The Personal Side of Relationship Banking

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Abstract:

I conduct an RCT with India's largest commercial bank, ICICI, to test an overlooked dimension of relationship lending: I show that personal interactions between borrowers and lender reduce their willingness to engage in moral hazard. Borrowers, who are randomly assigned to personalized treatment by either one or a group of relationship managers, show a significantly reduction in the number of late payment spells. Borrowers that get the most personalized attention also have shorter delinquency spells that occur later in the tenure of the loan, get larger loans going forward and have fewer complaints about bank services and can be more easily reached by their relationship manager.

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Introduction

Banks play a critical role in reducing information asymmetries and moral hazard problems in the lending process. This is especially true for small and private firms that are opaque and present many difficulties in how to assess their credit risk. To improve the accuracy of their credit assessment banks resort to relationship lending as a key tool for screening and monitoring potential borrowers. The idea is that a relationship lending approach increases the breadth and detail of the information that a loan officer can obtain about the borrower. Petersen and Rajan (1994) or Stein (2005), for example, emphasize the importance of soft information for bank lending decisions, especially in cases where hard or verifiable information is difficult to obtain. By relying on the direct relationship between loan officers and their clients, the former should be able to learn subtle information about a borrower's type, competence, quality of business or even personal integrity.

The main focus of the literature on relationship lending thus far has thus been in one direction: it emphasizes that lenders can obtain better information about their borrowers through in-person interaction[2]. However, relationship lending might also have an effect in the reverse direction. If borrowers have a personal relationship with their loan officer, their willingness to default might change. A borrower might feel more hesitant if he is defaulting on an individual person rather than an anonymous bank. Thus, the likelihood of the borrower to engage in moral hazard behavior might be reduced because of the relationship with a loan officer. This reluctance could either be the outcome of behavioral norms or fairness perceptions, which create non-pecuniary costs for a borrower of defaulting on "their" loan officer. In other words, relationship lending might create a feeling of reciprocity toward the loan officer.[3] An alternative, non-behavioral interpretation for the reluctance to default could assume that borrowers understand that their relationship with their loan officer has a lot of soft information embedded in it, which cannot be easily replicated with a new bank. So if the continuation value of working with this loan officer is larger than any outside loans the borrower can get, she rationally should be less willing to default. But importantly, both of these interpretations rely on a change in the behavior of the borrower, i.e. a reduction in their willingness to engage in moral hazard, rather than an improvement in the information basis of the bank.[4]

[2] For an interesting discussion of the forms of soft versus hard information and the way banks can produce this information, see Petersen (2004).

[3] The underlying model of "fair" behavior could be either one of "interdependent preferences" where people are concerned about the other person's type, as in the models of Levine (1998) or Gul and Pesendorfer (2005). In this case borrowers might act non-selfishly if they think the bank is of a fair type. Alternatively, preferences for fairness might be based on inferences about lenders intentions as in the seminal papers by Rabin (1993) or Geanakoplos, Pearce and Stacchetti (1989).

[4] A few recent papers that discuss the possibility that relationship lending might not only lead to better monitoring but also reduce the incentives of borrower to default are Puri et al (2010) or Drexler and Schoar (2012).

For that purpose I tests the impact of relationship lending in shaping the behavior of the borrower towards the lender. I show that borrowers have a lower likelihood of being delinquent and shorter delinquency spells, as well as higher levels of satisfaction with bank services, if they receive more personalized attention from the bank. I find that this effect is more pronounced if the client is assigned to a specific loan officer. I conducted a field experiment with India's largest commercial bank, on their portfolio of small business borrowers from July 2007 until April 2009.[5] Borrowers were randomly assigned to four different groups, which varied in the intensity of personalized attention that the borrower received from the bank. Personalized attention was provided through matching borrowers with individual relationship managers who help clients with any questions or problems they might have with their current loan (for example, missing bank statements, ATM cards, etc.) or if they need other assistance from the bank.

In the first treatment group which I call the high touch group (Group A), borrowers are assigned to a personal relationship manager who is the sole interface between the borrower and the bank and who can be directly reached by the borrower via phone or SMS. The high touch group receives a phone call from their personal relationship manager biweekly to check if the client has any issues with the loan. In case the client is late with a payment, the relationship manager will also remind the borrower to pay in time to avoid late fees. However, relationship managers will not engage in cross selling of other banking products so that borrowers do not feel that this is just a sales vehicle. Borrowers in the second group, medium touch (Group B), receive exactly the same treatment as the high touch group with one important difference: instead of interacting with a single relationship manager their contact person varies randomly every time. However, the frequency and content of the calls are otherwise identical to the first group. The comparison between these two treatment groups will allow me to test the importance of having a personal relationship with one contact person or if borrowers can develop a feeling of reciprocity even towards a larger set of relationship managers.

Borrowers in the third group, low touch (Group C), only receive a reminder call when a payment due date is approaching. The caller is randomly assigned and no attempts were made to establish a personal relationship with the client. This treatment group was added to rule out that the impact of the calls in Groups A and B is mainly a function of reminding customers that their payment is coming up. Finally, I also implement a control group (Group D), which is treated like the regular small business customer of the bank. These borrowers do not receive any regular check in calls

[5] The data from the study were released with a delay to protect the privacy of the bank's loan portfolio. ICICI's small business loan product provides uncollateralized loans of a size between $10,000 and $50,000. These loans are structured as overdraft facilities with a one year maturity. Credit assessments are based on a credit scoring mechanism and the loan is expected to be renewed at the end of the year if the borrower was not in default.

by a relationship manager or any other follow up. They do, however, receive an SMS reminding them of their due date.[6]

In order to isolate the personal cost of defaulting on the relationship, the experiment was set up in such a way that the relationship managers did not collect any soft (or hard) information on the borrower and were not involved in making loan renewal decisions at the end of the loan maturity. This was made clear to borrowers from the very beginning. In addition, it is also evident to the clients that the loan officer who makes the lending decision is completely separate from the relationship manager and is even located in a different part of India. Therefore, borrowers would not see the calls with their relationship managers as a way to collect information from them.

I first compare borrowers who receive more personalized treatment (those in the high and medium touch treatment groups, A and B) to the more hands off treatment groups (C and D) to show that higher attention from the bank matters. I find a 10 percent point reduction of the number of periods in which borrowers pay at least 30 days late, relative to the control. Since the overall propensity to be 30+ days late is 0.22 in the sample, this constitutes an economically very significant reduction in late payments. When restricting the sample to only those accounts that ever showed incidences of being late, I find an even stronger difference to the control group: about 20 percent reduction in the likelihood of ever having multiple late periods for Groups A and B. Interestingly, when looking at the dynamics of when borrowers fall late, I again find that the borrowers in the personalized treatment groups (A and B) outperform the control groups. They go into default later in the tenure of the loan and their default spells are much shorter (by as much as 30 days) than for the control group (C and D). When looking at the most serious defaulters who are 90+ days late in their payments, I do not see a significant difference between treatment and control groups. The reason most like is that bank has a separate department for collection on seriously delinquent loans, which broke any existing relationships. But unfortunately for compliance reasons, this process could not be changed for the experiment. In addition the power of this test is low since only 5% of loans reach 90+ days late.

In a second step, I test the differential impact of having one personalized relationship officer versus getting called by different loan officers each time. For that purpose I separately estimate the effects on the four treatment groups, particularly focusing on the difference between groups A (the high touch group that was a assigned a personal relationship manager) versus B (the medium touch group that gets a phone call from a random relationship manager). I find no significant difference between groups A and B in their likelihood of ever falling 30+ days late or

[6] All customers receive a reminder call if they are more than 15 days late in their payment. Within one week of moving in to delinquency, defined as 30+ days late, the customer will receive collection calls from the collections department of the bank.

having more than one late payment spell. However, when looking at the dynamics how borrowers repay, there are significant differences. The amount of time that the account is overdrawn is lower by 5% for Group A compared to the control group. There is no significant difference in account usage for Groups B and C. Similarly, the average first delinquency spell for borrowers in Group A is 35 days later than the control group, which is economically very significant since the loan maturity is one year. Again, treatment group B does not see a significant delay as to when they become delinquent relative to the control group. As a result, I also find that the internal assessment of the bank ranks the borrowers in the high touch treatment group (A) significantly higher at the end of the first loan term.

Furthermore, when looking at the soft dimensions in the interaction between relationship managers and borrowers, borrowers in Group A have significantly better outcomes: they have a two percentage point higher rate of being reached by their personal relationship manager compared to treatment Group B. Since borrowers can screen based on the number that is calling them, this shows high willingness to talk to their relationship manager in A. Borrowers in Group A have an eight percentage point lower likelihood of raising a complaint about their account. But when looking at the percentage of complaints that are unresolved conditional on having raised a complaint, I see that these are 5.7 % higher for the borrowers in Group A. This might suggest that the increased contact with the bank led the high touch customers to overall be happier with the bank relationship but be more outspoken when they have a problem and demand a higher level of service.

Finally, I conduct robustness tests to explore a limitation in how treatment Group B was implemented: The bank assigned only six relationship managers to this group (plus two temporary replacements). So many clients in Group B might have been called by the same one or two callers during the course of the experiment simply by random chance. As a result, the level of "familiarity" even in Group B would have been relatively high overall and, thus, could have muted the difference between treatments A and B. Therefore, I rerun all regression where I assign clients from Group B to Group A if by random chance they received the majority of their calls from only one caller. Since customers in Group B were randomly assigned to callers each time, this design does not compromise the integrity of the experimental strategy. Reassigning clients in the described way strengthens the results for Group A and weakens the ones for B. While the difference between A and B do not change significantly, these robustness tests suggest that an increase in the familiarity between the borrowers and their relationship manager is important to achieve the observed reduction in moral hazard behavior.

Overall, the results in this paper support the idea that the impact relationship banking is based on a two way interaction between the borrowers and the bank; not only does it allow a bank to collect more soft information about the borrower as has been previously shown, but it also reduces the willingness of borrowers to engage in moral hazard behavior and default. The experiment was set up to isolate only the second channel, the response of the borrowers, while preventing any improvement in information gathering by the bank. I show that more personalized attention by the bank leads to a reduction in late payment and default spells, as well as their attitude to the bank.

The rest of the paper is organized as follows: section 2 will provide an overview of the literature, and sections 3 and 4 will lay out the institutional background and details of the randomization. Sections 5 and 6 discuss the analysis and results. And section 7 concludes.

1. Literature Review

The role of relationship banking in helping banks to gather "soft information" about the borrowers has been widely discussed in the economic literature. Soft information plays a particularly important role in credit screening of small businesses, which are more opaque and have fewer measurable outcomes than large firms.

Rajan (1992) lays out the trade off inherent in collecting greater amounts of soft information. On the one hand, it allows the lender to charge a higher risk adjusted interest rate over time and thus recuperate the cost of screening small businesses, since outsiders do not have the same knowledge of the borrower. But, at the same time, it can have disincentive effects for the borrowers since the loan contract is now more performance sensitive. Some of the early papers that have examined the impact of creditor-borrower relationships on the pricing and availability of credit are Petersen and Rajan (1994), Berger and Udall (1995), Cole (1998), and Petersen (1999). Generally, these papers find evidence that is consistent with the idea that stronger reliance on relationship lending increases the availability of capital and reduces collateral requirements.

