bias is thus lower. The average length of the relationship with the most recent loan officer is 22 months, and the longest relationship length of each client averages 34 months.

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 a value of 1 when the loan officer is absent and 0 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 experienced a loan officer leave that is different from the leave being estimated. For example, if we estimate the effect of a maternity leave, we exclude clients who had their loan officer leave as a result of sickness, dismissal, or voluntary resignation. This leads to the following specification:

$$Y_{ijt} = C + \beta_{leave} leave_{ijt} + \sum_{l=1}^{l} (\beta_l Control_{l_{ijt}}) + \mu_t + \eta_i + \varepsilon_{ijt}, \quad (1)$$

where Y_{ijt} is the dependent variable for client i of loan officer j at time t, and its description is provided in Table A.1 of the appendix. The variable $leave_{ijt}$ is a dummy variable that takes a value of 1 if the loan officer j, the loan officer of client i, is absent at time t and 0 otherwise. The variable $Control_{l_{ijt}}$ is a control variable for loan officer j, the loan officer of client i, at time t; μ_t captures time fixed effects, and η_i captures client's fixed effects. Time is measured in months. Standard errors are clustered at the loan officer level.

[8] To control for time to maturity, we divide the loan cycle into 10 intervals, 1 being a newly issued loan and 10 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.

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:

$$Y_{ijt} = C + \beta_{leave}\, leave_{ijt} + \sum_{k=1}^{k}(\beta_{leave\times var_k}\, leave_{ijt} \times var_{k_{ijt}}) + \sum_{k=1}^{k}(\alpha_k\, var_{k_{ijt}}) + \sum_{i=1}^{l}(\beta_l\, Control_{l_{ijt}}) + \mu_t + \eta_i + \varepsilon_{ijt}, \quad (2)$$

where all the terms are similar to Equation (1), and $var_{k_{ijt}}$ are the variables that are interacted with the leave dummy: borrower size, borrower score, borrower gender, and relationship length. This last variable is a dummy that takes the value of 1 if the borrowers–loan officer relationship is longer than the median relationship length and 0 otherwise.

5. Results

5.1. Aggregated Effect of Loan Officer Turnover

In Table 3, we present results from an aggregate specification across all types of leave (i.e., *absent* takes a value of 1 if the loan officer is sick, is on maternity leave, is dismissed, or resigns). In the column (1) 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. Last, 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 absences increase by 6.09% the probability that those clients 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 Leave

The analysis in Table 4 is similar to the analysis in Table 3 but breaks out the different types of absences separately. The panel I of this table shows the results for sick leave. The sequence of dependent variables follows exactly the same setup as Table 3. In columns (1)–(3), we see that the probability that the client gets a new

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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)
Loan officer 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)
Loan officer 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)
Relationship 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	2,471,578	2,471,578	191,774	2,471,578	2,217,262	216,418	135,545	135,545	135,545	403,459
Adjusted R^2	0.081	0.084	0.090	0.200	0.185	0.325	0.668	0.401	0.812	0.655

