Does Soft Information Matters? Evidence From Loan Officer Absenteeism

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Abstract

This paper provides evidence that shocks to the relationship between loan officers and their borrowers affects the credit decisions of the bank as well as customers' repayment and borrowing behavior. When a loan officer unexpectedly has to be absent from the job, the existing borrowers of the absent loan officer are less likely to take on a new loan from this bank and are more likely to miss a payment. The reduction in the borrowing is explained by a lower number of loan applications and a reduction in the application approval rate. This findings suggest that clients are loyal to their loan officer, that the bank reduces lending when soft information is less available, and that loan officers have an important role in monitoring the clients.

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Introduction

Most credit programs are based on extensive interactions between loan officers and the businesses they lend to. This relationship based approach to lending is especially widespread for small and more opaque borrowers, where formal documentation of profits and record keeping is less reliable. The loan officer has the difficult role of solving the informational gap between the bank and the borrower by gathering soft information about potential borrowers. The relationships between loan officers and their clients often extends beyond information collection, and many times loan officers help borrowers assessing the financial needs of their business or even help ensuring that clients repay. The importance of relationship lending has been proposed in a myriad of theory papers, see for example Rajan (1992), Petersen, and Rajan (1994), Petersen, and Rajan (1995), Berger, and Udell (2002), Berger, Miller, Petersen, Rajan, and Stein (2005). However, there has been only little empirical research to document the role of loan officers in mitigating information asymmetries or moral hazard between the bank and its clients. A few notable exceptions are Herzberg, Liberti, and Paravisni (2010), and Liberti, and Mian (2009).

The novel contribution of this paper is that we study (exogenous) shocks to the loan officer-client relationship: Their impact on the credit provision to borrowers as well as the borrowers' behavior. Specifically the shocks we rely on are loan officer absentee spells due to sickness, pregnancy, resignation or layoffs. We work with a bank in Chile, BancoEstado, which lends to small businesses in the informal sector where credit screening relies mostly on soft information collected by loan officers. We obtained comprehensive data not only on the loan officers but also on the entire client portfolio each loan officer manages (client characteristics and repayment borrowing behavior).

Overall we find that loan officer absenteeism leads to significant changes in the borrowing and repayment behavior of client and the credit provision of the bank. In particular, when the original loan officer is absent we observe a 0.9% reduction in the probability of taking up a new loan from the bank (13% reduction as a fraction of the unconditional probability of taking up a new loan from the bank). This reduction is explained by changes in both the client application rate, and the bank approval rate. Specifically, on the client side, the application rate decreases in 0.68% (9% reduction as a fraction of the unconditional probability of applying for a new loan), and on the bank side the approval rate per application decreases in 4.3% (5.2% reduction as a fraction of the unconditional probability of approving a loan application). This switch in credit access is particularly interesting since we do not see a change in credit terms after a loan officer leaves, e.g. interest rates and loan maturity is unchanged on average. This is of course contingent only on the borrowers who do choose to take up a new loan. The effects on repayment behavior and borrowing outside the bank are different for different type of leaves. For example while a steep increase in borrowing outside the bank is observed after a loan officer gets sick, this reaction is not significant when the absenteeism is related to a loan officer pregnancy, layoff or resignation.

The fact that reactions to different type of absentee spells are different is expectable.

One of the reasons is that not all absentee spells are exogenous. In particular layoffs and resignation might be correlated with the prior performance of the loan officer's portfolio. Laid off loan officers might be let go due to the particularly poor performance of their portfolio; while resigning loan officers might be poached away by competitors due to their above average skills or performance. Pregnancies differ from the other absentee spells in that there is a long lead time which allows the bank and the loan officer to prepare the clients for the loan officer's leave in order to prevent potential problems. Therefore the most exogenous source of absenteeism in our sample are major sickness periods of loan officers. These spells are largely unexpected for both the bank and the loan officer, and are independent of the loan officers' portfolio characteristics.

We therefore separately study the effects of the different absentee spells on the loan officer's client portfolio. When only looking at sickness spells, we find that clients whose loan officer has to take a sickness leave are 1.2% less likely of renewing their loan with the bank during the months that the original loan officer is on leave (19% as a fraction of the unconditional probability of renewing the loan). These clients also show a 2.1% increase in the probability of borrowing outside the bank (13% increase as a fraction of the unconditional probability of borrowing outside the bank), and an increase of 1.1% in the probability of missing a payment (10% as a fraction of the unconditional probability of missing a payment). Interestingly, when looking at the credit portfolio of loan officers who were fired we see a much stronger drop in the likelihood of starting a new loan, a spike in non payment, and a significant increase in delinquency rates. These findings are consistent with an interpretation that the new incoming loan officer has an incentive to reduce the bank's exposure to bad loans and to report non-paying borrowers. [1] In comparison we find that clients of loan officers who were resigned (in most cases because they were hired away) do not see a change in their loan renewal probability. But they do experience an increase in missed payment. And finally, loan officers who leave due to pregnancy see no increase in missed payments. However, these clients show a drop in loan renewals during the time of the loan officer's leave. This drop in loan renewal rates during pregnancy leaves is almost entirely explained by a reduction in the number of loan applications, we conjecture that this decrease in the likelihood of applying for a new loan might be a form of 'loyalty' by the clients, who wait for the new loan until their loan officer is back from maternity leave. Overall these results suggest that the relationship between loan officers and their clients has first order effects on the borrowing behavior and the access to credit.

We also investigate whether there is an interaction effect between the characteristics of the borrowers in the loan officer's portfolio and the effect of loan officers leaving. In particular we are interested in client characteristics that proxy for the importance of soft information for the lending decision, such as credit score and average loan sizes of the borrower prior to the current loan, and length of the relationship between the loan officer

[1] See also Hertzberg, Liberty, and Paravisini (2010), who show that incoming loan officers have strong incentives to report bad news about the portfolio of a predecessor loan officer. While in our set up the fired loan officers could not suppress information about non payment they could have manipulated default rates by renewing loans for clients that are experiencing economic distress.

and the client (unfortunately we do no have balance sheet information for the borrowers).

Looking at the interaction effects for sickness leaves we observe that firms offset the reduction in lending by borrowing from other banks. The only exception are big firms with poor credit score. This shows that relationship lending is particularly important for firms with low credit score, where creditworthiness is more difficult to asses. We also observe in this table that small firms with good credit score do not show a deterioration in their repayment behavior. An interesting finding is that big firms with good credit score still show a deterioration in their repayment behavior, which suggests that their quality may be lower than their actual credit score shows.

When looking at the interaction effects for pregnancy and layoff leaves we find that big companies with good credit score not only show a deterioration in their repayment behavior, but also the deterioration is steeper for these firms compared to firms with worse credit score. This finding is consistent with the findings in Hertzberg, Liberty, and Paravisini (2010). In fact loan officers will have strong incentives to suppress bad news about large companies, because disclosing these news will strongly affect their wage. Furthermore, by hiding this information, the loan officer lets big companies in financial distress to keep good credit scores. As suggested by Hertzberg, Liberty, and Paravisini, when the loan officer has to leave the bank (either permanently or temporarily) the replacing loan officer will have strong incentives to disclose the real situation about these firms.

