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ABSTRACT

We report the results from a field experiment with a micro lender in Uganda to test the effectiveness of privately implemented incentives for loan repayment. Using a randomized control trial we measure the impact of three different treatments: Borrowers are either given a lump sum cash reward upon completion of the loan (equivalent to a 25% interest rate reduction on the current loan), a 25% reduction of the interest rate in the next loan the borrower takes from the bank, or a monthly text message reminder before the loan payment is due (SMS). We find that on average the size of the treatment effect is similar across all the treatment groups: borrowers in the treatment groups have a 7-9% increase in the probability of paying on time and the average days late drop by 2 days a month. The results suggest that simple text messages which help borrowers to better manage their repayment dates have similar effects as large changes in the cost of capital of 25% of interest. The impact of the cash back incentives are stronger for customers with smaller loans and less banking experience, the reduced future interest rate seemed to be most effective for customers with larger loans, while the SMS text messages were particularly effective for younger customers.

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1. Introduction

Financial markets in developing countries are often hampered by a severe lack of even basic financial infrastructure such as functioning credit bureaus, uniform disclosure rules or the ability to use collateral. These limitations substantially increase the cost of lending for banks since the overall applicant pool that lenders face is more opaque and the ex post enforcement of loans becomes more difficult as well, see for example Rajan and Zingales (1998), Djankov et al (2007) or Karlan and Morduch (2010) for differences in the access to finance across countries. The lack of market wide financial infrastructure blunts any enforcement or screening mechanisms that operate through downside incentives, if borrowers who defaulted on one bank can easily access other lenders.[2] To ensure timely repayment, banks have to rely more heavily on self-enforcing private arrangements such as contracts that operate via upside incentives.

But poor payment behavior of borrowers in developing countries might also be the result of limited financial planning on the part of small businesses paired with a difficult operating environment for small and even larger businesses. Firms face many external shocks to their operations on a day to day basis, for example infrastructure problems such as power outages, macro risks or even political problems. These shocks can affect the underlying volatility of cash flows and increase bankruptcy risk. But these small businesses often have only rudimentary financial management and accounting practices to manage these risks[3]. The lack of internal financial controls exaggerates the impact of shocks, if managers are unable to properly respond by adjusting the capital structure or planned investment programs.

In this study we contrast the importance of these different hypotheses for poor payment discipline of small businesses in developing countries and the types of interventions that can help to reduce late payments. We compare interventions that provide firms with steeper financial incentives for timely repayments to those that make it easier for firms to keep track of upcoming payments such as SMS reminders. If small businesses strategically delay repayment since they know that lenders have only limited enforcement mechanisms, then the provision of incentives

[2] See Hertzberg et al (2011) for an interesting example of a market wide change in the disclosure rules for credit bureaus in Argentina which allowed all the lenders to a firm public access to the firm's payment status with its other lenders.

[3] Karlan and Valdivia (2009) or Drexler, Fischer and Schoar (2011) show the impact that lack of financial literacy can have on small business owners.

for on-time payments should reduce the benefits of this behavior. Sending clients SMS reminders, however, should not have any impact under this hypothesis. In contrast, these results should be reversed if late payments are predominantly a function of the inability of small business to manage their finances: Here steeper incentives would not help, since payment failures are not based on a rational cost-benefit analysis of borrowers but are a function of their inability to manage the finances of the business. In this context SMS reminders could have an impact on ensuring better payment behavior if they help firms to improve their cash management. It is important to note that we have a specific form of strategic behavior in mind here: People willingly delay their payments since they are trading off the cost of incurring late fees on their existing loan against other possibly higher interest forms of finance (or not having access to finance all together). These incentives cannot help in the case of customers who have decided to default on their loans altogether.

We work with a bank in Uganda, UML, which predominately lends to small businesses in the semi-organized sector. To understand the role of dynamic incentives for loan repayment versus SMS reminders we set up three different treatment arms and a control group which received only the standard UML loan and no treatment. In the first treatment borrowers are promised to receive a 25% reduction in the monthly interest rate ex post, if they make all their monthly payments on time. It is paid as a onetime reward at the conclusion of the loan. We call this treatment “cash back”. This constitutes a very large reduction in the cost of capital and should thus provide strong incentives for borrowers to repay on time. The exception could be fast growing firms with very high return on capital. If these firms are credit constraint they might be willing to pay late and bear the higher interest cost, since the returns from investing are even higher than the savings from paying on time.