A few more recent papers compare the effect of individualized credit evaluation via loan officers versus rule based credit scoring based on hard information. These papers provide convincing evidence that relationship lending plays a role in improving the screening of borrowers and thus reduces the adverse selection between the bank and the borrower. For example, Qian, Strahan, and Yang (2011) study the reform of a Chinese bank that led to a delegation of credit risk assessment to the individual loan officer. The authors find that the predictability and performance of credit rating metrics improves. Berg, Puri, and Rocholl (2012) study a bank where loan decisions are based solely on hard information input by loan officers into a scoring system. They find that loan officers' discretion even plays a role in hard information lending, since loan officers can make a judgment on the data they collect. The authors show that loan officers use more scoring trials for loan applications that do not pass the cut-off rating in the first trial. Herzberg, Liberty, and Paravisini (2010) and Fisman, Paravisini and Vig (2012) examine the role of relationships by looking at loan officer turnovers. The first paper shows that after a turnover, the new loan officer has an incentive to reveal the poorly performing loans of the prior loan officer in order to have a clean slate. The second paper analyzes the role of social and ethnic ties for the credit screening of a loan officer. The authors find that loan officers find it easier to assess the credit quality of people with whom they share a similar ethnic and religious background, providing support for the idea that loan officers are important in collecting soft information.

Additional supportive evidence for the adverse selection channel comes from papers that relate the strength of the borrower- bank relationship with loan outcomes: Using data on Belgian small businesses, Degryse and Van Cayseele (2000) find that interest rates are positively associated with the duration of the firm's banking relationship. Chakravarty and Shahriar (2010) find the probability of extending credit to Bangladeshi cooperatives is positively associated with the strength of their relationship with MFIs. Using the unexplained variance in credit scoring models as a proxy for the amount of soft information, Agarwal (2010) finds it has significant predictive power for default rates on new SME loans from a U.S. bank. Similarly, Chang et al. (2010) use empirical evidence from China to show that relationship lending can be used as a substitute for hard information in credit scoring models and can also be used to predict loan defaults.

The current paper contributes to this literature by analyzing the incentive effects of the *borrower* not to engage in moral hazard behavior, which has been previously almost completely ignored. The only other papers that have discussed the idea that reduced default rates from relationship lending might not only be a function of improved monitoring but also a lower willingness of borrowers to default are Puri, Rocholl and Steffen (2010) and Drexler and Schoar (2012). The authors show that loans to borrowers who have a relationship with the bank before applying for a loan default much less than those without a relationship even after accounting for screening benefits. But neither of these papers can separately identify the impact of better screening by the bank from the borrower's willingness to abstain from moral hazard behavior as I do in this paper.

My paper is also related to the literature on how soft information lending affects the organizational structure of banks and their internal operations. Stein (1997, 2002) develops a model of how the internal organization of banks can either facilitate or hinder the use of soft information. The idea is that smaller, decentralized banks possess a comparative advantage relative to hierarchical ones in decisions based on soft information. This model is particularly relevant for the small business lending sector where hard financial information on potential borrowers is often unverifiable or difficult to obtain. Indeed, several authors (Nakamura (1994), Berger, Kashyap and Scalise (1995), Peek and Rosengren (1998)) find the share of assets invested in small business loans decreasing in bank size. Similarly, several empirical studies find a reduction in small business lending when large banks acquire small banks, relative to the preacquisition activity of the combined entities (Peek and Rosengren (1998), Berger et al (1998), Sapienza (1998)). Berger et al (2002) test the Stein model across a wide variety of dimensions, finding that within the SME lending sector, small banks lend to more difficult credit cases;

interact more personally with borrowers; have longer, more exclusive lender-borrower relationships; and are more effective at alleviating credit constraints.

There are also a few papers which have pointed out additional organizational risks of soft information lending: Banerjee, Cole, and Duflo (2009) show that one of the dangers of relationship lending is that loan officers can hide bad information about a firm, and evergreen loans until they are too late to save. 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.

2. Description of Experimental Set-Up

2.1. ICICI Bank's small business loan program

To implement the experiment I worked with ICICI bank, the largest commercial bank in India. The bank introduced a collateral-free small business loan product in 2005, which was intended for working capital or ad hoc investment purposes. The loan is set up as an overdraft facility with a predetermined limit. These are overdraft products for small businesses that function like a de facto credit card account. The target group of borrowers includes small manufacturers, trading companies and service providers. At the time of the product introduction in 2005, the small business sector constituted a relatively new set of clients for the bank. In order to reduce the overhead costs on the small business clients, ICICI did not want to depute individual loan officers to interact with each client. Therefore, the bank tried to rely on a credit scoring model and minimal interaction between the borrower and the bank when introducing the product.

The process of loan origination is done by loan officers who meet clients at the branches and provide an initial review of the eligibility criteria, collect documentation and forward the application files to a central credit processing agency ("CPA"). The credit appraisal is based on the characteristics of the business, such as business type, and hard information such as bank statements, references, credit reports, and financial information based on unaudited financial statements or income tax returns.

The small business loan product has two separate variants Smart Business Loan product (SBL) and SBL Power (Power). The SBL Power loan is differentiated from the standard SBL product in that it has a quicker approval time but, on average, has smaller loan sizes, at $10,937[7] compared to the standard SBL average of $24,523. Overdraft amounts for SBL overall range

[7]Throughout the paper all currency amounts have been converted to USD using the February 23, 2011 exchange rate of 1 USD = 45.331 INR

from \$5,515 to \$55,150 for businesses with annual sales from \$88,240 to \$3,308,994. All other features are the same between SBL and SBL Power. Each month, a borrower must pay an amount equal to 5% of their total outstanding balance including interest charges. Interest rates depend on the loan size and a fixed premium above an internal benchmark rate and are fixed at the time the loan is sanctioned but may be revised on renewal. All overdraft limits are sanctioned for a period of 12 months. Penalty interest rates and late fees are not used, though past due accounts may be contacted by collections staff and have their non-performance reported to credit agencies.

In the eleventh month after sanctioning the loan, the bank reviews account performance and decides whether to renew the loan for an additional year and whether to adjust to the overdraft limit. Accounts in the best standing have a maximum of two late payments that are never more than 30 days late (Category A accounts). These accounts are automatically renewed and their limits are adjusted based on the ratio of annual deposits to limit size. Accounts with more than three late payments or cautions by the bank are marked for further review (Category B and C accounts), while the most delinquent accounts are marked for closure (Category D and Caution 4 accounts).

3. Study Design

3.1. Experimental Set up

To test whether relationship lending and closer personal ties between the bank and the client do indeed affect the loyalty and repayment behavior of the clients, I conducted a randomized controlled study. I selected new loan clients to be included in our study based on their loan amount and location. Loans in smaller (non-CPA) cities[8] were initially excluded since the distribution network of the bank in small cities Is fundamentally different and might have introduced noise. Thus, from July 2007 to February 2008 the bank enrolled all new businesses that took at an SBL account of RS 500,000 (\$11,030) and above and that were in large cities. In January and February 2008, the selection criteria were expanded to include loans disbursed in small cities to allow a comparison to large metro areas, since by that time the operations of the bank in the smaller cities had been set up. The project randomized all clients into three treatment groups and a control group with different levels of follow-up intensity and personalization of the interaction between the client and the bank.

Group A: High Touch. The first type of treatment provided clients with a personal relationship manager, who was the sole interface between the borrower and the bank. The relationship manager would call the client twice a month, roughly in two week intervals. In addition, the

[8] For purposes of this study large, CPA cities include Ahmedabad, Bangalore, Chandigarh, Chennai, Delhi, Hyderabad, Jaipur, Kolkata, Ludhiana, Mumbai, and Udaipur.

client would have a direct phone number to reach his or her dedicated relationship manager. The goal of the call was for the relationship manager to establish trust with the client and to see if the borrower had any questions about the loan or needed help with any administrative issues related to the loan (e.g. if monthly statements had not been received, checks had not been deposited, etc.). The call was not set up as a sales pitch for other products and would never include cross selling of other products. The relationship manager would however remind the client if a payment deadline was coming up. These relationship managers were trained to handle any complaints or issues that clients have with the loan account. But it is important to note that it was made clear to the client that the relationship manager is not the loan officer who would make decisions about loan renewals later on. This is a common practice in Indian banking and would not strike the clients as unusual treatment.

Group B: Medium Touch. The second type of treatment provided clients with the same level of customer service the high touch clients received, but without the personalized relationship. Twice a month one relationship manager was randomly drawn from a pool of three candidates and assigned to contact each medium touch client. Clients were not provided with direct phone number access to any relationship managers. The goal of the call was to address any service issues and provide a reminder if any upcoming payments were due. The bank limited the pool of relationship managers to only four people at a given time (plus two replacement managers for two relationship managers who left), since these were able to cover all the calls that needed to be made in a month. One caveat is that even drawing from a pool of four to six relationship managers my result in clients quickly become acquainted with all of them, since they receive bi-weekly calls. This might reduce some of the difference with the personalized relationship manager provided to treatment Group A. Since the group of callers ended up smaller than I had initially expected, I also analyze the effect of the "within group" distribution of calls. By pure chance, some of the clients in Group B interacted primarily with only one or two callers, while others might have interacted with all six callers and thus had a much less personalized experience. In a set of robustness tests I will analyze this secondary randomization at the caller level for all treatment outcomes. Clients, who by random chance received calls from only one or two relationship managers, will be re-assigned to the high touch treatment group (A).

Group C: Low Touch. The third type of treatment consisted of only providing reminder calls when a payment deadline was approaching. In this case, a random caller was assigned monthly. The purpose of the call was strictly to remind the client about the coming payment, and no specific attempts were made to establish a personal relationship with the client. However, during the reminder calls any issues the clients raised were also addressed.

Group D: Control. Standard bank policy was that SBL and Power clients would receive SMS text reminders when an upcoming payment was due. Thus, each of the above treatment groups also received SMS reminders in addition to their monthly account statements.

Early in the study, the bank collections department initiated a new policy of providing direct reminder calls in addition to SMS messages to all clients with upcoming payments due. Because of this policy change some clients in the high touch, medium touch, and low touch treatment groups may have received multiple reminder calls, but otherwise would not have been greatly affected. On the other hand, there would no longer be a distinction between the low touch and control groups, and these loans should be pooled into a new control group collectively representing Groups C and D. However, because clients initially assigned to Group C may have received multiple calls while Group D clients would only have received calls from the collections department, I maintain the distinction between the treatment groups in the initial discussion and results.

3.2. Study Implementation

To implement the call outreach I initially hired and trained three relationship managers in collaboration with the bank, with an additional three managers hired during the course of the study. The bank selected relationship managers for their problem-solving skills, language proficiency in Hindi and English, general communication skills and ability to build trust over the phone. The callers were stationed at the bank's main call center in Mumbai under the joint supervision of a study research associate and the ICICI customer service team responsible for SBL and Power customers.