Overall our results suggest that the relationship between loan officers and their clients is important. It appears that even within the same bank loan officers find it difficult to transmit 'soft' information to a colleague. When loan officers have to go on leave unexpectedly, in particular due to sickness, we see that their clients are less likely to get a new loan within the bank. While small borrowers and high score borrowers are able to substitute the loss in credit access by taking on new loans outside the bank, big clients with poor credit score are not able to get outside funding. In addition borrowers show a deterioration in repayment behavior when their loan officer is absent. This might suggest that loan officers also play a role in reducing moral hazard behavior especially for small and opaque firms. Big firms show a steeper deterioration in their repayment behavior suggesting the loan officer also hide bad news from the bank by renewing loans to bad clients.

These results also shed an interesting new dimension on the pricing behavior of banks. We observe that clients do not experience an increase in interest rates when their loan officer leaves. So it seems that loan officers do not use soft information they have on borrowers to hold them up for higher margins. We also see that the deterioration in the repayment behavior is not accompanied by an increase in interest rates. This suggest that interest rates, at least for this segment of the market, react slowly to changes in the probability of default.

I Setting

We analyze the credit characteristics and repayment behavior of micro entrepreneurs of a large local bank operating in Chile, as well as how these characteristics and repayment behaviors change when the loan officer is absent for one month or longer. We study all of the clients borrowing from the micro-credit division of the bank. The micro credit division operates independently of the rest of the bank, and has its own lending technology, specially designed for micro credit businesses. The micro credit division operates in the branches of the bank but has separate personnel and office space. 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 the study.

The bank as well as its micro credit division is organized in 3 Zones: North of Chile, Metropolitan area, and South of Chile. The Metropolitan area consists of the capital city and the counties nearby. North of Chile consists of the rest 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, depending on the cities' population. Big cities can have more than one "módulo" depending on the number of clients in the city. In total, there are 22 "módulos". Each módulo has several branches, however not all branches offer micro-credit services. In total, the bank has 341 branches, of which 202 offer micro credit services.

A branch that offers micro credit services must have at least one loan officer, and may have one or more loan officer assistants. Loan officers assistants can only process pre-approved loans, [2] but cannot evaluate, or issue regular (non pre-approved) loans. Loan officers can issue pre-approved loans as well as regular loans. In this study we will focus on loan officers, because they have decision power in the lending process.

The allocation of loan officers to clients starts when the client chooses his branch. Clients can freely choose their branch but will usually choose 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. In particular, the main branch located in downtown Santiago is very popular and has many clients that do not live particularly close to the main office. Once the client has chosen his branch the allocation of new clients to loan officers works as follows: The clients goes to the branch, new clients are serviced in a first come first serve basis and are allocated to the loan officer that becomes available. Old clients, on the contrary, wait until their already assigned loan officer becomes available. Given this protocol, the allocation of new clients to loan officers is random within branches. To be conservative in this study, we cluster the standard errors at the loan officer level, but

[2] Pre-approved loans are loans offered to clients with good credit score, without checking their business or personal cash flows. This loans must be approved by the risk department before they can be offered to the client.

similar results are obtained when clustering the standard errors at the branch level. Each loan officer works in only one branch. A loan officer usually spends half of the day in the branch, meeting clients and processing loan paperwork. The other half of the day, he spends doing field work where he visits the businesses of clients who have requested a loan, and clients who are late with their payment. During field work, some of the loan officers also give financial advice to their clients. For example, in one of our field visits, a client asked his loan officer whether building a second story to expand his business was a profitable idea. According to loan officers, this type of situation happens quite often.

The loan decision for clients requesting a regular loan depends on two variables; the payment capacity of the client and the risk category of the client. The payment capacity (free cash flows the client has to pay back the loan) is estimated by the loan officer based on the client's; current business cash flows, investment opportunities, household expenses, and non-business related sources of income. The risk category is estimated by the risk department and depends on demographical characteristics of the client, his payment history with the bank, credit history with the rest of the Chilean financial system, [3] and finally the clients' history of defaults outside the financial system. The default history outside the financial system is purchased from the private institution, Dicom Equifax, and contains any reported default episodes that had happened within the last 2 years [4]. If the client is in

[3]This information is provided by the Bureau for Bank Regulation, and is available to all financial institutions.

[4]The Chilean law explicitly prohibits the disclosure of any default situations that were resolved more than 24 months before the report is issued. Report of default to Dicom Equifax is voluntary.

the best risk category he can get a loan with a maximum monthly installment equal to the payment capacity. If the client is in a lower risk category his monthly installments can be a fraction of the payment capacity.

In a rational framework, and if the loan officer is the only connection between the client and the bank, the loan officer will chose the loan size that maximizes his own utility function. He can do that by manipulating the estimated cash flows of the client in such a way that the lending technology of the bank recommends a loan size equal to the size that maximizes the loan officer's utility. [5] In practice there is a limit in the extent to which the loan officer can manipulate the information; Loans are reviewed by a credit committee, and this committee has a deep understanding of the cost structure of the businesses the bank works with. Therefore if the loan officer inflates the cash flows too much he will eventually be caught by the committee. In simple works the loan officer can manipulate information within the reasonable.

The salary of loan officers has a fixed base of 80% and a performance bonus of 20% that depends on the loan officer's portfolio loan size, and its default rate. The base salary ranges between US$ 1,000 and US$ 2,500 depending on the loan officer seniority. Anecdotal information obtained from the managers and loan officers suggests that a 20% variable wage generates strong performance incentives.

[5] We are assuming that the lending technology of the bank estimates a loan size that maximizes the bank utility when accurate information about the client is used. We are also assuming that the bank lending technology does not anticipate potential information manipulation by the loan officer

An alternative methodology used by banks to improve the loan officers' incentives to report accurate information is explored in Hertzberg, Liberti and Paravisini 2011. Hertzberg et all, show that loan officer rotation can improve the accuracy of the loan officers' reports. The basic intuition of their study is that bad information about a portfolio can be reported by the loan officer of the portfolio, or by a new loan officer that replaces the old one in the portfolio. Bad information reported by the loan officer that manages the portfolio is better for the loan officer career than bad news reported by a new loan officer that replaces him in the portfolio. Therefore, if rotation can happen, the loan officer has stronger incentives to disclose bad information than the case in which rotation never happens.

The work of Hertzberg, Liberty, and Paravisini is a seminal attempt to understand the relevance of loan officers in the lending channel. In our paper we try to add to this body of knowledge by exploring to what extent the relationship between the loan officer and the client, and the potential soft information that is generated in this interaction, can affect credit availability and credit characteristics. In order to answer our research questions we study what happens when the loan officer that has been working with the client suddenly has to leave the bank due to sickness, pregnancy, lay offs, or resignations.

II Data and Empirical Strategy

Using data from the internal records of the micro credit division of the bank, we construct a monthly panel of entrepreneurs' credit characteristics. The variables we obtained, directly from the bank records are; credit size, interest rate, maturity, grace period, credit score[6], and missed payment information divided according to the time elapsed since the payment was missed (these include payment missed less than 60 days ago, payment missed between 60 and 89 days ago and payment missed 90 or more days ago). In this paper, we call default any payment in arrears for more than 90 days. Missed payments of less than 90 days are not considered default. Based on the bank records, we reconstruct the length of the relationship between the loan officer and the client, which is defined as the number of months the client and the loan officer have been working together.