In the second treatment we provide longer term and more back loaded incentives in order to isolate the incentive effect on fast growing firms. We call this treatment arm “future interest reduction”. Customers are given a 25% reduction in the interest rate of their *next* loan (again a reduction from 4% to 3% monthly) if current loan payments are all made in time. For an average growth in loan size of 5% the benefit of this treatment is comparable to the one for the cash back treatment. But this incentive should be most effective for businesses that foresee a stronger growth trajectory and thus will require larger loans going forward.[4]

Finally, in the third treatment we compare these financial incentives to an intervention where borrowers receive SMS reminders every month three days before the payments are due. The idea is that if borrowers live very busy and unstable lives, SMS alerts might prevent them from missing payments due to oversight. Cell phone use is widespread in Uganda and only about 1% of the borrowers in this treatment group did not accept to be part of it because they did not own a cell phone. And lastly we have a control group that does not receive any additional treatment from the usual loan provisions of the bank.

We find that all of the three different treatments have a similar impact in terms of magnitudes on the number of days that borrowers pay late or the likelihood to have a perfect repayment profile relative to the control group. On average the borrowers in the treatment groups see a 7-9% increase in the probability of paying perfectly and the average number of days late drop by 2 days. These results allow us to benchmark the economic benefits of the different treatments against each other. It is interesting to see that the SMS treatment which is almost costless for the bank to implement has the same economic effect on late payments as a 25% reduction in the interest rate. A large fraction of borrowers previously seem to have paid late not for strategic reasons but because they were unable to keep track of their payment schedule without the help of simple reminders. These findings support the idea that small businesses in developing countries suffer from lack of financial management which might affect their payment behavior.

We then analyze whether the different treatment arms have heterogeneous treatment effects across subgroups of borrowers. Interestingly, we see that borrowers with smaller loans (smaller than the median $450) respond more strongly to cash back and SMS treatments, which could suggest that these borrowers look for more immediate benefits. In contrast, borrowers with larger loans respond more strongly to the promise of future interest reductions but do not show much sensitivity to cash back or SMS reminders. It seems that borrowers with larger loans are on faster

[4] Under reasonable assumptions about the firms' discount rate the net present value of the future interest rate reduction is 15% higher than the savings from the cash back at the time of the reward. Using the average loan amount and term, we calculated the average cash back reward. Then using the same figures, we projected the interest payments for the next loan assuming a 20% grow in the loan amount under the regular interest rate (4% monthly) and the reward one (3% monthly). We compare the savings from the cash back to the net present value of the flow of savings on interest for the duration of the future loan.

growth trajectories and therefore respond more strongly to the benefit of a future interest rate reduction than small borrowers. In addition, our results do not seem to be purely driven by tighter credit constraints for small borrowers (i.e. they cannot respond to the future interest rate reduction since they have a very immediate need for capital), since the smaller firms also respond strongly to the SMS reminders.

We also rule out that small versus larger loans only proxy for other factors such as the experience pattern of the borrowers, since often clients with larger loans could be on a third or fourth loan renewal cycle while clients with smaller loans might still be in the first or second cycle. However, we find that the correlation between loan size and loan cycle is only 14%. In addition we find that less experienced borrowers, who are on their first or second loan cycle, respond more strongly to the incentive treatments. Moreover, the subgroup of younger borrowers (below 30 years of age) responds significantly stronger to SMS reminders than older borrowers. We believe that this result indicates a difference in familiarity with mobile technology across generations.

There is a growing number of papers that test the impact of credit on firm growth and document large but heterogeneous returns to capital. De Mel, McKenzie and Woodruff (2008) document the impact of a cash-grant program on small businesses in Sri Lanka and find very high returns on capital but also large heterogeneity between borrowers. Similarly, Karlan and Zinman (2010) show large returns on a loan expansion experiment in South Africa. Evidence based on quasi experimental work suggests that credit expansion in the banking sector has a large impact on firm growth; see for example Banerjee and Duflo (2004), Cole (2009) or Udry and Anagol (2006). Several papers have also shown the impact of the cost of capital or the structure of the loan on the take up of credit and the ex ante selection effects on borrower types, e.g. Karlan and Zinman (2011) or Fischer (2010). But in contrast there are no papers that study the impact of ex post financial incentives or SMS reminders to help borrowers manage their loan payments.