The managers were trained in line with ICICI's protocols to handle typical customer service issues. In addition, I provided basic scripts for high touch and medium touch customer service calls and trained the relationship managers to log all study calls in a standardized way, including whether clients were reached, what issues they had if any, and their responses when prompted about repayment. Typical client issues included failing to receive monthly account statements or other services they had signed up for. There were also many requests for information about the status of account transactions or bank charges policies. When an issue arose that the relationship managers could not handle directly, they explained the process to forward the complaint to a higher level. After complaints were forwarded, I were not able to directly track the resolution of specific client issues. However, I can generate a proxy measure by seeing whether the same complaint is raised on the subsequent call.

The relationship managers began contacting study clients in October 2007 and continued through April 2009. Initial contact with clients in all treatment groups began with welcome calls between one to four months after the loan was disbursed. At this time the relationship managers reviewed the terms of the product and answered any questions. For the high touch and medium touch clients, they also explained that they would be receiving bi-monthly outreach calls to address any service issues they might have. In subsequent months each client received the appropriate calls depending on their treatment group. A few clients requested not to receive further customer service calls and were removed from future calling lists. But they are, of course, included in the analysis.

Of the six total relationship managers employed, only one remained on the team during the entire course of the study. Whenever a relationship manager moved on, they simply explained to their high touch clients that a new relationship manager would be taking over in order to make the transition as seamless as possible. When relationship managers were sick or on vacation, the other two managers explained to the absent managers' high touch clients that they were phoning on their relationship manager's behalf, and proceeded with the standard outreach calls.

Finally, from April 2009 to June 2009 I conducted an exit survey of all clients in large cities in order to understand how customers used their overdraft accounts and measure the impact of relationships on client perceptions of the bank. In order to encourage objective responses, I hired three callers external to the bank and trained them off-site. I developed and pre-tested a survey instrument in English in April and May 2009, prepared a Hindi translation, and implemented the survey in June 2009. Unfortunately the response rate to the survey is relatively low which limits the inference one can draw from it. I will report the results from the survey in section 6.3 and associated Appendix Tables below.

Two events during the course of the study may have had an impact on results. First, the bank implemented a new scorecard for SBL loans in August 2007 that would have been in use for SBL loans disbursed from October 2007 onward. Indeed, the October-November volume of SBL disbursals fell by around 50% compared to the July-September averages; Power disbursals, which do not depend on the same scorecard, remained stable. While it is possible the scorecard change may have introduced additional heterogeneity and noise into the client cohorts, randomization prevents this from biasing our treatment effects.

In addition, the 2008 financial crisis may have had direct or indirect effects on study outcomes. Again, randomization protects us from bias in the estimated results. But, if small businesses have less discretion in their repayment behavior in bad economic times, the average size of the estimated effect might be a lower bound of the steady state impact of relationship lending. On the other hand, Indian financial markets were relatively insulated from the global effects of the crisis.

4. Data Description

I obtained three major sources of data for this study. The bank provided daily and monthly repayment reports for all clients in the study, in addition to information on business incorporation type, geographic location, loan size, and any loan modifications. Moreover, during the course of making calls to high and medium touch clients, the relationship managers collected information on their complaints and queries. Finally, an exit survey was conducted among all clients to assess satisfaction based on the type of loan treatment and follow up calls they received.

4.1. Loan Characteristics

In total, there were 1,319 individual accounts, which are described in the first column of Table 1. When looking at the geographic distribution of loans, it is clear that a large fraction (50%) of loans were sanctioned in North India, of which three quarters were in Delhi or the surrounding areas. Over 20% of loans were sanctioned in the west region. About 19% of loans were sanctioned in South India, with equal numbers disbursed in the southern states of Andhra Pradesh, Karnataka, and Tamil Nadu, and a smaller number in Orissa. In East India the majority of loans were made in the city of Kolkata in West Bengal. This distribution of loans is representative with the overall distribution of SME lending activities for ICICI overall. One also see that less than 20% of loans were made in non-CPA (small) cities, since these types of loans were initially excluded from the study.

Nearly two-thirds of the clients incorporated are sole proprietorships. Partnerships were a distant second, at 19% of businesses, followed by private limited and other incorporation types. The average initial loan limit was $20,723. Descriptive statistics for each of the different treatment groups are reported in columns (2) through (10) of Table 1. To ensure that random assignment was conducted successfully, I verify that the distribution across the observable characteristics known at the time of account sanctioning did not vary significantly across the groups. The distribution of each of the treatment groups was tested against that of the control group (Group D) using chi-squared significance tests for categorical variables and one-way Anova for continuous variables. The only significant difference was found in the average loan limit of treatment Group B, which had a p value of 07. However, the difference loses its significance when the SBL and SBL Power products are examined individually.

4.2. Outcome Variables

The primary data for the analysis is daily and monthly payment transactions based on the bank's transaction database, which records standard information on each client's end of day account balance as well as cumulative deposits and withdrawals in the month. It also includes the total amount due by month's end, paid and unpaid current due amounts, and paid and unpaid past due amounts. In addition, the data allow us to confirm the past due amounts and days late as well as any changes in overdraft limits.

Using this database one can establish on any given day a client's overdraft usage, whether any payments are past due, by what amount, and for how many months. Monthly downloads are generated between the 15th and 18th of each month by the bank's collections department and are a comprehensive snapshots of client status. I also confirm the monthly payment statistics for each client with daily transactions data, which provides more continuous information about the progression of each client's payment and delinquency behavior[9].

Figure 1 illustrates the progression of each of the monthly client cohorts through the course of the study. The earliest study cohort, disbursed in July 2007, began receiving relationship calls in October 2007; that is, in the fourth month since account sanctioning and the first month of collection of repayment data. For later cohorts, relationship calls typically began in the second month of the account, and all study outcomes are based on the first eleven months of the loan. Results are also limited to the first year of the account to isolate the effects of the experiment from the effects of changes in loan size, account closures, and other events that may occur as a result of account renewal processes at the end of the first year.

The primary study outcomes are binary indicators of late payment and the intensive margin statistics measuring the frequency of delinquency, use of overdraft accounts and internal ratings of the bank about the client quality. Based on the first eleven months of the account, I can construct indicators for whether the client ever reached a given number of days late in repayment, with a past due account defined as being 30 days or more past due. Using the daily repayment data, I construct indicators for whether clients are ever 30 or more days past due (which de facto is 31+ days since current), 60 or 90 days past due.

Table 2 reports summary statistics for these primary outcome measures, as well as additional account variables. As shown in Column (1), 14.1% of all clients were ever past due, with a standard deviation of 34.8%. This figure drops substantially when looking at longer delinquency tenures. Only 3.2%, 1.4% and 1.0% of clients were ever 30+, 60+ or 90+ days past due, respectively. The associated standard deviations were 17.6%, 11.9% and 9.9%. Restricting the sample to those clients located in large city areas where the bank maintains a CPA facility, as shown in Columns (3) and (4) does not change the delinquency results significantly.

On the intensive margin, one can construct variables that measure the path and shape of delinquencies. From the repayment data one can determine the number of distinct instances that a client fell delinquent (Number of Late Periods). The mean number of late periods was 0.22 with a standard deviation of 0.63. Among the 186 clients that were ever delinquent, I construct an indicator variable for clients that had multiple delinquencies during the study (More than One Late Period if Ever Late). Of these ever delinquent clients, 31.2% had more than one late period, with a standard deviation of 46.5%.

Additional outcome variables describe average SBL account utilization measured as the average daily loan balance over the study duration (Average Overdraft Usage). The mean and standard deviation of this variable was 65.3% and 27.2%, respectively. I also construct a binary indicator for an increase in loan size (Limit Change) and the number of days from when the account was

[9] The monthly report provided for November 2008 contained errors and was dropped from the analysis.

sanctioned to the first delinquent day (First Delinquent Day). I use the limit change variable as an indicator since I could not obtain data on the size of the new limit for all accounts. Overall, 13.2% of clients received a limit change while the mean first delinquent day was 128 from account disbursement. The standard deviations for these variables were 33.9% and 86.2 days, respectively.

In addition, during the course of making biweekly calls to clients in treatment Groups A and B, I obtain information on their complaints and queries. All the data were recorded by the relationship managers in a standardized format, with open-ended comments. Complaints were classified by the nature of the call based on increasing customer dissatisfaction: simple queries, service requests, issues, disputes, and formal complaints. The most common topics raised related to account charges, interest rates, account statements and activating additional services. I construct binary indicators for whether a client ever raised any kind of issue, dispute, or a complaint that the relationship managers had an opportunity to address (Ever Complaint). Of the 659 clients in treatment Groups A and B, 55.7% fell in to this category. The mean number of issues, disputes or complaints raised among all clients (Number of Complaints) was 1.5 with a standard deviation of 2.2. I also examine a restricted subsample of accounts that had registered at least one complaint during study and the mean number of issues, disputes or complaints (Complaints if Ever Complaint) among this group was 2.7, with a standard deviation of 2.4.

4.3. Endline Survey

Finally, I conducted a customer survey to evaluate client satisfaction with the loan produce and the borrowers perception of the bank across a number of dimensions. The survey was conducted by phone one month after the end of the experiment. It was implemented by a professional survey company not the bank to ensure that borrowers would not feel restricted in what they could say about the bank. Particularly important were items measuring client satisfaction on a scale from 1-5 for initial loan size, interest rates, branch customer service and the renewal process. Other dimensions measured included client satisfaction with the initial application process, call center service, email or web customer service, and their overall satisfaction with the SBL account. Clients were also asked how intensively they used their account and for what purposes, what fraction of their bills they used their accounts for, whether they would like to continue to receive customer service calls (or begin to receive customer service calls if they were in treatment Groups C or D), and reasons for any late payments. However, the attrition rates in the survey were very high, on average around 30%. When conducting bounds estimation to bound the magnitude of the attrition impact, I find that the significance but even the sign of the results depends critically on the assumptions made behind the bound estimates. Details are available in the appendix.

5. Results

5.1. Repayment Behavior

As a first step in examining the impact of personal banking relationships on borrower behavior I analyze the impact on their repayment parameters. One would expect the default rates for those clients who received additional attention from the bank to be lower relative to the control group. In Table 3, I report the results from OLS regressions with robust standard errors of different delinquency measures on the treatment dummies for Groups A, B, and C and selected control variables. Treatment Group D (control group) serves as the omitted category.[10] I first investigate the impact of the treatment on variables that capture the extensive margin of late payments. As reported in Column (1), I estimate that accounts in Group A and B have a significant decrease of 0.09 and 0.10 in the number of late periods, respectively, when compared to the control group. Similarly, Column (3) shows that among accounts which are ever late, those in Groups A and B were negatively associated with having multiple late periods compared to the control group, with coefficients of -21.7% and -24.5%, respectively. In both cases, the coefficient on treatment Group C was insignificant as was the difference between treatment Group A and Group B. These results suggest that the interactions between the relationship manager and client not only prevented late payments overall, but in particular reduced the likelihood of repeated late payment spells. The stronger reduction in repeated late payment spells but not first time late payments might suggest that it is difficult for SMEs in India to avert all incidences of late payments given the volatile economic environment. However, SMEs in the higher touch treatment (Groups A and B) seem to pay more attention to not slipping into repeated late payments. When comparing the personalized manager provided to Group A with the randomized manager assigned to Group B, there is no significant difference in the coefficients on the treatment dummies, suggesting that function of the relationship manager itself may have been sufficient to generate an impact, irrespective of who was actually serving in the role.