The panel is merged with two additional data sources; a database of the SBIF (or the Spanish acronym for Bureau for Bank Regulation), and a database from human resources department. SBIF is an institution that oversees the aggregated risk of the financial system in Chile and supervises and enforces that the banks follow the risk guidelines established by the Chilean law for bank operations, which in general lines follows Basel II. Each bank is required to report to SBIF the total credit amount, and missed payments of each client. SBIF aggregates the information by customer and makes it available to all formal financial

[6]Chile does not have a centralized credit score, each financial institution designs its own credit score for internal policy

institutions. Therefore, financial institutions make their lending decisions based on the aggregated credit amount and default rate of each client in the formal financial system. The variables in the SBIF database are total consumption credit, total commercial credit, total mortgage, total consumption credit in default, total commercial credit in default, and total mortgage in default. The amounts of default in the SBIF database are divided into default from 30 to 59, default between 60 and 89 days and default of more than 90 days. The database of human resources department contains the information on all temporary and permanent loan officers' leaves, including sick leaves, pregnancy leaves, layoffs and resignations. It also contains the loan officers' starting date, as well as other demographic variables about the loan officer such as age, sex, marital status, and home address.

The panel covers 3-years (2006-2008) and includes observations from 187,000 clients and 480 loan officers. In the estimations, we only include loan officers that had at least 50 active clients in their portfolio, where active clients are defined as clients having at least $10,000 Chilean in debt (approximately US$ 20).

In table I, we present the number of leaves, the average length of each leave, and its standard deviation. All of the information is presented by month. A loan officer is considered absent in a particular month if during that month he was absent for more than half of the working days. We have 32 loan officers that had sick leaves, and a total of 43 sick leave episodes (some loan officers where sick more than once during the study period). The average length of each sick leave was 2.12 months, with a standard deviation of 1.18. We have 33 loan officers that took pregnancy leaves and 34 episodes of 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 maternal leaves in Chile are significantly longer than maternal leaves in the United States. We also have 26 loan officers who were laid off and 15 loan officers that voluntarily resigned from their job.

In table 2 we present the characteristics of the loan officers' and their portfolios. We observe that 51% of the loan officers are women, the average age is 32.6 years, 58% are married, they have in average an experience at the bank of 3.7 years, 64% work in urban areas. The average number of clients per loan officer is 569, of which 339 are active (have more than US$ 20 in loan outstanding).

In table 3, we present demographic information about the clients and information about their loans inside and outside of the bank. The average age for the clients is 47, 62% of them are men, and 71% are married. The average length of the relationship with their loan officer is 11 months. The average credit with the bank (sum of all the outstanding loans) for a client is $2,315,000 Chilean (approximately US$ 4,600), 59% of the clients have loans outside the bank, and the average size of the credit outside the bank is $1,372,000 Chilean (approximately US$ 2,750). In table 3, we see that the probability that a client applies for a new loan at the bank at is 6.5%, the probability that the loan gets approved is 83/% and the probability that the client gets a loan outside the bank is 16.5%. The average size of a new loan is $1,850,000 (about US$ 3,700), the average maturity is 27 months, the average interest rate is 1.69% monthly nominal, and the average grace period is 118 days, the average grace period is high because the agricultural clients usually have a 1 year grace period. Finally, in table 3, we can observe that clients have very few savings; only 36% of them save and the average total savings is $94,000 (about US$ 190).

To estimate the effect of a loan officer leave on the credit availability and the repayment behavior of the client, we estimate a panel regression at the client level where we include a dummy variable that takes the value of 0 when the loan officer is present and the value of 1 when the loan officer is absent. Each panel regression includes; time and client fixed effect, controls for cyclical effects associated to the time to maturity of the loan, and controls for the characteristics of the loan officer. To make the results more robust we exclude from the estimations the clients that have experienced a loan officer leave that is different from the leave that we estimate. For example, if we estimate the effect of a pregnancy leave, we exclude from the panel all clients for which their loan officer has been sick, has been laid off, or has voluntarily left his job.

The basic equation (used to estimate tables IV to VIII) can be written as:

$$Y = C + \beta_{leave} dummy_{leave} + \Sigma \beta_i Control_i + time_{fe} + client_{fe} \tag{1}$$

where Y is the dependent variable. The $dummy_{leave}$ is a variable that takes the value of 0 when the loan officer is present and 1 when he is absent. C_i are control variables, $time_{fe}$

are time fixed effects, and $client_{fe}$ are client fixed effects. Standard errors are clustered at the loan officer level.

In tables **??** to XII we estimate how the characteristics of the client affect the effect of the loan officer leaves. In particular we study how the effect of the leaves changes with the length of the relationship with the loan officer, the loan size of the client, and the credit score of the client. The equation estimated for these tables is similar to equation 1, but includes interaction terms, the complete equation is:

$$Y = C + \beta_{leave} dummy_{leave} + \Sigma \beta_{leave \times var_i} dummy_{leave} \times var_i + \Sigma \beta_i Control_i + time_{fe} + client_{fe} \tag{2}$$

Where all the terms are similar to equation 1, and var_i is the variable that is interacted with the leave dummy.

It is important to note that not all absentee spells can be considered exogenous. In particular layoffs and resignation might be correlated with the prior performance of the loan officer's portfolio. Laid off loan officers might be let go due to the particularly poor performance of their portfolio; while resigning loan officers might be poached away by competitors due to their above average skills or performance. Pregnancies differ from the other absentee spells in that there is a long lead time which allows the bank and the loan officer to prepare the clients for the loan officer's leave in order to prevent potential problems. Therefore the most exogenous source of absenteeism in our sample are major sickness periods of loan officers. These spells are largely unexpected for both the bank and the loan officer, and are independent of the loan officers' portfolio characteristics.

III Results

In table **??** we present the effect of loan officer absenteeism for all type of leaves. Each column presents a regression of a dependent variable as a function of the dummy variable for the loan absenteeism and a set of control variables. The dummy variable takes the value 0 when the loan officer is working and 1 when the loan officer is not working, therefore the coefficient we estimate for this variable captures the effect of the loan officer absenteeism. In the first column of table **??** we observe that loan officer absenteeism generates a reduction of 0.086% in the probability that the client gets a loan from the bank, which represents a 13% reduction as a fraction of the unconditional probability of getting a loan from the bank. In the second and third columns 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 for new loans decreases in 0.068%, which represents a 8.8% decrease as a fraction of the unconditional probability to apply for a new loan, and the approval rate decreases in 4.3%, which represents a 5.2% decrease as a fraction of the unconditional approval rate. In columns four to eight we observe that the effects on the rest of the variables is not significant.

The analysis in table V is similar to the analysis in table **??**, but only considers sickness absenteeism. We observe that when the loan officer is absent because of an illness the clients experience a reduction of 1.19% in the probability of renewing their loan in the bank, which represent a 18.5% decrease as a fraction of the unconditional probability of getting a new loan from the bank. The reduction in the probability of getting a loan is explained mainly by a reduction of 0.94% in the probability that the client applies for a new loan. The probability of approval per application reduces in 3.69% however this reduction is not statistically significant. In the fourth column we observe that when the loan officer gets sick the probability that the client gets a loan outside the bank increases in 2.15%, which represents an increase of 13.4% as a fraction of the unconditional probability of getting a loan outside the bank. In the fifth column we observe that when the loan officer is sick there is an increase of 1.07% in the probability that the client misses a loan payment, which represents a 10% increase as a fraction of the unconditional probability of missing a payment. In columns six to eight we observe that the effect of a sickness leave on the rest of the variables is not statistically significant.