Notes. We present the effect of all the sources of turnover on the credit characteristics and credit behavior of the borrowers. Each column represents one regression where *Leave* is a dummy that takes a value of 1 in the months that a loan officer is on leave and 0 otherwise. The columns are organized as follows: (1) renewal probability, (2) application probability, (3) approval probability, (4) probability of getting credit from other banks, (5) probability of missing one payment, (6) probability of default for clients who have been delinquent on their loans for more than 60 days, (7) monthly nominal interest rate, (8) maturity, (9) log loan size at the bank, and (10) log loan size outside the bank. Estimations in columns (7)–(9) are restricted to clients that get a new loan at the bank, and the estimation in column (10) 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, and the number of clusters is 468.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4 The Effects of Sickness Leave, Maternity Leave, Dismissals, and Resignations on Credit Availability, Credit Characteristics, and Repayment Behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sick leave	−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)
N	2,330,375	2,330,375	180,045	2,330,375	2,084,266	64,616	126,327	126,327	126,327	376,316
Adjusted R^2	0.081	0.084	0.098	0.206	0.189	0.123	0.671	0.402	0.814	0.657
Maternity leave	−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)
N	2,323,326	2,323,326	179,517	2,323,326	2,078,045	64,493	125,750	125,750	125,750	375,519
Adjusted R^2	0.080	0.084	0.095	0.207	0.189	0.125	0.668	0.399	0.814	0.658
Dismissal	−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)
N	2,254,407	2,254,407	175,166	2,254,407	2,018,055	61,956	123,161	123,161	123,161	366,175
Adjusted R^2	0.081	0.085	0.090	0.204	0.189	0.125	0.667	0.398	0.812	0.658
Resignation	−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)
N	2,211,139	2,211,139	171,361	2,211,139	1,978,681	60,954	120,488	120,488	120,488	358,069
Adjusted R^2	0.081	0.084	0.095	0.205	0.190	0.125	0.669	0.398	0.813	0.659

Notes. We present four panels that show the effects of sick leave, maternity leave, dismissals, and resignations on the credit characteristics and credit behavior of the borrowers. The columns are organized as follows: (1) renewal probability, (2) application probability, (3) approval probability, (4) probability of getting credit from other banks, (5) probability of missing one payment, (6) probability of default for clients who have been delinquent on their loans for more than 60 days, (7) monthly nominal interest rate, (8) maturity, (9) log loan size at the bank, and (10) log loan size outside the bank. Estimations in columns (7)–(9) are restricted to clients that get a new loan at the bank, and estimation in column (10) 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. The number of clusters is 391 in the first and second sets of regressions, 389 in the third set of regressions, and 379 in the fourth set of regressions.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

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 divided into two separate parts: 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 maternity 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 maternity 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 and 6, we break out the analysis for each type of leave separately to study how access to credit and repayment behavior change in the month that precedes the leave. 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 leave 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

Table 5 The Effects of Sickness and Maternity Leave in the Month That Precedes the Leave and in the Month That Follows the Leave

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					I: Sick leave					
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)
*Lead*1	−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)
*Lag*1	−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)
N	2,342,688	2,342,688	181,045	2,342,688	2,095,095	65,093	127,049	127,049	127,049	378,489
Adjusted R^2	0.081	0.084	0.099	0.206	0.189	0.124	0.671	0.402	0.815	0.658
					II: Maternity leave					
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)
*Lead*1	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)
*Lag*1	−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)
N	2,335,434	2,335,434	180,616	2,335,434	2,088,667	64,929	126,492	126,492	126,492	377,430
Adjusted R^2	0.080	0.084	0.095	0.206	0.189	0.125	0.669	0.399	0.814	0.658

Notes. We present two panels that show the effects of sickness (panel I) and maternity leave (panel II) on the credit characteristics and credit behavior of the borrowers. *Leave* is a dummy that takes a value of 1 in the months that a loan officer is on leave and 0 otherwise. *Lead*1 is a dummy that takes a value of 1 in the month before the loan officer goes on leave and 0 otherwise, and *Lag*1 is a dummy that takes a value of 1 in the month after the loan officer comes back from leave and 0 otherwise. Each column represents two regressions for sick leave and maternity leave, respectively. The columns are organized as follows: (1) renewal probability, (2) application probability, (3) approval probability, (4) probability of getting credit from other banks, (5) probability of missing one payment, (6) probability of default for clients who have been delinquent on their loans for more than 60 days, (7) monthly nominal interest rate, (8) maturity, (9) log loan size at the bank, and (10) log loan size outside the bank. Estimations in columns (7)–(9) are restricted to clients that get a new loan at the bank, and estimation in column (10) 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, and the number of clusters is 391.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6 The Effect of Dismissals and Resignations in the Month That Precedes the Leave