In Columns (2) and (4) the sample is now limited to clients located in larger (CPA) cities in order to focus only on those borrowers that had full access to all the facilities of the bank. I repeat the same regressions as in Columns (1) and (3) and the impact of the treatment, as measured by the coefficients of the treatment dummies, becomes slightly more pronounced relative to the full SBL sample.

Columns (5) and (6) look at any client who had spells of 90+ days late payments. The results in these show that the treatment did not have a significant impact on whether a client ever became delinquent at the 90+ days threshold. This might be explained by the fact that clients are handed

[10] I also repeated all analysis using a logit estimator instead of linear probability models and the results are very similar in magnitude and significance. Since there are a number of linear controls in the specification, I prefer the linear probability model.

over to a specialized collection unit once a borrower is more than 90 days late and, at this point, the relationship with the original relationship manager becomes unimportant important. I was not able to prevent the bank from using this standard collection process on their borrowers for compliance reasons. In addition, less than five accounts per treatment group reached this delinquency threshold during the study. Given the sample sizes, this limited level of delinquencies is likely below the minimum magnitude required to detect a treatment effect.

As shown in Table 4, the above results are robust to testing the impact of the pooled treatment definition utilized to account for the impact of the bank's implementation of reminder calls to the control group (Group D) and low touch group (Group C). Columns (1) through (4) show the treatment dummy for the Group A & B pooled treatment effect is negatively associated with both the number of late periods and having multiple late periods among those accounts that were ever late. Similar to the earlier results discussed, the pooled specification also had no significant impact on whether an account was ever 90+ days delinquent. Although the coefficients on the treatment dummies are negative they are insignificant.

Taken together, Tables 3 and 4 suggest that the enhanced relationship developed through repeated contact with the relationship manager limits the delinquency of clients. So while clients in the higher touch treatment (Groups A and B) do significantly better relative to the control groups, I do not find a significant difference *between* A and B. Based on these results, I can establish that the higher frequency of interaction and increased attention given to clients in both groups A and B has a positive effect on repayment. But I do not see a differential effect between A and B on the repayment dimension.

I now turn to analyze the timing and path of clients' payment behavior. If a lot of non payment spells of SMEs are driven by economic shocks rather than by strategic behavior, one would not expect any differential response to the treatment interventions, since SMEs might not be able to prevent being exposed to a shock. Remember that the middle of our experiment coincides with the financial crisis. So while it might have been unavoidable that the SMEs were exposed to a shock, they might be able to control how they respond to an economic shock. E.g. all SMEs might have some months during the term of the loans where they have low cash balances. But if they have a better relationship with ICICI bank they might try to prioritize the payments to ICICI over other lenders. So conditional on having a late payment spell one would observe that it occurs later in the time of the loan, since the SME owner is trying hard to prevent falling late. Columns (1) and (2) of Table 5 show the results from a regression where the independent variable is "the first delinquent day" using the standard regression set up. For Group A, the first delinquent day was approximately 35 days later relative to the control group. The coefficient is also significantly larger than the magnitude of treatment B, which shows an average onset of delinquency in 23 days. The result for B is not significantly different from the control group. This finding suggests that indeed treatment group A leads to improved payment management.

The results displayed in the next four columns examine the bank's response at account renewal. In Columns (3) and (4) the dependent variable is a dummy for whether the bank gave a given borrower an increase in their limit (limit change) at the end of the loan term. This is a sign that in the eyes of the bank a given customer performed well. It is important to note that the department in the bank that made the loan limit decisions had no contact with our experiment and did not observe any of our interactions with the borrowers. They just saw the repayment behavior. The coefficient on the Group A dummy indicates that these clients were approximately 4.8% more likely to receive a limit change at renewal, while the coefficients on the dummies for Group B and C are both insignificant and small. The next two columns analyze the internal classification that the bank assigns to a borrower after observing the first loan term – this is similar to an internal credit score. As noted earlier, the Category A designation is a dummy variable derived from the bank's internal review process for clients with less than two late payments that were never more than 30 days late, and indicates those accounts with the highest level of credit performance. Column (5) shows that Group A and B clients from the full SBL sample are 7.5% and 7.2% more likely to receive this designation, respectively.

Finally, Columns (7) and (8) use average overdraft usage of the loan facility as the dependent variable. Overall loan usage was between 5.0-6.0% lower for treatment Group A, depending on whether I condition on the full sample or only the larger cities. However, the outcome is not surprising, since high account usage is mechanically correlated with more delinquent borrowers, since these carry a bigger balance. When looking at the pooled specification shown in Table 6, the only consistently significant impact of the pooled treatment dummy is on Average Overdraft usage. These results suggest that after having looked at all of the borrower characteristics in terms of both delinquency and behavioral parameters, the bank responds more favorably to Group A clients at the time of renewal. This outcome could potentially be interpreted as a summary statistic for how a client "looks" according to the unobservable characteristics. While these unobservable characteristics are unknown to the econometrician, they might flow into the assessment of the client at loan renewal. Therefore, the fact that the high touch group also has a higher likelihood of getting a limit change at the point of loan renewal suggests that this treatment has a beneficial impact on the bank firm relationship. These results are a first indication that the personalized treatment of borrowers in the high touch Group A has a significantly positive impact on loan level outcomes.

5.2. Adjusting for Relationships in Group B

As mentioned above, the number of relationship managers who were assigned to making calls in treatment Group B was relatively small, totaling only six people over the one year duration of our experiment. So by random chance a number of the clients in treatment Group B received at least 50% of their calls from only one relationship manager. I identify 23 such cases, representing 7% of the total Group B clients. These clients would have had an experience with the bank that more closely resembles the set up for treatment Group A than B. I therefore rerun the previous regressions, but I reassign these 23 clients from treatment Group A to B. Since calls were randomly assigned this reassignment does not corrupt the randomization set up.

The results from this exercise are reported in Table 7. The regressions follow exactly the same set up as the prior ones with the one difference that treatment Group A is now slightly increased by the 23 clients which received a high touch treatment in Group B. As shown in Columns (1) and (2), the reassignment increased the effect of the treatment on the intensive margin variables for Group A. Relative to the control, Group A now shows a 0.10 reduction in the number of late periods a 22.5% lower likelihood of having multiple late periods. In contrast, the reassignment had the opposite effect on the coefficients of the treatment dummy for Group B, who now have a 0.09 reduction in the number of late periods and are 23.9% less likely to have multiple delinquent periods. As before, there was no impact for either Group A or Group B on whether a client was ever 90+ days late.

When looking at the account behavior variables in Columns (5) through (8), a similar pattern emerges. Relative to the control, Group A clients experienced their first delinquent day 37 days later, were 7.7% more likely to receive the Category A distinction and utilized their overdraft facility 4.9% less. All three of these coefficients are higher than the unadjusted specification. The coefficients on the Group B treatment dummies moved in the opposite direction under reassignment, and remain insignificant for all variables except the Category A designation. As shown in Column (6), Group A was 4.2% more likely to receive a limit change on renewal, a slight decrease compared to original results. The coefficient on the Group B dummy was insignificant.

Overall, the results show that the effect of the interaction between borrower and bank become stronger when I reassign the borrowers from treatment Group B to A, who had received more personalized treatment in B. While the reassignment does not change the significance level of the effects dramatically, the estimated coefficients on average become larger and, the effect goes in the expected direction in all cases.

5.3. Complaint Outcomes

The next set of regressions examines the softer factors in the relationship between clients and their relationship managers. For that purpose, I analyze whether clients were reachable by their relationship managers, the complaints that relationship managers reported and the status of the resolution of these claims utilizing the records from the relationship calls. The regression set up is parallel to the earlier specifications. The control variables are the same and the results are robust to omitting region, disbursement month and incorporation type fixed effects. The sample is restricted to clients in treatment Groups A and B, as these are the only clients for whom one can measure complaints since they received personalized attention in resolving their complaints.

Table 8 displays the results of OLS regressions of customer reachability statistics on the treatment A dummy with additional controls. As reported in Column (1), having a dedicated relationship manager made clients in Group A 1.6% more likely to respond to the biweekly calls relative to Group B. A similar result is found in Column (2), which displays the reachability results for larger (CPA) cities, finding Group A clients 1.5% more likely to be reached compared to Group B. When examining the reachability statistics on a more granular level, the coefficients on the Group A dummy are insignificant for the first call of the month, while Columns (5) and (6) show that Group A clients are 2.2% and 1.8% more likely to be reached during the second call of the month. Interestingly, conditional on having not been reached during the first call, there is a significant difference in reachability between Group A and B on the second call of the month, suggesting that Group A clients do make an extra effort to talk to their relationship manager at least once per month.

As with the delinquency regressions, the reachability results may also be affected by a select number of Group B clients being provided with Group A type treatment solely through random chance. Therefore, I rerun the reachability regression using the same specifications but replace the treatment dummy with a variable representing the share of calls placed by the two most frequent callers. The results, presented in Table 9, show that the greater the concentration of calls placed by these two individuals, the more likely the client was to be reached. As shown in Column (1), doubling the share of calls placed by the top 2 callers leads to a 9.3% increase in the overall reachability of high touch clients, with the increase in reachability of the first and second calls of the month 11.9% and 6.6%, respectively. All coefficients are significant at the 1% level. These reachability results suggest that the closer the relationship with the manager, the more likely the client is to answer the call.

Table 10 reports the results of the regression of the complaint variables on the Group A dummy variable and selected controls. For all specifications, a complaint is defined as the client raising an issue, dispute or complaint as noted on the call log. These three categories were pooled together as there was considerable overlap in the topics raised. Column (1) shows that Group A is negatively associated with having ever complained, with an 8.2% reduction relative to treatment Group B at a 95% significance level. Group A clients also have an increased number of complaints as shown in Column (2); however, this difference is not significant when looking at the entire sample. When conditioning on clients who registered at least one complaint, Column (3) shows that Group A clients register a significant difference of 0.66 more complaints relative to Group B, indicating that while Group A clients are less likely to complain, those that do complain more. The specification in Column (4) examines the resolution of each complaint raised. A complaint is considered unresolved if the same issue is brought up again by the client in any of the four calls occurring subsequent to the issue initially being raised; however, the results are robust to reducing this time frame further. The coefficient on the Treatment A dummy indicates the percentage of unresolved cases relative to the total number of complaints per customer is 5.7% higher for Group A clients compared to Group B. These results are robust to limiting the definition of complaints to excluding the issue of a client not receiving his or her statement, which comprised nearly half of all issues raised. One explanation could be that the personal connection between clients and their relationship managers led to increased expectations of service. This expectation can on the one hand increase the demand for service, i.e. clients raise their problems on the call instead of giving up on the bank before they even try to resolve an issue. But higher expectation might also shade how people respond to the calls.