A large and rapidly growing literature outside of finance and economics has focused on the impact of reminders and SMS text messages in particular on changing people's behaviors. The majority of these papers focus on health related interventions such as immunization, smoke cessation, out patience attendance, maternal health, exercise and weight loss, etc. (for a review see Kaplan, 2006). The results documented in these studies show very mixed success. Also, in

Political Science, Dale and Strauss (2009) show that SMS text messages that are impersonal yet unlikely to be ignored are effective on getting people to vote. The authors conducted a nationwide experiment during the 2006 elections in the US and showed that the use of SMS reminders resulted in a 3 percentage points increase in the likelihood of voting.

The use of SMS messages has only recently become of interest in the consumer finance literature. Some studies have used reminders and text messages to test the impact on the savings behavior of individuals. Kast et al. (2010) find that using text messages as reminders and feedback mechanisms increases savings rates for low income customers in Chile. Karlan et al. (2010) report the results of three different field experiments in Bolivia, Peru and the Philippines that use text messages to encourage savings. The paper test the prediction of their model that shocks to attention can change intertemporal choices by bringing attention to future expenditure opportunities. They find that reminders in the form of SMS text messages in Bolivia and Philippines, or letters in the case of Peru increased savings on average by six percent and improve people's probability of achieving savings goals by three percentage points. While the paper compares the effects of reminders to other treatments related to the salience of savings and future expenditures, they do not compare them to any monetary incentive.

Our paper adds to this literature in two dimensions. First, we look at the impact of SMS on loan repayments rather than savings targets. This difference is important since late payments of loans is often interpreted as a strategic choice by a borrower who delays repayment since he knows that enforcement is difficult or because he is capital constraint and has outside opportunities for the money which exceed the interest rate in case of late payments. Our results suggest that for a significant fraction of the borrowers this interpretation does not apply, since they seem to simply mismanage their payment dates and pay back in time if prompted by an SMS. Second, our intervention was designed with the objective of comparing the impact of the SMS reminders with pecuniary incentives so that we can shed some light on the "price-equivalent" effect of the treatment. This approach is similar to Bertrand et al. (2010) that found that some psychological features of advertising letters could affect loan demand as much as a reduction of 25% in the interest rate. Similarly, we find that SMS reminders have a comparable impact on the repayment behavior of borrowers to a 25% reduction of current or future interest rates in case the borrower has a perfect repayment history in the current loan.

The rest of the paper is structured as follows. The second section presents the experimental set up, the third section provides details on implementation and in the four section we describe the data sources and data collection procedures. The fifth section discusses the results of the study and finally section six concludes.

2. Experimental Set up

The experiment was conducted with Uganda Microfinance Limited (UML), a Microfinance Institution, which has 27 branches in different locations across Uganda and became a regulated deposits taking institution in 2005. In 2008 UML had over 25,000 customers, a loan portfolio of $24 Million and a default rate of 4%. Although most of UML's business loans are collateralized, it is very hard to seize the assets after a customer has defaulted. In addition, since Uganda did not have a Credit Bureau at the time, UML did not have the ability to incentivize timely repayment based on the threat of affecting a borrower's credit history.

In collaboration with the bank we conducted focus groups and client interviews to understand the viability of different incentive schemes for borrowers. We decided on three treatments to randomly assign to loan customers:

- Cash Back: Customers selected to participate in the Cash Back incentive, would receive at the end of the loan period a cash back payment equivalent to 25% of the interest that they paid on their loan if they have paid all their loan installments on time. Interest rate for these customers was 4% monthly, so in practice this incentive meant approximately a reduction to a 3% monthly rate conditional on perfect repayment and only realized at the end of the loan period. At the end of the loan period, bank staff would review all payments for the duration of the loan and verify that all of them were made on time, and that the loan was not prepaid before completion of 50% of the balance. The customer was invited to the branch to receive a check for the amount equivalent to 25% of the total interest was paid, and a paper certificate of being a good and valued customer and an on-time payer.