In tables VI, VII, and VIII we present the effect of loan officers' pregnancies, layoffs, and resignations absenteeism on the credit conditions of the client. Layoffs have the strongest effect on credit characteristics. When a loan officer is fired, the clients in his portfolio experience a 1.73% decrease in the probability of renewing their loans, which represents a 27% decrease as a fraction of the unconditional probability of getting a new loan. The reduction in the probability of getting a new loan is explained both by a strong reduction in the application rate for new loans, and by a strong decrease in the approval rate per application. Layoffs also increase the probability that the client misses a payment and even the probability of that the client defaults its loan payment. In particular the probability of missing a payment increases in 1.4%, which represent a 13.1% increase as a fraction of the unconditional probability of missing a payment, and the probability of default increases in 0.5% which represents a 27% increase as a fraction of the unconditional probability of entering default. Resignation absenteeism only affects the probability of missing a payment, specifically the probability of missing a payment when the loan officer resigns increases in 1%, which represent a 9.3% increase as a fraction of the unconditional probability of missing a payment. Pregnancy leaves only show a significant effect on the probability of renewing the loan with the bank, in particular when a loan officer leaves because she gets pregnant the probability that her clients renew their loans with the bank decreases in 1.05%, which represents a 16.4% decrease as a fraction of the unconditional probability of renewing the loan with the bank. This reduction is mostly explained by a sharp reduction in the probability that the client applies for a new loan. In particular the probability that the client applies for a new loan decreases in 0.96%, which represents a 12.4% decrease as a fraction of the unconditional probability of applying for a new loan.

In tables IX to **??**, we study how the characteristics of the client affect the effect described in the previous analysis. In particular we explore to what extent the length of the relationship with the loan officer, the size of the client, and the credit score of the client affect the effect of loan officer absenteeism on the borrowers credit characteristics. The baseline parameters are estimated for clients with loans below the median size, credit scores below the median size, and relatively new relationships with their loan officers.

In table IX we observe that the effects of loan officers absenteeism on credit strongly depend on the characteristics of the clients. In particular, the decrease in the probability that the client applies for a new loan is not present for clients with big size loans. The increase in the probability of getting a loan outside of the bank is even larger for big size clients with good credit score, but disappears for big clients with bad credit score. The increase in the probability of missing a payment disappears for small clients with good credit score, but it is still present for the biggest clients even when they have good credit score.

In table X we present the interactions effects between pregnancy leaves, and the characteristics of the clients. We observe similar results than in table IX. However there is one major difference; for pregnancy leaves we observe that big clients with good credit score have a substantial increase in the probability of missing a payment and in the probability of entering into default.

In table XI we present the interaction effects between layoffs, and the characteristics of the clients. We observe that the decrease in the probability of getting a new loan from the bank, and the increase in missed payments and default rates, disappear for small clients with above average credit score, and get weaker for big companies with below average credit score. Surprisingly the probability of getting a new loan from the bank, and the increase in missed payments and default rates, increase for big companies with above average credit scores. For this category of companies the probability of getting a new loan decreases in 4.3%, the increase in missed payments reaches 10.1%, and the increase in the delinquency rates reaches 6.1%. The probability of borrowing outside of the bank only increases for big companies with above average credit score, further the probability to borrow outside of the bank decreases for big companies with below average credit score.

In table **??** we present the interactions effects between resignation leaves and the characteristics of the clients. We observe that clients with short term relationships with the bank do not experience a reduction in their probability of getting a new credit after a loan officer resigns, however clients with long term relationships with the resigned loan officer do experience a reduction in the probability of getting a new loan from the bank. In particular for each additional month of relationship between the client and the loan officer there is a decrease of 0.04% in the probability that the clients gets a new loan from the bank. We also observe that the probability of missing a payment is 5.7% higher for small clients with below average credit score and short term relationships with their loan officer. This effect disappears for small firms with above average credit scores and decreases for big companies with below average credit scores. Surprisingly the effect does not disappear for big companies with above average credit score.

In figures 1 to 4 we study how the effect of the absenteeism evolves in time. We can only plot these effects for sickness and pregnancy leave. Laid off, and resigned officers do not return to the bank and therefore there is no information to construct the figures. In figure 1 we plot the probability of getting a new loan for the 5 months that precede a sickness leave, the months of the sickness leave, and the 5 months that follow the sickness leave. We observe a slight decrease in the probability of getting a loan in the months that precede the sickness leave, we observe a sharp decrease in the probability of getting a loan during the months of the leave, but this effect completely disappears by the second month after the loan officer is back to work.

In figure 2 we plot the probability that the client misses a payment during the five months that precede a sickness leave, the months of the sickness leave, and the five months that follow a sickness leave. We observe that the probability of missing a payment is stable in the months that precede the leave, it experiences an increase during the months of the leave and declines after the leave.

In figure 3 we plot the probability the the client gets a new loan from the bank in the five months that precede a pregnancy leave, in the months of the pregnancy leave, and in the five months that follow a pregnancy leave. We observe an increase in the probability that the client gets a new loan during the fourth month that precedes the leave, this effect decreases during the third and second months that precede the leave. There is a sharp decrease in the probability of getting a new loan during the month of the leave, but this effect disappears as soon as the loan officer comes back from the maternity leave.

In figure 4 we plot the probability that the client misses a payment in the five months that precede a pregnancy leave, in the months of the pregnancy leave, and in the five months that follow a pregnancy leave. We observe that the probability that the client default is not significantly affected by pregnancy leaves, the only exception is the fourth month that follows the leave were there is an increase in the probability that the client misses a payment.

IV Analysis

A consistent finding in the paper is that loan officer absenteeism generates a significant decrease in the probability that the client gets a new loan from the bank. The decrease is explained by a reduction in the probability that the client applies for a new loan and by a decrease in the probability that a loan application is approved by the bank. The reduction in the probability that the client applies for a new loan can be explained as a loyalty effect; the client is willing to postpone his decision to get a loan until his loan officer returns from the leave. Another possibility is that loan officers give advice to clients about the right time to apply for a new loan, thus if the loan officer is absent the client prefers to postpone his borrowing decision. The reduction in the probability that the bank approves a loan application is probably a consequence of a loss of soft information. However, a reduction in the approval rate can also reflect that loan officers inefficiently increase loan approval rates over time. This will happen for example if the loan officer rolls over debt to hide under performing loans. This last explanation is consistent with the fact that we find a strong decrease in approval rates for clients whose loan officer is fired.

After a loan officer leave there is also an increase in the probability that the client misses a payment. One explanation is that the loan officer has an important role in monitoring the clients. An alternative explanation is that loan officers "hide" bad news about clients, and that this bad news are released when the loan officer has to leave the bank either temporarily or permanently.

Further during sickness leaves clients increase their probability to borrow outside the bank. One explanation is that banks can take measures to retain clients as long as they can anticipate a loan officer leave. However sickness leaves are unexpected, and therefore the bank does not have time to respond and avoid the fled of some clients.

Surprisingly none of the leaves affect the interest rate of new loans, this suggest that the bank does not use their soft information to hold up clients. It also shows that loan officers have decision power in the lending decision but not in the pricing of the loans.