5.4. Survey Outcomes

The final set of results tests the responses to an endline survey conducted in June 2009 where each client was asked to rate their satisfaction with the SBL product across a variety of characteristics on a 1 to 5 scale. Although survey response rates vary by question, from a low of 62% to a high of 69%, overall attrition rates are very high. As I will show below the attrition rate is too high to draw any conclusive evidence from the survey results. While the results go in the right direction when using the survey responses without taking into account attrition, once I make imputations for missing responses the results are highly sensitive to the assumptions behind the imputations. For full disclosure I am reporting these results in the Appendix, Tables 1 and 2. But I do not use these results to draw inference about the impact of the experiment.

Table 1 of the Appendix shows the results of ordered logit regressions on the survey response outcomes without correcting for any potential response bias. As before I report the results on the treatment dummy representing Group A and B compared to the pooled control groups C and D. Satisfaction with branch customer service and the renewal process are both positively associated with the treatment group, while the reverse is true of satisfaction with interest rates. The effect on self-reported delinquencies is also similar, with the Group A and B clients 5.2% more likely to respond to having ever been late with payment. All coefficients are significant at the 10% level. In contrast, there is no significant effect on the loan size and overall product satisfaction categories.

Given the attrition rate of around 30%, I test the sensitivity of the results to two different methods of correction for non-responses. The first method, as shown in Columns (1) and (5) of Appendix Table 2, estimates a minimum treatment effect by imputing the highest satisfaction score to non-responders if they were assigned to the control group and the lowest satisfaction score if they were assigned to one of the three treatment groups. These imputations present the toughest test since it assumes that the missing respondents would have answered in the worst possible way. Similarly, the maximum treatment effect, shown in Columns (4) and (8), is estimated by imputing the lowest satisfaction score to the non-responders in the control group while the highest satisfaction scores are imputed for treatment group non-responders. The second method follows the approach utilized by Kling and Liebman (2004) whereby the minimum treatment effect (maximum treatment effect) is estimated by imputing the mean plus (minus) .25 standard deviations for the non-responders in the control group while the survey score of non-responders in the treatment groups is estimated by imputing the mean minus (plus) .25 standard deviations. As illustrated in Appendix Table 2, the treatment effect is highly sensitive to assumptions about the non-responders, which is not surprising given that nearly one-third of clients did not respond. At the lower boundary, the treatment effect is strongly and significantly negative for all categories except interest rate satisfaction, while the effect reverses at the upper boundary. Relative to the maximum/minimum adjustments, the Kling and Liebman boundary specification reduces the treatment effect range and in some cases reduces the significance of the estimates as well. In contrast to the unadjusted specifications, the Kling and Liebman analysis does yield some differences between Group A and Group B. However, there does not appear be a consistent impact, as in some categories satisfaction is higher among those who received the personalized relationship manager, while in others the reverse is true.

6. Conclusions

This research project aims to understand how relationship lending can shape borrowers' attitudes towards lenders and the willingness of borrowers to engage in moral hazard behavior. The literature so far has predominantly focused on the reverse direction, i.e. that relationship lending improves the monitoring of clients though better information gathering. But the results in this paper suggest that even when the bank does not collect any additional information about the borrowers, having a higher level of contact and more personalized outreach to the borrower improved repayment behavior and the satisfaction of borrowers. By running a randomized control trial with ICICI Bank, the largest private bank in India, I am able to isolate the effect of relationship lending on client behavior. When comparing different treatment groups with varying personalized attention between the bank and the borrowers, I find significantly better repayment behavior, such as lower delinquency rates, fewer delinquent periods and a later onset of the first default for the high touch treatment group. When looking at non-financial outcomes, borrowers assigned to dedicated relationship managers are less likely to complain about services and have higher rates of answering the phone when called compared to the other groups. But conditional on registering a complaint, borrowers with a personalized relationship manager tend to be more vocal and complained more frequently, in particular when issues were not addressed.

Overall, the results demonstrate that greater attention and more personalized services from the bank have a positive effect on borrower repayment behavior, which when taken together with the reachability and complaint results, seems to signal a greater loyalty on the part of these clients. This greater loyalty could either be the outcome of a behavioral bias such as fairness, i.e. clients might find it difficult to default on a loan officer who has been nice to them before. Or it could also be a rational tradeoff if clients believe that in an economy where personal relationships are very important, it would be detrimental to default on the relationship with the loan officer, since the future continuation value from the relationship could be high. In the context of this experiment, the first explanation is more reasonable, since it was made clear to the borrowers from the very beginning that the relationship managers are not involved in any loan renewal or other underwriting decisions. But there might be other contexts where the second channel is more important.

More broadly the results suggest that credit risk and repayment behavior of borrowers are context dependent. Borrowers do not seem to have fixed and immutable types but respond to (small) process changes or the treatment they experience from their bank. A related point seems to emerge from Cadena and Schoar (2011). The role of context dependence does not only have a possible impact on the efficiency or viability of the bank. But it might also affect the ability of borrowers to build a better credit score and as such could have longer lasting impact on their financial success. Of course, this is only a first study but there are many open questions that deserve further research. In particular, we do not know if greater loyalty leads to a reduction in the overall level of default across all lending relationships of a borrower. Or if it only results in a crowding out dynamic, since clients prioritize whom to default on based on their relationship with the bank or the loan officer. Similarly, it will be important to understand the different levers that banks have to create loyalty in their customers and how these interact in equilibrium if many banks are using similar techniques.

References

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

Allen N. Berger & Nathan H. Miller & Mitchell A. Petersen & Raghuram G. Rajan & Jeremy C. Stein, 2002."Does Function Follow Organizational Form? Evidence From the Lending Practices of Large and Small Banks," NBER Working Papers 8752.

Berger, Allen N., Kashyap, Anil K and Scalise, Joseph M., 1995. "The Transformation of the U.S. Banking Industry: What a Long, Strange Trip It's Been," *Brookings Papers on Economic Activity*, 55-218

Berger, Allen N. and Gregory F. Udell. 1995. "Relationship lending and lines of credit in small firm finance," *Journal of Business*, 68: 351-382.

Cadena, Ximena and Antoinette Schoar, 2011, "Remembering to Pay? Reminders versus Financial Incentives for Loan Payments," NBER Working Paper No. 17020.

Chang, Chun, Liao, Guanmin, Yu Xiaoyn and Ni, Zheng, 2010, "Information from Relationship Lending: Evidence from Loan Defaults on China," European Banking Center Discussion Paper No.2009-01

Chakravarty, Sugato and Abu Zafar Shahriar, 2010. "Relationship Lending in Microcredit: Evidence from Bangladesh," Working Papers 1004, Purdue University, Department of Consumer Sciences.

Cole, Rebel A., 1998. "The importance of relationships to the availability of credit," *Journal of Banking and Finance*, vol. 22(6-8), pages 959-977.

Degryse, Hans and Patrick Van Cayseele, 2000. "Relationship Lending within a Bank-Based System: Evidence from European Small Business Data," *Journal of Financial Intermediation*, vol. 9(1), pages 90-109.

Drexler, Alejandro and Antoinette Schoar, 2012, "Do Relationships Matter? Evidence from Loan Officer Turnover," Working Paper.

Fisman, Ray, Daniel Paravisini and Vikram Vig, 2012, "Cultural Proximity and Loan Outcomes," Unpublished Working Paper.

Geanakoplos, J., Pearce, D., Stacchetti, E. (1989). "Psychological games and sequential rationality". Games and Economic Behavior 1, 60–7

Harhoff, Dietmar and Timm Körting, 1998. "Lending Relationships in Germany: Empirical Results from Survey Data," CIG Working Papers FS IV 98-06, Wissenschaftszentrum Berlin (WZB), Research Unit: Competition and Innovation (CIG).

Hertzberg, Andrew, Jose Liberti and Daniel Paravisini, 2010, "Information and Incentives inside the Firm: Evidence from Loan Officer Rotation," *Journal of Finance*, 65(3): 795-828.

Kling, J. and J. Liebman, 2004, "Experimental Analysis of Neighborhood Effects on Youth." unpublished manuscript.

Levine, D. (1998). "Modeling altruism and spitefulness in experiments". Review of Economic Dynamics 1, 593–622.

Nakamura, Leonard I., 1994. "Small Borrowers and the Survival of the Small Bank: Is Mouse Bank Mighty or Mickey?" *Federal Reserve Bank of Philadelphia Business Review*, November/December, 3-15.

Paravisini, Daniel and Antoinette Schoar, 2012, "The Information and Agency Effects of Scores: Randomized Evidence from Credit Committees," Unpublished Working Paper.

Peek, Joe and Rosengren, Eric S., 1996. "Small Business Credit Availability: How Important is Size of Lender?" in Saunders, A. and Walter I., (eds.) Financial System Design: The Case for Universal Banking. Irwin, Burr Ridge IL, pp. 628-655

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

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

Petersen, Mitchell A. and Raghuram G. Rajan. 1995. "The Effect of Credit Market Competition on Lending Relationships," *Quarterly Journal of Economics*. 110(2), 407-443.

Peek, Joe and Rosengren, Eric S., 1998. "Bank Consolidation and Small Business Lending: It's Not Just Bank Size That Matters," *Journal of Banking and Finance* 22, 799-819.

Puri, Manju, Jörg Rocholl and Sascha Steffen, 2010, "On the Importance of Prior Relationships in Bank Loans to Retail Customers," Working paper.

Rabin, M. (1993). "Incorporating fairness into game theory and economics". American Economic Review 83 (5), 1281–1302.

Qian, J., Strahan, P. E., and Z. Yang, 2012, "The impact of incentives and communication costs on information production: evidence from bank lending," Working Paper.

Rajan, Raghuram, 1992, "Insiders and Outsiders: The Choice between Informed and Arm's-

Length Debt," *The Journal of Finance* 47(4), 1367–1400.

Sapienza, Paola, 1998. "The Effects of Banking Mergers on Loan Contracts," Working Paper, Northwestern University

Stein, Jeremy C., 1997. "Internal Capital Markets and the Competition for Corporate Resources*,"* *Journal of Finance* 52, 111-133

Stein, Jeremey, 2002. "Information Production and Capital Allocation: Decentralized vs. Hierarchical Firms." Journal of Finance, 57, October 2002, pp. 1891-1921.