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					I: 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)
*Lead*1	−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)
N	2,254,407	2,254,407	175,166	2,254,407	2,018,055	61,956	123,161	123,161	123,161	366,175
Adjusted R^2	0.081	0.085	0.090	0.204	0.189	0.125	0.667	0.398	0.812	0.658
					II: 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)
*Lead*1	−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)
N	2,211,139	2,211,139	171,361	2,211,139	1,978,681	60,954	120,488	120,488	120,488	358,069
Adjusted R^2	0.081	0.084	0.095	0.205	0.190	0.125	0.669	0.398	0.813	0.659

Notes. We present two panels that show the effects of dismissals (panel I) and resignations (panel II) on the credit characteristics and credit behavior of the borrowers. *Leave* is a dummy that takes a value of 1 in the months that a loan officer is on leave and 0 otherwise. *Lead*1 is a dummy that takes a value of 1 in the month before the loan officer goes on leave and 0 otherwise. The columns are organized as follows: (1) renewal probability, (2) application probability, (3) approval probability, (4) probability of getting credit from other banks, (5) probability of missing one payment, (6) probability of default for clients who have been delinquent on their loans for more than 60 days, (7) monthly nominal interest rate, (8) maturity, (9) log loan size at the bank, and (10) log loan size outside the bank. Estimations in columns (7)–(9) are restricted to clients that get a new loan at the bank, and estimation in column (10) 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. The number of clusters is 389 in the first set of regressions and 379 in the second set of regressions.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7 The Effects of Sick Leave and Maternity Leave Interacted with Client Gender, Client Size, and Credit Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					I: Sick leave					
Leave	−2.56***	−2.59***	−2.17	6.01***	2.93***	12.00	0.06	1.10	−0.09	−0.02
	(0.65)	(0.59)	(5.65)	(1.90)	(0.78)	(9.36)	(0.08)	(1.99)	(0.11)	(0.08)
Leave × *Gender*	−0.87*	−1.13**	2.21	−0.37	1.30**	2.72	0.07	−2.31	0.03	−0.04
	(0.50)	(0.48)	(5.68)	(1.02)	(0.63)	(7.07)	(0.10)	(1.78)	(0.09)	(0.06)
Leave × *Size*	1.38***	2.05***	−5.76	−6.09***	0.18	−17.33***	−0.08**	0.42	0.22*	0.12
	(0.43)	(0.57)	(4.77)	(2.06)	(0.59)	(6.28)	(0.03)	(1.76)	(0.12)	(0.10)
Leave × *Score*	1.51***	1.42***	4.02	1.35*	−5.00***	−2.35	−0.01	−1.78	−0.13*	0.07
	(0.43)	(0.49)	(4.86)	(0.81)	(0.70)	(10.72)	(0.06)	(2.02)	(0.08)	(0.06)
Leave × *Relationship*	0.58	0.46	2.73	−1.04	−1.03***	−5.89	−0.10	2.17	0.09	−0.02
	(0.37)	(0.43)	(6.05)	(1.57)	(0.38)	(6.43)	(0.07)	(2.46)	(0.09)	(0.12)
N	2,320,485	2,320,485	179,448	2,320,485	2,081,198	64,353	126,095	126,095	126,095	374,419
Adjusted R^2	0.081	0.084	0.097	0.206	0.189	0.123	0.671	0.401	0.814	0.657
					II: Maternity leave					
Leave	−1.71***	−1.57**	−5.12	0.42	3.07***	8.41*	0.04	0.42	−0.19*	0.16
	(0.54)	(0.61)	(3.98)	(0.65)	(0.64)	(5.02)	(0.08)	(1.78)	(0.11)	(0.13)
Leave × *Gender*	−0.97**	−1.13**	−3.08	0.21	0.75**	6.36	0.04	0.94	0.05	−0.02
	(0.41)	(0.46)	(3.36)	(0.55)	(0.34)	(7.67)	(0.06)	(1.96)	(0.09)	(0.07)
Leave × *Size*	0.93*	0.81	7.80	−1.90**	−0.65	−3.96	−0.05	0.72	0.32***	0.06
	(0.52)	(0.66)	(4.78)	(0.89)	(0.58)	(4.46)	(0.06)	(1.54)	(0.09)	(0.11)
Leave × *Score*	0.81*	0.78	1.16	1.41	−4.65***	−8.62	0.06	−2.54*	−0.14**	−0.07
	(0.47)	(0.51)	(4.39)	(1.07)	(0.62)	(15.30)	(0.06)	(1.54)	(0.07)	(0.06)
Leave × *Relationship*	0.13	0.44	−5.25	1.17	0.08	0.63	−0.01	0.26	−0.07	−0.17*
	(0.34)	(0.38)	(3.31)	(1.27)	(0.54)	(7.02)	(0.05)	(1.33)	(0.10)	(0.09)
N	2,313,644	2,313,644	178,940	2,313,644	2,074,989	64,241	125,515	125,515	125,515	373,678
Adjusted R^2	0.080	0.084	0.094	0.207	0.189	0.124	0.669	0.399	0.814	0.658