All the previous effects are strongly affected by the clients' characteristics. For example clients with small loans and poor credit score, experience the strongest reduction in the probability of getting new loans when the loan officer is absent. This is not surprising since we expect these companies to strongly rely on soft information in order to access the financial markets. Companies with credit size above the median and credit score below the median also experience a significant decrease in the probability of getting a new loan. Further, this type of companies cannot replace the credit crunch with outside borrowing.

Also big companies with good credit score can offset the credit crunch from the original lender by borrowing outside the bank. This finding shows that for client with good credit score, financial institutions are willing to skip the use of soft information in their lending decision. Surprisingly, this category of companies still shows a strong deterioration of their repayment behavior when the original loan officer is absent. It is unlikely that this category of companies get their financial situation deteriorated as a consequence of the loan officer leave, therefore we conjecture that the worsening of the repayment behavior is a disclosure of an already deteriorated financial situation. The loan officer will suppress this information to increase the portion of his salary that depends on performance. As a consequence the company will maintain an artificial "high credit score" and will keep getting funding from the bank. When the loan officer leaves, the incoming loan officer has incentives to disclose the real situation of the company. Not doing so will reduce its expected salary because the company will eventually default. This type of moral hazard between loan officers and the bank is extendedly described in Hertzberg, Liberty, and Paravisini (2010).

The strong effect of loan officer absenteeism on the clients credit characteristics and availability suggest that soft information strongly affects the lending decision of the bank, it also shows that soft information is not easily transferrable even among loan officers in the same financial institution.

V Conclusion

This paper examines the relevance of soft information in the credit provision to borrowers as well as the borrowers' behavior. We estimate the effect of soft information by studying the change in credit conditions during sickness leaves, pregnancy leaves, layoffs and resignations.

We find that soft information has first order effects on the credit availability and repayment behavior of entrepreneurs. In particular we show that when the original loan officer is absent, and the client has to work with a less informed loan officer, there is a significant reduction in the probability of getting a loan from the bank, a significant increase in the probability that the client misses a payment, and an important increase in the borrowing outside the bank.

These effects strongly depend on the characteristics of the client. For example, during loan officer leaves, clients with poor credit score experience a larger reduction in the probability of getting a new loan from the bank. On the flipside, clients with good credit score experience a smaller decrease in lending from the original bank, furthermore clients with good credit score also find it easier to offset the credit crunch by borrowing outside of the bank.

We also find that the deterioration of the repayment behavior is particularly large for small clients with poor credit score, this is expectable as this type of clients may need stronger monitoring to control their repayment behavior. Surprisingly we also find that big clients with good credit score also experience a significant deterioration of their repayment behavior. The last result suggest that loan officers suppress bad information about bigger clients by rolling over debt to financially distressed firms.

In short this study finds evidence that soft information strongly affects companies access to credit and repayment behavior, that loan officer play a crucial role in collecting and reporting this soft information, and that transferring the soft information is not trivial even within loan officers in the same financial institution.

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Tables

Table I: Absenteeism Statistics

	number of officers that were absent	number of episodes	average length (in months)	sd length
sick	32	43	2.12	1.18
pregnancy	33	34	4.64	1.12
layoff	26	26		
resignation	15	15		

Table II: Summary Statistics Loan Officers

	N	mean	sd	median
sexo (0=man)	370	0.51	0.5	
age (years)	370	32.6	4.7	31.8
married (0=yes)	370	0.42	0.49	
number of children	370	0.77	0.9	1
experience (years)	370	3.7	2.6	3.2
area (1=city)	293	0.64	0.48	
total clients	480	569	207	576
active clients (loan > US$ 20)	480	339	112	341

Table III: Summary Statistics by Client

	N	mean	sd	median
age	156,148	47.47	12.18	47.54
sex (0=man)	185,724	0.384	0.486	
married(0=yes)	153,882	0.292	0.439	
relationship length	186,632	11.15	7.11	9.30
prob. miss payment	186,632	0.114	0.231	
prob. default	186,632	0.026	0.108	
prob. loan renewal	186,632	0.053	0.078	
prob. application	186,632	0.065	0.091	0.037
prob. approval	96,473	0.833	0.308	1
total credit with bank	186,632	2,315,067	3,216,246	1,027,614
prob. outside credit	186,632	0.165	0.151	0.148
outside credit (1=yes)	186,632	0.587	0.370	0.571
total outside credit	186,632	1,131,148	2,632,198	117,470
new loan average size	86,438	1,853,098	2,316,258	1,035,338
new loan maturity (months)	86,798	27.12	21.14	21.67
interest (monthly %)	86,798	1.69	0.55	1.86
grace period	84,619	118	140	59
savings (1=yes)	186,632	0.360	0.364	0.3
total savings	186,632	94,131	1,816,458	955

Table IV: All Leaves

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06443	0.07777	0.82851**	0.16198	0.10724	0.01838	1.6629***	27.171
(not from regression)	(0.24552)	(0.2678)	(0.37693)	(0.36843)	(0.30942)	(0.13431)	(0.58114)	(24.033)
Constant	0.40832***	0.43452***	0.91577***	0.21417***	0.04529***	0.08597***	1.6056***	23.07***
	(0.00632)	(0.00645)	(0.01786)	(0.00499)	(0.00367)	(0.0036)	(0.0184)	(1.049)
after dummy	-0.00864***	-0.00675***	-0.04338***	0.00011	0.00102	-0.00042	0.0058	-0.003
	(0.00191)	(0.00217)	(0.01167)	(0.00369)	(0.00214)	(0.00087)	(0.0139)	(0.569)
experience loan officer	-0.00004	-0.00013***	0.00076***	-0.00001	-0.0002**	-0.00004	0.0009**	-0.02
	(0.00004)	(0.00005)	(0.00028)	(0.00006)	(0.00008)	(0.00003)	(0.0004)	(0.014)
sex loan officer	-0.00236***	-0.00199**	-0.00806	-0.0001	-0.00084	-0.00016	0.0194**	-0.091
	(0.00086)	(0.00102)	(0.00573)	(0.001)	(0.00138)	(0.0006)	(0.0085)	(0.254)
relationship length	0.00012**	0.00013**	0.00028	0.00002	0.00069***	0.00021***	-0.0002	0.019
	(0.00006)	(0.00006)	(0.00037)	(0.00007)	(0.00009)	(0.00003)	(0.0006)	(0.017)
N obs	2820731	2820731	219512	2820731	2820731	2820731	176131	176131
R-squared	0.079	0.082	0.1	0.203	0.416	0.266	0.658	0.424