Figure 1: Study Overview

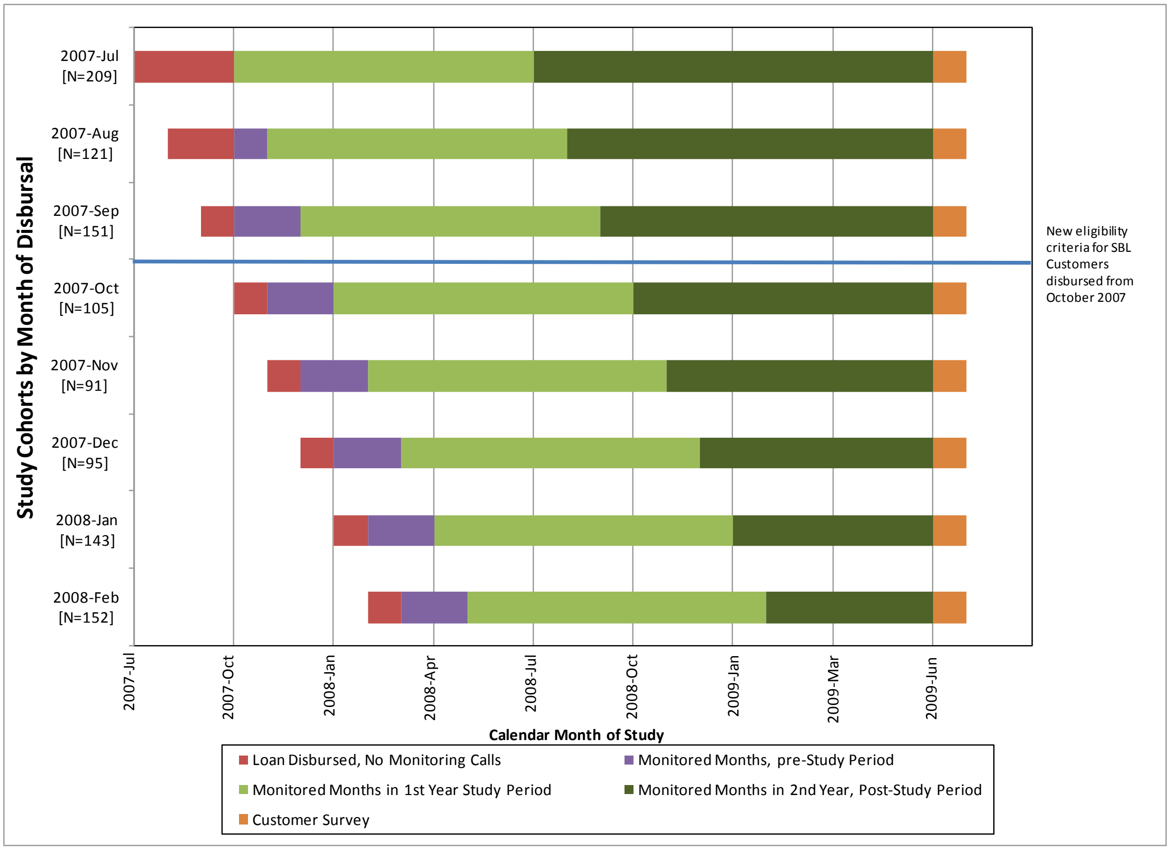

Table 1: Sample Size and Randomization

This table reports sample size and randomization checks for the treatment and control groups groups. The distribution of each of the treatment groups was tested against that of the control group (Group D) using chi-squared significance tests for categorical variables and one-way Anova for continuous variables and none of the differences were significant. Column (1) reports the sample size and distribution for the entire study cohort as a whole. Columns (2) thorugh (5) report the sample size and distribution for each of the four treatment groups, while Columns (6) through (10) report the same break out but restrict the sample size to those clients that were located in a metropolitan area where the bank maintains a credit processing facility (CPA city). Geographic Region is a dummy for the location of the client. Constitution Type is a dummy for incorporated firms versus partnerships. Distribution Year is the year the overdraft facility was started. Initial Loan Limit is the maximum allowable loan per account, standard deviations are in parenthesis below. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. CPA standard for cities that have a processing facility of the bank, which is equivant to being a regional headquarter of the bank.

Variable	Overall	Full SBL				CPA			
	Sample	A	B	C	D	A	B	C	D
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Accounts	1319	320	339	324	336	266	281	271	268
Geographic Region									
East	10%	12%	9%	9%	10%	14%	10%	10%	12%
North	50%	52%	47%	50%	50%	54%	50%	51%	54%
South	19%	18%	22%	20%	16%	17%	20%	10%	15%
West	21%	17%	22%	22%	23%	14%	20%	20%	19%
Constitution Type									
Proprietor	66%	66%	67%	67%	63%	68%	65%	69%	62%
Partnership	19%	21%	18%	19%	19%	19%	18%	16%	19%
Private Ltd	11%	10%	9%	10%	14%	11%	10%	11%	16%
Other, incl Missing	4%	3%	6%	3%	4%	2%	6%	3%	4%
Distribution Year									
2007	60%	61%	59%	61%	57%	73%	71%	73%	72%
2008	40%	39%	41%	39%	43%	27%	29%	27%	28%
Loan limit ($000)	20.7	21.3	19.4*	21.2	21.1	21.6	19.7*	21.3	21.5
	(12.0)	(12.5)	(10.8)	(12.3)	(12.3)	(12.6)	(10.8)	(12.6)	(12.9)
Product Group									
SBL Power	29%	28%	32%	29%	29%	26%	30%	29%	29%
SBL	71%	73%	68%	71%	71%	74%	70%	71%	71%
City Size									
CPA City	82%	83%	83%	84%	80%				
Non CPA City	18%	7%	17%	16%	20%				

Table 2: Descriptive Statistics

This table reports summary statistics of the account parameters. Full SBL in Columns (1) and (2) refers to the entire sample while Columns (3) and (4) restrict the sample to only those accounts located in cities where the bank maintains a CPA facility. Past Due variables are dummies that take a value of one if the account ever reached the stated delinquency threshold and zero otherwise. Number of Late Periods is the number of times an account went delinquent within the loan period before the borower ultimately repaid. More Than One Late Period if Ever Late is a dummy that takes a value of one if an account registered more than one late period. First Delinquent Day refers to the number of days from when an account was sanctioned until the first delinquent period was reached. Average Overdraft Usage is calculated as the average daily loan balance as a percentage of the initial loan limit across the life the account was in the study. Average Limit is the initial loan limit of the overdraft facility. Limit Change is a dummy that takes a value of one if the initial account limit was either raised or reduced at account renewal. Ever Complained is a dummy variable that takes a value of one if a customer ever registered a complaint, dispute or issue during the course of the study. Number of Complaints is the number of complaints, disputes or issues registered during the course of the study while Number of Complaints if Ever Complained measures the same figure, but restricts the sample to only those acounts that registered at least one complaint, dispute or issue. Percent of Unresolved Complaints measures the number of unresolved complaints as a percentage of total complaints per account.

Characteristic	Full SBL		CPA	
	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)
Past Due				
1+ Days	14.1%	34.8%	14.5%	35.3%
30+ Days	3.2%	17.6%	3.2%	17.7%
60+ Days	1.4%	11.9%	1.5%	12.1%
90+ Days	1.0%	9.9%	1.1%	10.5%
# Late Periods	0.22	0.63	0.23	0.67
More than 1 Late Period if Ever Late	1.53	0.93	1.55	0.95
First Delinquent Day	127.85	86.18	124.53	86.13
Average Account Usage	65.3%	27.2%	64.7%	27.7%
Average Limit (USD)	$20,611	$11,929	$20,887	$12,185
Limit Change	13.2%	33.9%	15.1%	35.8%
Total Account Observations	1319		1086	
Ever Complained	55.7%	49.7%	57.6%	49.5%
# of Complaints	1.51	2.24	1.55	2.25
# Complaints if Ever Complained	2.71	2.39	2.70	2.38
% Not Resolved	12.1%	23.4%	12.5%	23.7%
Total Complaint Observations	659		547	

Table 3: Deliquency Outcomes

This table reports regression results using delinquency variables as a dependent variable on treatment dummies representing Groups A, B and C and a host of control variables. Treatment Group D serves as the ommitted category. Number of Late Periods is the number of times an account went delinquent within the loan period. More than One Late Period if Ever Late is a dummy that takes a value of one if an account registered more than one late period conditional of having at least one late period. 90+ Days is a dummy that takes the value of one if the account was ever 90+ days delinquent and zero otherwise. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy that is one for accounts that are located in metropolitan areas (CPA). For each dependent variable, two specifications are reported. The first utilizes the entire sample while second restricts the sample to include only accounts located in CPA cities. For the latter specification, the dummy variable for large city is omitted. All regressions include fixed effect controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Number of Late Periods		More than One Late period if Ever Late		90+ Days	
	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment						
A	**-0.0912***	**-0.0939**	**-0.217****	**-0.267****	**0.00721**	**0.00903**
	(0.0513)	(0.0577)	(0.105)	(0.109)	(0.00765)	(0.00940)
B	**-0.101****	**-0.109***	**-0.245****	**-0.287****	**0.00213**	**-0.000471**
	(0.0512)	(0.0590)	(0.0954)	(0.111)	(0.00664)	(0.00743)
C	**-0.0643**	**-0.0519**	**-0.0724**	**-0.0470**	**0.00656**	**0.00775**
	(0.0533)	(0.0625)	(0.0996)	(0.114)	(0.00754)	(0.00918)
SBL Power	**0.170*****	**0.179*****	**0.164**	**0.126**	**0.00685**	**0.00508**
	(0.0512)	(0.0577)	(0.104)	(0.115)	(0.00832)	(0.00969)
Loan Limit	**0.0469**	**0.0640**	**-0.0122**	**-0.0475**	**-0.00487**	**-0.00709**
	(0.0370)	(0.0417)	(0.0964)	(0.106)	(0.00837)	(0.00982)
Large City	**0.0272**		**0.0945**		**0.00862**	
	(0.0492)		(0.121)		(0.00825)	
Constant	**-0.794**	**-0.560**	**0.591**	**1.182**	**0.0574**	**0.102**
	(0.534)	(0.578)	(1.319)	(1.467)	(0.122)	(0.138)
N	1,319	1,086	186	158	1,319	1,086
R-Squared	0.031	0.034	0.114	0.143	0.014	0.016

Table 4: Deliquency Outcomes on Pooled Treatment Groups

This table reports regressions results using delinquency variables on a dummy representing treatment Groups A and B combined. Treatment Groups C and D are pooled as well and serve as the control group. I also include the same control variables as in Table 2. Number of Late periods is the number of times an account went delinquent within the loan period. More than One Late Period if Ever Late is a dummy that takes a value of one if an account registered more than one late period conditional of having at least one late period. 90+ Days is a dummy that takes the value of one if the account was ever 90+ days delinquent and zero otherwise. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy variable that takes a value of one for accounts that are located in metropolitan areas. For each dependent variable, two specifications are reported. The first utilizes the entire sample while the second restricts the sample to include only accounts located in CPA cities. For the latter specification, the dummy variable for large city is omitted. All regressions also include fixed effect controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Number of Late Periods		More than One Late Period if Ever Late		90+ Days	
	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA
	(1)	(2)	(3)	(4)	(5)	(6)
Group A & B Dummy	**-0.0645***	**-0.0754***	**-0.198*****	**-0.253*****	**0.00136**	**0.000256**
	(0.0350)	(0.0396)	(0.0693)	(0.0756)	(0.00561)	(0.00659)
SBL Power	**0.170*****	**0.179*****	**0.176***	**0.135**	**0.00687**	**0.00507**
	(0.0512)	(0.0579)	(0.102)	(0.112)	(0.00832)	(0.00971)
Loan Limit	**0.0464**	**0.0643**	**-0.00430**	**-0.0413**	**-0.00463**	**-0.00667**
	(0.0369)	(0.0415)	(0.0948)	(0.103)	(0.00825)	(0.00970)
Large City	**0.0251**		**0.0877**		**0.00874**	
	(0.0492)		(0.121)		(0.00827)	
Constant	**-0.810**	**-0.594**	**0.451**	**1.098**	**0.0571**	**0.0984**
	(0.536)	(0.581)	(1.293)	(1.427)	(0.122)	(0.139)
N	1,319	1,086	186	158	1,319	1,086
R-Squared	0.030	0.033	0.110	0.142	0.013	0.014