Notes. Panel I shows the interaction effects of turnover change with different characteristics of the borrower for sick leave, and panel II shows the interaction effects for maternity leave. All interactions are the product of two dummy variables and therefore take the value of 1 if both dummy variables are equal to 1 and 0 otherwise. The columns are organized as follows: (1) renewal probability, (2) application probability, (3) approval probability, (4) probability of getting credit from other banks, (5) probability of missing one payment, (6) probability of default for clients who have been delinquent on their loans for more than 60 days, (7) monthly nominal interest rate, (8) maturity, (9) log loan size at the bank, and (10) log loan size outside the bank. Estimations in columns (7)–(9) are restricted to clients that get a new loan at the bank, and estimation in column (10) 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, and the number of clusters is 391.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

our hypothesis that these types of absences are not planned in advance.

A different story emerges for maternity leave. 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, maternity leave is planned, and loan officers seem to provide their clients with sufficient access to financing 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. Although this result is not statistically significant, it might still be an indication that the bank limits credit to borrowers of poorly 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 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, and we look at heterogeneous treatment effects for borrowers with longer relationships with their loan officers.

Within the portfolio of loan officers who are on a sick leave, we see very strong heterogeneous treatment effects. The negative effects of sick leave on access to credit and repayments are particularly strong for small, female borrowers with low credit scores. In contrast, the