Table V: Sick Leave

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.064	0.07717	0.82944**	0.16136	0.10755	0.01845	1.6681***	27.316
(not from regression)	(0.24476)	(0.26686)	(0.37613)	(0.36787)	(0.30981)	(0.13458)	(0.5818)	(24.222)
Constant	0.41159***	0.43714***	0.65602***	0.21505***	0.04524***	0.08602***	1.6116***	22.732***
	(0.00676)	(0.00691)	(0.01919)	(0.00585)	(0.00401)	(0.00401)	(0.0218)	(1.31)
after dummy	-0.01185***	-0.0094**	-0.03691	0.02148**	0.01065**	-0.00007	0.009	-0.501
	(0.00378)	(0.0037)	(0.0263)	(0.00934)	(0.00455)	(0.00185)	(0.0364)	(1.453)
experience loan officer	-0.00006	-0.00016***	0.001***	-0.00005	-0.00024***	-0.00002	0.001**	-0.002
	(0.00005)	(0.00006)	(0.00036)	(0.00008)	(0.00009)	(0.00004)	(0.0005)	(0.018)
sex loan officer	-0.00209**	-0.00157	-0.00754	0.00154	-0.00068	-0.00026	0.0193*	-0.231
	(0.00105)	(0.0012)	(0.00739)	(0.00119)	(0.00151)	(0.00075)	(0.0103)	(0.307)
relationship length	0.00011*	0.00009	0.0005	0.00007	0.00082***	0.00022***	-0.0004	0.023
	(0.00006)	(0.00007)	(0.00043)	(0.00009)	(0.0001)	(0.00004)	(0.0007)	(0.021)
N obs	2336957	2336957	180340	2336957	2336957	2336957	144852	144852
R-squared	0.079	0.083	0.098	0.205	0.428	0.279	0.659	0.418

Table VI: Pregnancy Leave

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06391	0.07717	0.8281**	0.16152	0.10758	0.01845	1.668***	27.266
(not from regression)	(0.24458)	(0.26686)	(0.3773)	(0.36801)	(0.30984)	(0.13459)	(0.58151)	(24.137)
Constant	0.40799***	0.43485***	0.67516***	0.2144***	0.04295***	0.08697***	1.6029***	22.8***
	(0.00669)	(0.00683)	(0.01916)	(0.00589)	(0.00414)	(0.00405)	(0.0223)	(1.286)
after dummy	-0.01049***	-0.00955**	-0.01622	0.00258	0.00577	0.00258	0.033	1.571
	(0.00345)	(0.00434)	(0.02358)	(0.00315)	(0.00596)	(0.00202)	(0.0383)	(1.192)
experience loan officer	0.00001	-0.00009	0.00097***	-0.00002	-0.00015	-0.00003	0.001*	0
	(0.00005)	(0.00006)	(0.00034)	(0.00008)	(0.0001)	(0.00004)	(0.0005)	(0.018)
sex loan officer	-0.00152	-0.00095	-0.01043	0.00155	-0.00006	-0.00072	0.0213**	-0.255
	(0.0011)	(0.00125)	(0.00742)	(0.00123)	(0.00153)	(0.00069)	(0.0106)	(0.317)
relationship length	0.00007	0.00007	0.0003	0.00008	0.00081***	0.00024***	0.0002	0.011
	(0.00006)	(0.00007)	(0.00044)	(0.00008)	(0.0001)	(0.00004)	(0.0007)	(0.022)
N obs	2329815	2329815	179800	2329815	2329815	2329815	144229	144229
R-squared	0.079	0.082	0.095	0.206	0.429	0.279	0.656	0.41

Table VII: Layoffs

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06449	0.07761	0.83089**	0.16232	0.10686	0.01837	1.6643***	27.284
(not from regression)	(0.24562)	(0.26756)	(0.37485)	(0.36874)	(0.30894)	(0.13428)	(0.57796)	(24.124)
Constant	0.4113***	0.4374***	0.66369***	0.21561***	0.04497***	0.0869***	1.6017***	22.47***
	(0.00686)	(0.00701)	(0.02003)	(0.00591)	(0.00424)	(0.00409)	(0.0213)	(1.282)
after dummy	-0.01729***	-0.01191***	-0.0734***	-0.01134	0.01397**	0.005*	0.038	0.724
	(0.004)	(0.0046)	(0.02772)	(0.00822)	(0.00621)	(0.00277)	(0.0309)	(1.434)
experience loan officer	-0.00003	-0.00013**	0.00095***	-0.00006	-0.00026***	-0.00005	0.0011**	-0.004
	(0.00005)	(0.00006)	(0.00037)	(0.00009)	(0.0001)	(0.00004)	(0.0005)	(0.019)
sex loan officer	-0.00254**	-0.00202	-0.01278	0.00166	-0.00089	-0.00017	0.0221**	-0.229
	(0.00113)	(0.0013)	(0.00781)	(0.00133)	(0.00146)	(0.00075)	(0.0108)	(0.322)
relationship length	0.0001	0.00009	0.00037	0.00008	0.00083***	0.00024***	-0.0001	0.022
	(0.00007)	(0.00007)	(0.00044)	(0.00009)	(0.00011)	(0.00004)	(0.0007)	(0.022)
N obs	2260617	2260617	175457	2260617	2260617	2260617	141211	141211
R-squared	0.08	0.083	0.09	0.203	0.427	0.278	0.657	0.414

Table VIII: Resignation

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06429	0.07741	0.83052**	0.16183	0.10708	0.01843	1.6692***	27.258
(not from regression)	(0.24527)	(0.26724)	(0.37518)	(0.3683)	(0.30922)	(0.13452)	(0.58051)	(24.152)
Constant	0.41166***	0.43715***	0.67673***	0.21513***	0.04674***	0.08652***	1.6067***	22.65***
	(0.00695)	(0.00711)	(0.01986)	(0.00602)	(0.00423)	(0.00413)	(0.022)	(1.351)
after dummy	-0.0066	-0.00602	-0.04223	-0.00281	0.01006***	-0.00074	0.045	-1.063
	(0.00402)	(0.00396)	(0.02951)	(0.00894)	(0.00383)	(0.0022)	(0.06)	(2.149)
experience loan officer	-0.00005	-0.00015**	0.00097***	-0.00007	-0.00027***	-0.00005	0.001*	-0.001
	(0.00005)	(0.00006)	(0.00037)	(0.00008)	(0.0001)	(0.00004)	(0.0005)	(0.02)
sex loan officer	-0.00244**	-0.00192	-0.00933	0.00144	-0.00132	-0.00047	0.0214*	-0.292
	(0.00117)	(0.00133)	(0.00826)	(0.00127)	(0.00156)	(0.00075)	(0.0113)	(0.328)
relationship length	0.00011	0.00009	0.00042	0.00007	0.00085***	0.00024***	-0.0001	0.024
	(0.00007)	(0.00007)	(0.00045)	(0.00009)	(0.00011)	(0.00004)	(0.0007)	(0.023)
N obs	2217276	2217276	171648	2217276	2217276	2217276	138141	138141
R-squared	0.079	0.082	0.094	0.204	0.43	0.281	0.658	0.41