Table 5: Account Behavior Variables

This table reports regression results of account behavior variables as dependent variable on the treatment dummies (Groups A, B and C.) Treatment Group D serves as the ommitted category. First Delinquent Day is the number of days from when an account was sanctioned until the first delinquent period was reached. Limit Change is a dummy equal one if the initial account limit was raised at account renewal. Category A is dummy that indicates whether accounts were classified with the lowest credit risk at account renewal. Average Overdraft Usage is calculated as the average daily loan balance as a percentage of the initial loan limit for the duration the account was in the study. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy variable equal one for accounts that are located in metropolitan areas. For each dependent variable, two specifications are reported. The first utilizes the entire sample while second restricts the sample to include only accounts located in CPA cities. For the latter specification the dummy variable for large city is omitted. All regressions include fixed effects for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	First Delinquent Day		Limit Change		Category A		Average Overdraft Usage	
	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment								
A	**34.89***	**38.52***	**0.0475***	**0.0500***	**0.0753****	**0.0616**	**-0.0516****	**-0.0582****
	(18.85)	(20.37)	(0.0251)	(0.0292)	(0.0371)	(0.0412)	(0.0212)	(0.0239)
B	**23.73**	**25.89**	**0.0126**	**0.0160**	**0.0715****	**0.0682***	**-0.0281**	**-0.0390***
	(16.49)	(18.86)	(0.0232)	(0.0272)	(0.0363)	(0.0403)	(0.0203)	(0.0228)
C	**26.69**	**18.27**	**0.0224**	**0.0255**	**0.0141**	**0.0167**	**-0.00382**	**-0.0159**
	(18.44)	(20.12)	(0.0241)	(0.0283)	(0.0362)	(0.0403)	(0.0208)	(0.0233)
SBL Power	**-30.05***	**-22.13**	**-0.235*****	**-0.264*****	**-0.0581**	**-0.0625**	**0.0177**	**0.00705**
	(17.47)	(19.36)	(0.0239)	(0.0276)	(0.0368)	(0.0409)	(0.0212)	(0.0241)
Loan Limit	**-16.34**	**-10.40**	**-0.0877*****	**-0.0881*****	**0.0471**	**0.0580**	**0.00806**	**0.0140**
	(15.78)	(16.98)	(0.0239)	(0.0275)	(0.0339)	(0.0368)	(0.0190)	(0.0213)
Large City	**11.21**		**-0.0126**		**-0.0562**		**-0.0714*****	
	(24.39)		(0.0193)		(0.0399)		(0.0226)	
Constant	**340.2**	**261.5**	**1.404*****	**1.165*****	**-0.0536**	**0.00925**	**0.550***	**0.364**
	(226.6)	(239.9)	(0.371)	(0.387)	(0.527)	(0.515)	(0.294)	(0.300)
N	186	158	1,319	1,086	1,319	1,086	1,319	1,086
R-Squared	0.155	0.177	0.148	0.152	0.132	0.127	0.041	0.042

Table 6: Account Behavior Variables on Pooled Treatment Groups

This table reports regression results of account behavior on a dummy representing treatment Groups A and B combined. Treatment Groups C and D serve as a pooled control group. I include the same control variables as in Table 4. First Delinquent Day is the number of days from when an account was sanctioned until the first delinquent period was reached. Limit Change is a dummy equal one if the initial account limit was raised at account renewal. Category A is dummy that indicates whether accounts were classified with the lowest credit risk at account renewal. Average Overdraft Usage is calculated as the average daily loan balance as a percentage of the initial loan limit for the duration the account was in the study. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy variable equal one for accounts that are located in metropolitan areas. For each dependent variable, two specifications are reported. The first utilizes the entire sample while second restricts the sample to include only accounts located in CPA cities. For the latter specification the dummy variable for large city is omitted. All regressions include fixed effects for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	First Delinquent Day		Limit Change		Category A		Average Overdraft Usage	
	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Group A&B Dummy	**16.30**	**23.41***	**0.0185**	**0.0198**	**0.0664****	**0.0566****	**-0.0376****	**-0.0403****
	(12.63)	(13.15)	(0.0174)	(0.0202)	(0.0260)	(0.0286)	(0.0148)	(0.0167)
SBL Power	**-33.48****	**-25.15**	**-0.235*****	**-0.264*****	**-0.0581**	**-0.0627**	**0.0177**	**0.00709**
	(16.82)	(18.20)	(0.0239)	(0.0276)	(0.0368)	(0.0409)	(0.0212)	(0.0241)
Loan Limit	**-19.25**	**-12.48**	**-0.0863*****	**-0.0867*****	**0.0474**	**0.0578**	**0.00726**	**0.0132**
	(15.37)	(16.33)	(0.0239)	(0.0276)	(0.0338)	(0.0367)	(0.0191)	(0.0213)
Large City	**15.21**		**-0.0125**		**-0.0558**		**-0.0711*****	
	(24.17)		(0.0193)		(0.0398)		(0.0226)	
Constant	**384.3***	**293.6**	**1.397*****	**1.151*****	**-0.0520**	**0.0215**	**0.557***	**0.371**
	(219.0)	(232.2)	(0.372)	(0.385)	(0.527)	(0.514)	(0.295)	(0.300)
N	186	158	1,319	1,086	1,319	1,086	1,319	1,086
R-Squared	0.142	0.169	0.146	0.150	0.132	0.127	0.040	0.041

Table 7: Delinquency Outcomes and Account Behavior, Adjusted Treatment Groups

This table reports regression results of delinquency outcomes and account behavior variables on treatment dummies representing Groups A, B and C. Borrowers in Treatment Group B who received 50% or more calls from a single caller were included in Treatment Group A. Treatment Group D serves as the ommitted category. I include the same comtrol variables as in Table 4. The desctription of the ependent variables can be found in Tbales 3 and 5. All regressions include controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Number of Late Periods	More than One Late period if Ever Late	90+ Days Late	First Delinquent Day	Limit Change	Category A	Average Overdraft Usage
	Full SBL	Full SBL	Full SBL	Full SBL	Full SBL	Full SBL	Full SBL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Caller Share Adj. Treat							
A	**-0.101****	**-0.225****	**0.00616**	**37.00****	**0.0428***	**0.0774****	**-0.0487****
	(0.0504)	(0.105)	(0.00732)	(18.67)	(0.0243)	(0.0364)	(0.0206)
B	**-0.0905***	**-0.239****	**0.00291**	**21.69**	**0.0153**	**0.0689***	**-0.0297**
	(0.0523)	(0.0958)	(0.00694)	(16.61)	(0.0237)	(0.0371)	(0.0207)
C	**-0.0642**	**-0.0728**	**0.00657**	**26.80**	**0.0224**	**0.0141**	**-0.00385**
	(0.0533)	(0.0996)	(0.00754)	(18.44)	(0.0241)	(0.0362)	(0.0208)
SBL Power	**0.170*****	**0.164**	**0.00685**	**-30.49***	**-0.235*****	**-0.0581**	**0.0177**
	(0.0512)	(0.104)	(0.00832)	(17.45)	(0.0239)	(0.0368)	(0.0212)
Loan Limit	**0.0477**	**-0.0123**	**-0.00484**	**-16.39**	**-0.0877*****	**0.0469**	**0.00805**
	(0.0370)	(0.0963)	(0.00838)	(15.75)	(0.0239)	(0.0339)	(0.0191)
Large City	**0.0271**	**0.0950**	**0.00854**	**10.47**	**-0.0131**	**-0.0562**	**-0.0711*****
	(0.0492)	(0.122)	(0.00822)	(24.40)	(0.0193)	(0.0399)	(0.0226)
Constant	**-0.800**	**0.259**	**0.0568**	**345.5**	**1.401*****	**-0.0521**	**0.552***
	(0.534)	(1.351)	(0.122)	(229.0)	(0.371)	(0.527)	(0.295)
N	1,319	186	1,319	186	1,319	1,319	1,319
R-Squared	0.031	0.113	0.014	0.157	0.147	0.133	0.041

Table 8: Client Reachability by Relationship Managers

This table reports regression results of adminstartive data about client reachability for the relationships calls on a dummy representing treatment Group A. Treatment Group B serves as the control group. Percent Reachable Overall refers to the percent of all calls from the relationship manager in which the client was successfully contacted. Percent Reachable Monitoring 1 is the percent of calls in which the client was reached during the first call of the month. Percent Reachable Monitoring 2 refers to the percent of calls in which the client was reached during the second call of the month. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy variable that takes a value of one for accounts that are located in metropolitan areas where the bank maintains a credit processing agency. For each dependent variable, two specifications are reported. The first utilizes the entire sample while the second restricts the sample to include only accounts located in CPA cities. For the latter specification the dummy variable for large city is omitted. All regressions include fixed effect controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	% Reachable Overall A & B		% Reachable Monitoring 1 A & B		% Reachable Monitoring 2 A & B	
	Full SBL	CPA	Full SBL	CPA	Full SBL	CPA
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment A	**0.0161****	**0.0154***	**0.00991**	**0.0127**	**0.0216****	**0.0183***
	(0.00725)	(0.00793)	(0.00796)	(0.00880)	(0.00869)	(0.00935)
SBL Power	**-0.0102**	**-0.0182**	**-0.0160**	**-0.0206**	**-0.00515**	**-0.0160**
	(0.0119)	(0.0134)	(0.0127)	(0.0145)	(0.0141)	(0.0156)
Loan Limit	**0.00316**	**-0.00157**	**0.00116**	**-0.00544**	**0.00555**	**0.00214**
	(0.0119)	(0.0135)	(0.0116)	(0.0132)	(0.0145)	(0.0162)
Large City	**0.00740**		**-0.00509**		**0.0169**	
	(0.0109)		(0.0118)		(0.0140)	
Constant	**0.870*****	**0.889*****	**0.916*****	**0.929*****	**0.825*****	**0.851*****
	(0.167)	(0.196)	(0.161)	(0.192)	(0.205)	(0.234)
N	659	547	659	547	659	547
R-Squared	0.078	0.094	0.065	0.069	0.064	0.083

Table 9: Client Reachability by Relationship Managers, Adjusted Treatment Group A