Table 8 The Effects of Dismissal and Resignation Interacted with Client Gender, Client Size, and Credit Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					I: Dismissal					
Leave	−2.64***	−2.18***	−11.65	0.62	2.91***	17.23**	0.10	−1.40	0.02	0.18*
	(0.55)	(0.50)	(7.30)	(1.48)	(0.86)	(7.56)	(0.10)	(1.76)	(0.09)	(0.10)
Leave × *Gender*	0.36	0.13	7.04	−1.09	1.34***	16.41**	−0.03	−0.13	−0.03	−0.19***
	(0.46)	(0.71)	(6.56)	(1.31)	(0.39)	(6.94)	(0.08)	(1.69)	(0.06)	(0.05)
Leave × *Size*	0.69	1.19***	2.88	−2.15**	−0.59	−10.18	−0.06	1.26	0.08	−0.02
	(0.46)	(0.41)	(5.84)	(0.87)	(0.56)	(8.48)	(0.06)	(1.51)	(0.09)	(0.08)
Leave × *Score*	0.66	0.03	4.39	0.71	−4.41***	−1.09	0.08	1.72	−0.07	−0.17**
	(0.55)	(0.55)	(5.81)	(0.96)	(0.71)	(13.01)	(0.08)	(1.71)	(0.09)	(0.07)
Leave × *Relationship*	−0.21	0.31	−9.85**	−0.48	0.48	−12.26*	−0.09	0.09	0.01	−0.01
	(0.51)	(0.70)	(4.58)	(1.65)	(0.47)	(6.67)	(0.07)	(2.22)	(0.10)	(0.08)
N	2,245,094	2,245,094	174,601	2,245,094	2,015,097	61,698	122,938	122,938	122,938	364,387
Adjusted R^2	0.081	0.085	0.089	0.204	0.189	0.125	0.667	0.398	0.812	0.658
					II: Resignation					
Leave	−0.39	−0.99	8.97	−1.27	3.96***	11.70	−0.01	0.46	−0.07	0.22*
	(0.74)	(0.86)	(8.99)	(1.96)	(0.81)	(8.12)	(0.11)	(2.58)	(0.14)	(0.12)
Leave × *Gender*	−0.14	0.23	−8.04	−1.48	0.32	−2.92	0.07	1.11	−0.07	−0.09
	(0.69)	(0.68)	(6.50)	(1.21)	(0.48)	(9.28)	(0.07)	(1.39)	(0.10)	(0.10)
Leave × *Size*	−0.18	0.36	−8.23	1.26	−1.42**	−19.25*	−0.02	0.33	0.19	0.11
	(0.56)	(0.58)	(7.83)	(2.45)	(0.56)	(10.07)	(0.08)	(1.59)	(0.13)	(0.09)
Leave × *Score*	0.62	0.85	−4.29	1.20	−3.87***	14.39	0.04	−1.25	0.01	−0.21
	(0.81)	(0.84)	(4.22)	(1.06)	(0.76)	(30.87)	(0.06)	(3.29)	(0.10)	(0.16)
Leave × *Relationship*	−1.30	−1.22	−5.87	0.47	−0.25	−11.22	−0.00	−2.24	−0.07	−0.07
	(0.80)	(0.82)	(8.54)	(1.46)	(0.60)	(12.44)	(0.08)	(4.06)	(0.15)	(0.18)
N	2,201,978	2,201,978	170,812	2,201,978	1,975,840	60,702	120,272	120,272	120,272	356,328
Adjusted R^2	0.081	0.084	0.094	0.205	0.190	0.124	0.669	0.397	0.813	0.659

Notes. Panel I shows the interaction effects of turnover change with different characteristics of the borrower for dismissals, and panel II shows the interaction effects for resignations. All interactions are the product of two dummy variables and therefore take the value of 1 if both dummy variables are equal to 1 and 0 otherwise. The columns are organized as follows: (1) renewal probability, (2) application probability, (3) approval probability, (4) probability of getting credit from other banks, (5) probability of missing one payment, (6) probability of default for clients who have been delinquent on their loans for more than 60 days, (7) monthly nominal interest rate, (8) maturity, (9) log loan size at the bank, and (10) log loan size outside the bank. Estimations in columns (7)–(9) are restricted to clients that get a new loan at the bank, and estimation in column (10) 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. The number of clusters is 389 in the first set of regressions and 379 in the second set of regressions.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

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 2.56% 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 borrowers and borrowers with lower credit scores increases by 6.01%, which represents an increase of 35.52% as a fraction of the unconditional probability of borrowing outside of the bank. This effect is even more pronounced for clients with good credit scores. They experience a 7.04% increase in the probability of borrowing outside of the bank, which represents a 43.5% 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 6.09% and significant at the 1% level), which suggests that these large borrowers are not constrained in their access to financing 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. Surprisingly, the length of the relationship does not seem to affect the impact of the leave on the borrowers.

In panel II of Table 7 we look at the impact of maternity leave 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 borrowers with good credit scores. Although 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 panel I of Table 8), we find very limited differentiation by borrower gender, size, or credit score. As before, we see that access to financing 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 are receiving additional credit despite their high leverage, and once a new loan officer comes in, the portfolio is consolidated to a reasonable risk level. Interestingly, for clients with a long relationship with their loan officer, the decrease in the approval probability is 9.85% higher compared with the decrease for clients with a short relationship. This might indicate that low-quality loan officers try to hide their bad past lending decisions by renewing loans to underperforming clients.

Finally, in panel II 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 their 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 replacements. As a result, even borrowers with bad observable characteristics do not suffer an important reduction in their access to financing.