Table IX: Sick Leaves Interaction Effects

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.064	0.07717	0.82944**	0.16136	0.10755	0.01845	1.6681***	27.316
(not from regression)	(0.24476)	(0.26686)	(0.37613)	(0.36787)	(0.30981)	(0.13458)	(0.5818)	(24.222)
constant	0.41156***	0.43711***	0.65631***	0.21518***	0.04481***	0.08647***	1.6119***	22.722***
	(0.00676)	(0.00691)	(0.01922)	(0.00587)	(0.00401)	(0.00401)	(0.02183)	(1.312)
after dummy	-0.02337***	-0.02368***	-0.01813	0.06823***	0.04719***	0.0147**	0.0703	-0.192
	(0.00727)	(0.00787)	(0.06035)	(0.02584)	(0.01174)	(0.00688)	(0.05724)	(2.89)
experience loan officer	-0.00006	-0.00016***	0.001***	-0.00005	-0.00024**	-0.00002	0.001*	-0.003
	(0.00005)	(0.00006)	(0.00036)	(0.00008)	(0.00009)	(0.00004)	(0.00051)	(0.018)
sex loan officer	-0.00212**	-0.0016	-0.00754	0.00152	-0.00061	-0.00026	0.0192*	-0.233
	(0.00106)	(0.00121)	(0.00741)	(0.00119)	(0.00151)	(0.00075)	(0.01031)	(0.308)
relationship length	0.00011*	0.00009	0.00049	0.00007	0.0008***	0.00022***	-0.0004	0.023
	(0.00006)	(0.00007)	(0.00043)	(0.00009)	(0.0001)	(0.00004)	(0.00066)	(0.021)
after dummy x rel length	-0.00008	-0.00013	0.00071	-0.00052	0.0002	-0.00026*	-0.0013	-0.024
	(0.00024)	(0.00027)	(0.0022)	(0.00069)	(0.00034)	(0.00015)	(0.00427)	(0.172)
after dummy x size	0.00932	0.01502*	-0.05553	-0.06901***	-0.00848	-0.00614	-0.049	-0.353
	(0.00586)	(0.0078)	(0.06586)	(0.02371)	(0.01126)	(0.00533)	(0.06939)	(2.506)
after dummy x score	0.00573	0.00253	0.04171	-0.00169	-0.08885***	-0.02109***	0.0437	0.718
	(0.0077)	(0.00845)	(0.06495)	(0.01321)	(0.01516)	(0.00617)	(0.06117)	(1.657)
after dummy x size x score	0.01462	0.01811	-0.0054	0.02417*	0.0098	0.00654	-0.0617	0.21
	(0.0089)	(0.01142)	(0.07484)	(0.01312)	(0.01106)	(0.00611)	(0.10458)	(2.967)
nobs	2335195	2335195	180255	2335195	2335195	2335195	144800	144800
adjr2	0.08	0.083	0.097	0.206	0.428	0.278	0.659	0.417

Table X: Pregnancy Leaves Interaction Effects

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06391	0.07717	0.8281**	0.16152	0.10758	0.01845	1.668***	27.266
(not from regression)	(0.24458)	(0.26686)	(0.3773)	(0.36801)	(0.30984)	(0.13459)	(0.58151)	(24.137)
constant	0.40798***	0.43491***	0.67481***	0.21467***	0.04241***	0.08732***	1.6034***	22.787***
	(0.00668)	(0.00682)	(0.01915)	(0.00591)	(0.00414)	(0.00405)	(0.02227)	(1.289)
after dummy	-0.02164***	-0.02506***	-0.05177	-0.00439	0.06719***	0.02973***	0.0439	3.004
	(0.00636)	(0.00775)	(0.05967)	(0.00795)	(0.01076)	(0.00616)	(0.05555)	(2.255)
experience loan officer	0.00001	-0.00009	0.00097***	-0.00002	-0.00015	-0.00003	0.001*	0
	(0.00005)	(0.00006)	(0.00034)	(0.00008)	(0.0001)	(0.00004)	(0.00053)	(0.018)
sex loan officer	-0.00156	-0.00095	-0.01087	0.00166	-0.00001	-0.0007	0.0217**	-0.259
	(0.00111)	(0.00125)	(0.00742)	(0.00123)	(0.00153)	(0.00069)	(0.01056)	(0.317)
relationship length	0.00007	0.00007	0.00033	0.00007	0.00081***	0.00024***	0.0002	0.012
	(0.00006)	(0.00007)	(0.00044)	(0.00008)	(0.0001)	(0.00004)	(0.00068)	(0.022)
after dummy x rel length	0	0.00034*	-0.00294**	0.00078	-0.00028	-0.00023	0.0033	-0.065
	(0.00018)	(0.00019)	(0.00147)	(0.00048)	(0.0003)	(0.00015)	(0.00274)	(0.085)
after dummy x size	0.01049	0.01012	0.09238*	-0.01384	-0.03753***	-0.0199***	-0.0796	0.82
	(0.00668)	(0.00794)	(0.05533)	(0.01074)	(0.0129)	(0.00536)	(0.05951)	(2.586)
after dummy x score	0.00808	0.00789	0.04262	0.02294	-0.10039***	-0.03967***	-0.0639	-2.729
	(0.00632)	(0.00725)	(0.09996)	(0.01653)	(0.01403)	(0.00526)	(0.09349)	(2.099)
after dummy x size x score	0.00145	0.00044	-0.02755	-0.01403	0.03643**	0.02244***	0.0893	-0.489
	(0.00529)	(0.00598)	(0.10455)	(0.01252)	(0.01496)	(0.00524)	(0.10205)	(3.21)
nobs	2328077	2328077	179718	2328077	2328077	2328077	144176	144176
adjr2	0.079	0.082	0.094	0.206	0.429	0.279	0.656	0.41

Table XI: Layoffs Interaction Effects

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06449	0.07761	0.83089**	0.16232	0.10686	0.01837	1.6643***	27.284
(not from regression)	(0.24562)	(0.26756)	(0.37485)	(0.36874)	(0.30894)	(0.13428)	(0.57796)	(24.124)
constant	0.41123***	0.43729***	0.66345***	0.21561***	0.04447***	0.08727***	1.6015***	22.48***
	(0.00686)	(0.007)	(0.02)	(0.00593)	(0.00422)	(0.00409)	(0.02136)	(1.287)
after dummy	-0.02724***	-0.02398***	-0.11509	0.0178	0.0725***	0.03567***	0.1508	-1.584
	(0.00616)	(0.00682)	(0.08533)	(0.01676)	(0.015)	(0.00814)	(0.1013)	(1.846)
experience loan officer	-0.00003	-0.00012**	0.00096***	-0.00006	-0.00026***	-0.00005	0.0011**	-0.004
	(0.00005)	(0.00006)	(0.00037)	(0.00009)	(0.0001)	(0.00004)	(0.00053)	(0.019)
sex loan officer	-0.00255**	-0.00203	-0.01278	0.00163	-0.00087	-0.00016	0.0222**	-0.233
	(0.00113)	(0.0013)	(0.00781)	(0.00133)	(0.00146)	(0.00075)	(0.01083)	(0.322)
relationship length	0.0001	0.00009	0.00038	0.00009	0.00083***	0.00024***	-0.0001	0.022
	(0.00007)	(0.00007)	(0.00044)	(0.00009)	(0.00011)	(0.00004)	(0.00067)	(0.022)
after dummy x rel length	-0.00015	-0.00019	-0.00259	-0.00091	-0.00028	-0.00028**	-0.0022	0.054
	(0.00025)	(0.00026)	(0.00252)	(0.00072)	(0.00058)	(0.00012)	(0.00276)	(0.131)
after dummy x size	0.01342***	0.02134***	0.07303	-0.03089***	-0.02611*	-0.02227***	-0.1314	0.755
	(0.0051)	(0.00405)	(0.09106)	(0.01087)	(0.01355)	(0.00853)	(0.11153)	(2.735)
after dummy x score	0.01802**	0.01596*	0.15002	-0.00518	-0.09861***	-0.04211***	0.0097	-0.158
	(0.009)	(0.00912)	(0.10817)	(0.009)	(0.01372)	(0.00783)	(0.12972)	(2.001)
after dummy x size x score	-0.01616*	-0.02124**	-0.11933	0.02335*	0.02795**	0.02492***	0.0792	3.671
	(0.00899)	(0.00917)	(0.13463)	(0.01362)	(0.01298)	(0.00872)	(0.16744)	(4.276)
nobs	2258928	2258928	175377	2258928	2258928	2258928	141161	141161
adjr2	0.08	0.083	0.09	0.203	0.426	0.278	0.657	0.414