This table reports regression results of adminstrative data where the independent variable % calls from top 2 is defined as in Table 7: Borrowers in Treatment Group B who received 50% or more calls from a single caller were included in Treatment Group A. Percent Reachable Overall refers to the percent of all calls from the relationship manager in which the client was successfully contacted. Percent Reachable Monitoring 1 is the percent of calls in which the client was reached during the first time the relationship managerd called in a given period. Percent Reachable Monitoring 2 refers to the percents of calls in which the client was reached during the second time the relationship manager called. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy variable that takes a value of one for accounts that are located in metropolitan areas. All regressions include fixed effect controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Reachable Overall A & B	% Reachable Monitoring 1 A & B	% Reachable Monitoring 2 A & B
	Full SBL	Full SBL	Full SBL
	(1)	(2)	(3)
% Calls from Top 2	**0.0929*** **	**0.119*** **	**0.0655** **
	(0.0206)	(0.0224)	(0.0257)
SBL Power	**-0.00788**	**-0.0105**	**-0.00539**
	(0.0120)	(0.0129)	(0.0142)
Loan Limit	**0.00443**	**0.00431**	**0.00498**
	(0.0118)	(0.0117)	(0.0145)
Large City	**0.00879**	**0.00183**	**0.0168**
	(0.0111)	(0.0122)	(0.0140)
Constant	**0.763*** **	**0.734*** **	**0.788*** **
	(0.168)	(0.165)	(0.206)
N	659	659	659
R-Squared	0.090	0.085	0.065

Table 10: Customer Complaint Outcomes

This table reports regression results of customer complaint outcomes on a dummy representing treatment Group A. Treatment Group B serves as the control group. The data is derived from the records of the bimonthly relatinship calls conducted during the study period and the sample size is restricted to clients in Group A or Group B, as they were the only treatment groups whose complaints were recorded. Ever Complaint is a dummy variable that takes a value of one if a customer ever registered a complaint, dispute or issue during the course of the study. Number of Complaints is the number of complaints, disputes or issues registered during the course of the study while Number of Complaints if Ever Complained measures the same figure but restricts the sample to only those acounts that registered at least one complaint, dispute or issue. Percent of Unresolved Complaints measures the number of unresolved complaints as a percentage of total complaints per account. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. Large city is a dummy variable that takes a value of one for accounts that are located in metropolitan areas where the bank maintains a credit processing agency. All regressions include fixed effect controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. R-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Ever Complaint	**Number of Complaints**	**# of Complaints if Ever Complaint**	**% of Unresolved Complaints**
	Full SBL	Full SBL	Full SBL	Full SBL
	(1)	(2)	(3)	(4)
Treatment A	**-0.0822****	**0.232**	**0.661*****	**0.0570*****
	(0.0387)	(0.173)	(0.240)	(0.0183)
SBL Power	**0.00133**	**0.224**	**0.548**	**0.0109**
	(0.0550)	(0.247)	(0.335)	(0.0257)
Loan Limit	**0.0411**	**0.0607**	**-0.355**	**-0.0265**
	(0.0513)	(0.230)	(0.308)	(0.0227)
Large City	**-0.00851**	**0.0747**	**0.360**	**0.0356**
	(0.0621)	(0.278)	(0.407)	(0.0290)
Constant	**0.153**	**0.00380**	**5.670**	**0.346**
	(0.691)	(3.095)	(4.172)	(0.306)
N	659	659	367	659
R-Squared	0.055	0.062	0.195	0.055

Appendix Table 1: Customer Satisfaction Outcomes on Pooled Treatment Groups

Ordered logit regressions of customer responses to an endline survey that asked about their satisfication with the SBL overdraft product on a dummy representing treatment Groups A and B combined. Treatment Groups C and D serve as the control group. No imputations for missing observations are included. Loan size measures customer satisfaction with the size of the limit of the overdraft account. Interest Rates refers to satisfaction with the interest charged on the overdraft product, while Branch Customer service refers to satisfaction with the service provided by bank branch offices. Renewal Process measures customer satisfication with the account renewal process conducted at the end of the first year, while Average Rating refers to satisfaction with the SBL product as a whole. Ever Late is a dummy variable which takes a value of one if the customer ever self-reported making late payments on their overdraft account and the coefficients shown are marginal effects from a probit regression. All dependent variables except Ever Late measure customer satisfaction for the listed category on a one to five scale spanning very dissatisfied to very satisfied. SBL Power is an indicator for a loan type that has a quicker approval time but are usually given for smaller overdraft amounts. Loan limit is the log of the maximum allowable loan provided per account. All regressions include fixed effect controls for 4 different geographic regions, 8 different disbursement months of the SBL product and 6 different types of incorporation of the banking client. Pseudo r-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Loan Size	Interest Rates	Branch Customer Service	Renewal Process	Average Rating	Ever Late
	(1)	(2)	(3)	(4)	(5)	(6)
Group A&B Dummy	**0.0580**	**-0.279****	**0.312****	**0.264****	**0.0627**	**0.0522****
	(0.124)	(0.124)	(0.128)	(0.125)	(0.130)	(0.0253)
SBL Power	**-0.0290**	**0.168**	**-0.0710**	**0.149**	**0.180**	**0.0531**
	(0.177)	(0.177)	(0.184)	(0.180)	(0.185)	(0.0396)
Loan Limit	**0.139**	**0.0546**	**-0.117**	**0.0161**	**0.0698**	**0.0132**
	(0.160)	(0.159)	(0.164)	(0.161)	(0.166)	(0.0338)
N	868	863	829	823	863	828
R-Squared	0.00883	0,00799	0,0109	0,0104	0,0116	0.0266

Appendix Table 2: Treatment Bounds for Customer Satisfaction Outcomes

Table 2 reports summary data from the ordered logit regressions of customer responses to an endline survey in June 2009 that asked about their satisfaction with the SBL overdraft product on a dummy representing treatment Groups A and B combined. Treatment Groups C and D serve as the control group. All dependent and indepeendent variables are defined as in Appendix Table 1. Lower bound (upper bound) imputes the highest satisfaction score to non-responders if they were assigned to the control group (treatment group) and the lowest satisfaction score if they were assigned to one of the three treatment groups (control group). The specifications reported in Columns (2) and (6) estimate a minimum treatment effect by imputing the mean plus (minus) .25 standard deviations for the control group (treatment groups) while Columns (3) and (7) estimate a maximum treatment by imputing the mean minus (plus) .25 standard deviations to the control group (treatment groups). All regressions include controls for geographic regions, disbursement months and different types of incorporation of the banking client. Pseudo r-squared and sample size are reported at the bottom of the table and robust standard errors for all coefficients are reported in parentheses. The symbols ***,**,* indicate significance levels of 1%, 5% and 10%, respectively.

	Loan Size				Interest Rates			
	Lower Bound	Mean -.25 SD	Mean +.25 SD	Upper Bound	Lower Bound	Mean -.25 SD	Mean +.25 SD	Upper Bound
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Group A&B Dummy	**-1.785*** **	**-0.308*** **	**0.437*** **	**1.850*** **	**-2.027*** **	**-0.611*** **	**0.154**	**1.605*** **
	(0.108)	(0.0990)	(0.0994)	(0.109)	(0.155)	(0.0997)	(0.0982)	(0.107)
SBL Power	**-0.0808**	**0.0118**	**0.0254**	**0.0156**	**0.0508**	**0.0822**	**0.0826**	**0.128**
	(0.144)	(0.139)	(0.139)	(0.144)	(0.149)	(0.139)	(0.139)	(0.145)
Loan Limit	**0.154**	**0.123**	**0.0983**	**-0.0404**	**0.0601**	**0.0103**	**-0.0145**	**-0.0403**
	(0.130)	(0.126)	(0.126)	(0.131)	(0.134)	(0.126)	(0.126)	(0.132)
CPA Cities	**-0.0881**	**-0.254***	**-0.218**	**0.267**	**0.643*** **	**-0.358** **	**-0.319** **	**-0.328***
	(0.174)	(0.149)	(0.150)	(0.176)	(0.185)	(0.148)	(0.149)	(0.174)
N	1,319	1,319	1,319	1,319	1,319	1,319	1,319	1,319
R-Squared	0.0769	0.00715	0.00825	0.0797	0.0923	0.0128	0.00496	0.0642

	Branch Customer Service				Renewal Process			
	Lower Bound	Mean -.25 SD	Mean +.25 SD	Upper Bound	Lower Bound	Mean -.25 SD	Mean +.25 SD	Upper Bound
Group A&B Dummy	**-1.831*** **	**-0.229** **	**0.665*** **	**2.099*** **	**-1.840*** **	**-0.679*** **	**1.144*** **	**2.069*** **
	(0.154)	(0.0991)	(0.100)	(0.113)	(0.153)	(0.101)	(0.105)	(0.155)
SBL Power	**-0.0805**	**-0.0530**	**-0.0581**	**-0.0516**	**0.0124**	**0.0696**	**0.0696**	**0.122**
	(0.148)	(0.139)	(0.139)	(0.148)	(0.147)	(0.138)	(0.138)	(0.149)
Loan Limit	**-0.0308**	**-0.0284**	**-0.0658**	**-0.170**	**0.0112**	**0.0243**	**-0.0310**	**0.0104**
	(0.133)	(0.126)	(0.126)	(0.133)	(0.133)	(0.126)	(0.126)	(0.135)
CPA Cities	**1.381*** **	**0.382** **	**0.420*** **	**0.410** **	**1.052*** **	**0.0897**	**0.170**	**-1.260*** **
	(0.184)	(0.148)	(0.149)	(0.174)	(0.183)	(0.147)	(0.147)	(0.182)
N	1,319	1,319	1,319	1,319	1,319	1,319	1,319	1,319
R-Squared	0.0749	0.00687	0,0152	0.103	0.0734	0.0132	0,028	0.0933

	Average Rating				Ever Late			
	Lower Bound	Mean -.25 SD	Mean +.25 SD	Upper Bound	Lower Bound	Mean -.25 SD	Mean +.25 SD	Upper Bound
Group A&B Dummy	**-1.957*** **	**-0.361*** **	**0.425*** **	**1.936*** **	**0.370*** **			**-0.124*** **
	(0.156)	(0.100)	(0.100)	(0.111)	(0.0238)			(0.0218)
SBL Power	**-0.0510**	**0.0797**	**0.0794**	**0.0631**	**0.0569**			**0.0256**
	(0.147)	(0.140)	(0.140)	(0.146)	(0.0382)			(0.0324)
Loan Limit	**0.0163**	**0.0477**	**0.0212**	**-0.0822**	**-0.00241**			**0.0115**
	(0.132)	(0.128)	(0.128)	(0.132)	(0.0338)			(0.0286)
CPA Cities	**1.547*** **	**0.368** **	**0.412*** **	**0.412** **	**-0.316*** **			**-0.136*** **
	(0.187)	(0.150)	(0.151)	(0.177)	(0.0502)			(0.0422)
N	1,319	1,319	1,319	1,319	1,249			1,249
R-Squared	0.0866	0.0115	0,0131	0.0928	0.215			0.0545