5.5. Loan Officers' Client Selection

We also study the cross-sectional differences in the proportion of delinquent borrowers who get new loans from the replacing loan officer compared with the proportion of delinquent borrowers who get new loans from the original loan officer. As opposed to the preceding analysis, here we do not include loan fixed effects; therefore, we capture changes in loan officers' lending decisions, and not changes in borrowers' behavior.

We find that the replacement of a loan officer on sick or maternity leave reduces the proportion of borrowers with short-term arrears that get new loans. This is probably an indication that the replacement loan officer does not have the soft information necessary to distinguish which of these clients are of low quality and which of them just have a short-term liquidity problem. However, neither the replacement of a loan officer on sick leave nor the replacement of a loan officer on maternity leave changes the proportion of borrowers in default who get new loans, which indicates that both the original and the replacement loan officers are strict in cutting credit to bad borrowers.

Interestingly, the replacement of a dismissed loan officer reduces the proportion of borrowers in default that get new loans compared to that under the original loan officer. This is probably an indication that the dismissed loan officer used to grant loans to poor-performing borrowers either to hide his own poor past lending decisions or to benefit privileged borrowers, possibly friends and family.

Finally, the replacement of a resigned loan officer reduces credit neither to borrowers with short-term delays nor to borrowers in default. This supports the idea that the resigning loan officer is able to transfer the soft information to his replacement.[9]

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 it 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 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, because we focus on serious and unexpected illnesses, the outgoing loan officer usually does not have time to transfer any soft information to the replacement. 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

[9] The details of these findings are found in Table A.2 in the appendix.

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, such as resignations, which can be planned for in advance. These are cases in which 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. Maternity-related absences are somewhere in the middle: although 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 driven not only 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 where employees rely heavily on tacit knowledge, managing employee turnover becomes central 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 provide incentives for employees to train their replacement and transmit any soft information to the new person. In situations where the departing employee has few or no 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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Appendix

Table A.1 Variable Definitions

Variable	Definition
(1) *Renewal probability$_t$*	Equals 1 if a client's loan is renewed in month t and 0 otherwise
(2) *Application probability$_t$*	Equals 1 if the client applied for a loan in month t and 0 otherwise
(3) *Approval probability$_t$*	Equals 1 if the loan application was a approved and 0 if it was rejected
(4) *Probability of credit from other banks$_t$*	Equals 1 if a client gets a loan at a different bank in month t and 0 otherwise
(5) *Probability of missing one payment$_t$*	Equals 1 if a client misses a payment in month t and 0 otherwise
(6) *Probability of default$_t$*	Equals 1 if a client misses a payment in month t and 0 otherwise (defined only for clients in arrears of 60 days or more at $t-1$)
(7) *Monthly nominal interest rate*	The nominal interest rate in Chilean pesos
(8) *Maturity*	The maturity of the loan in months
(9) log(*Loan size at the bank*)	The natural logarithm of the loan amount at the bank in Chilean pesos
(10) log(*Loan size outside the bank*)	The natural logarithm of the summation of all the loans at other banks in Chilean pesos

Table A.2 Proportion of Delinquent Borrowers That Get New Loans

	(1)	(2)
Sick leave	-1.17^{***}	0.02
	(−2.81)	(0.19)
N	3,851	4,359
Maternity leave	-0.76^{**}	−0.09
	(−2.01)	(−1.27)
N	3,486	3,231
Dismissal	0.02	-0.42^{***}
	(0.05)	(−3.23)
N	3,281	2,895
Resignation	0.17	0.08
	(0.29)	(0.54)
N	1,677	1,554

Notes. We present four panels that show the simple difference in the proportion of delinquent borrowers that get a new loan from the replacement compared with the proportion of delinquent borrowers that get a new loan from the original loan officer. Column (1) presents the difference for borrowers in arrears for less than 60 days, and column (2) presents the difference for borrowers in arrears for more than 89 days. Rates are expressed in percentages. The t-test of the difference is presented in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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