Table XII: Resignations Interaction Effects

	renewal rate	application rate	aproval rate	outside loan	missed payment	delinquency rate	interest rate	maturity
unconditional mean	0.06429	0.07741	0.83052**	0.16183	0.10708	0.01843	1.6692***	27.258
(not from regression)	(0.24527)	(0.26724)	(0.37518)	(0.3683)	(0.30922)	(0.13452)	(0.58051)	(24.152)
constant	0.41155***	0.43706***	0.67668***	0.21526***	0.04647***	0.08701***	1.607***	22.635***
	(0.00694)	(0.0071)	(0.01987)	(0.00604)	(0.00423)	(0.00413)	(0.02205)	(1.355)
after dummy	-0.00279	-0.00666	0.04354	-0.0172	0.05716***	0.01106	-0.0367	3.27
	(0.00707)	(0.00867)	(0.08036)	(0.02109)	(0.01755)	(0.00754)	(0.11663)	(2.596)
experience loan officer	-0.00005	-0.00015**	0.00097***	-0.00007	-0.00028***	-0.00005	0.001*	-0.001
	(0.00005)	(0.00006)	(0.00037)	(0.00008)	(0.0001)	(0.00004)	(0.00053)	(0.02)
sex loan officer	-0.00246**	-0.00196	-0.00937	0.00138	-0.00128	-0.00048	0.0216*	-0.299
	(0.00117)	(0.00133)	(0.00826)	(0.00127)	(0.00156)	(0.00075)	(0.01129)	(0.328)
relationship length	0.00011	0.00009	0.00043	0.00007	0.00084***	0.00024***	-0.0001	0.024
	(0.00007)	(0.00007)	(0.00045)	(0.00009)	(0.00011)	(0.00004)	(0.0007)	(0.023)
after dummy x rel length	-0.00035*	-0.00038	-0.0024	-0.00053	0.00011	-0.0003**	0.0053	-0.209*
	(0.00021)	(0.00029)	(0.0025)	(0.00053)	(0.00035)	(0.00013)	(0.00452)	(0.122)
after dummy x size	-0.0023	0.00342	-0.04712	0.0228	-0.03303*	-0.00284	-0.0062	-0.693
	(0.0072)	(0.00837)	(0.09094)	(0.02438)	(0.01929)	(0.00742)	(0.11564)	(4.747)
after dummy x score	0.00653	0.01038	0.0771	0.02717	-0.07919***	-0.01557**	-0.0149	2.356
	(0.01697)	(0.0171)	(0.09597)	(0.01956)	(0.02185)	(0.00722)	(0.1185)	(2.424)
after dummy x size x score	-0.00127	-0.00376	-0.14077	-0.01943	0.02939	0.00329	0.0439	-5.39
	(0.01495)	(0.0164)	(0.1037)	(0.0192)	(0.0216)	(0.00731)	(0.14145)	(6.313)
nobs	2215608	2215608	171572	2215608	2215608	2215608	138094	138094
adjr2	0.079	0.083	0.094	0.205	0.429	0.28	0.658	0.409

Figure 1: Probability of Getting a New Loan Around a Sick Leave

In this figure we present the probability that a client gets a new loan before the officer goes on a sick leave, during the officer's sick leave, and after the loan officer return to his duties. The time is expressed in months and time 0 represents the time where the loan officer was absent. The solid line represent the probability, the dashed lines represent a 95% confidence interval. The probabilities are estimated using a linear probability model.

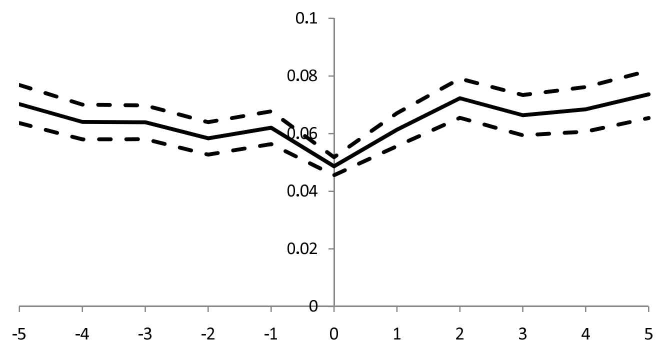

Figure 2: Probability of Missing a Loan Payment Around a Sick Leave

In this figure we present the probability that a client misses a payment before the officer goes on a sick leave, during the officer's sick leave, and after the loan officer return to his duties. The time is expressed in months and time 0 represents the time where the loan officer was absent. The solid line represent the probability, the dashed lines represent a 95% confidence interval. The probabilities are estimated using a linear probability model.

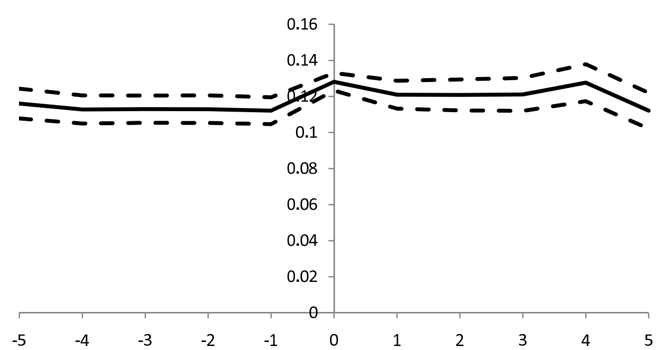

Figure 3: Probability of Getting a New Loan Around a Pregnancy Leave

In this figure we present the probability that a client gets a new loan before the officer goes on a pregnancy leave, during the officer's pregnancy leave, and after the loan officer return to his duties. The time is expressed in months and time 0 represents the time where the loan officer was absent. The solid line represent the probability, the dashed lines represent a 95% confidence interval. The probabilities are estimated using a linear probability model.

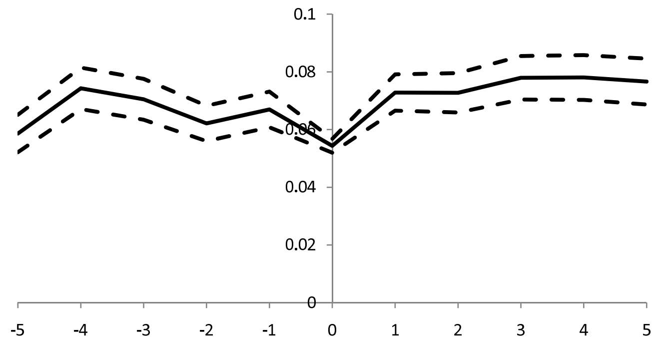

Figure 4: Probability of Missing a Loan Payment Around a Pregnancy Leave

In this figure we present the probability that a client misses a payment before the officer goes on a pregnancy leave, during the officer's pregnancy leave, and after the loan officer return to his duties. The time is expressed in months and time 0 represents the time where the loan officer was absent. The solid line represent the probability, the dashed lines represent a 95% confidence interval. The probabilities are estimated using a linear probability model.