- Future Interest Rate Reduction: Customers selected to receive this incentive would receive a preferential interest rate of 3% in their future loan with UML when they repaid their current loan perfectly on time for every installment for the duration of the loan, and as with the Cash

Back incentive, to get the reward, the loan could not be prepaid before completion of 50% of the balance. In monetary terms, this incentive is in general stronger than the cash back one. Using standard assumptions for discount rates and average values for loan size and term, the net present value of the interest rate reduction incentives is higher than the cash back savings for any business expecting to receive a future loan that is at least 5% larger than the current one. However, if customers exhibit hyperbolic discounting and value the present disproportionately, the promise of a future reward may not be as compelling as the expectation of a surer one for their current loan in the near term.

- SMS reminders: Customers selected for this treatment would agree to provide their mobile number and would receive standard financial conditions for their loans, but will get a monthly text message three days before their payment day, thanking them for banking at UML and reminding them about the importance of paying on time. We had three possibilities for the message depending on the customer's characteristics and preferences. At the time of disbursal, customers assigned to the SMS reminder treatment could decide if they wanted their message in English, in Luganda, or in symbols designed for those who could not read either of those 2 languages. We hired a local company, SMS Media to send messages to about 450 customers on a monthly basis for the duration of their loans. Success delivery rate was 97%, 2% of messages arrived late and 1% did not arrive due to network difficulties.

All customers selected for any of the treatments signed a written contract with detailed information explaining the incentive they would receive. They also received detailed explanation in person about the incentive they were offered and the fact that it was for a pilot project so it was a special offer that would only be valid for that particular loan, and they had the opportunity to ask questions. In the case of the Cash Back and the Future Interest Rate Reduction, it was very clear, both in the written copy that they received as well as during the meeting for disbursement that they would have to perfectly pay on time every installment and not prepay the loan before completion of 50% of the balance to get the reward.

3. Implementation

To test the impact of incentives we selected the Micro Corporate Credit (MCC) loan customers getting loans with a term of up to 12 months. These are individual business loans targeted towards micro and small businesses, intended to be invested for productive use, such as for working capital or a capital investment. Businesses are only eligible for this product if they have been operating for a minimum of one year, and generally the individual must have some form of collateral to cover at least 80% of the principal loan amount, such as household chattels, a vehicle, a land sales agreement, etc. There is a fixed interest rate on this product of 4% per month, and there are only very rare exceptions to this interest rate. We selected this product, the MCC, because it was a small business loan, with relatively short maturity terms and with a high volume of monthly loan disbursements in urban and rural areas. At the time of implementation, about 50% of the loan portfolio at UML was MCC loans. The other 50% included group loans, mortgages, school loans, and consumption loans for salaried customers.

We selected five branches to implement the pilot project: three urban branches (Kajjansi, Kyengera and Nakawa) and two rural branches (Kiboga and Mityana). Selected branches had been operating for at least three years, had a rapid flow of customers and monthly disbursements, had necessary branch support and sufficient staff for adequate implementation and would offer an appropriate physical location for constant monitoring and to hold private meetings with customers at the time of disbursement.[5]

Project implementation started in all five branches during the last week of April 2008. We produced project materials and trained branch staff on project procedures including the use of a randomization software to randomly assign all customers approved for an MCC loan to one of the three incentives or a control group at the time of disbursement. We decided to randomize at the loan officer desktop because it was the most efficient way of including all approved customers in the study minimizing the interference with regular procedures at the bank. We design a small piece of software that would work within Excel and would allow for easy randomization of customers. The loan administrator would simply have to input the client name, ID number, loan amount and interest rate, then click a button that said "get loan type." The

[5] Incentive assignment was confidential since different rewards were offered to different people.

program would then generate a response that indicated whether the client should be assigned to group 1, 2, 3 or 4, and would make an unalterable record of the entry. The program was installed in the loan administrator's computer at each of the branches. The procedure was designed in a way that we could make sure that each customer was assigned to a random group and loan officers did not have any power to change or adjust the selection process, so that the assignment was in fact completely random. The random assignment was designed such that the control group, the Cash Back, and the Future Interest Rate Reduction each had a 22% chance of being drawn while the SMS Reminder group had a 34% chance. Since we expected the SMS reminder to have a smaller impact than the monetary incentives, we increased the sample size to increase the statistical power to assess the size of the impact. Customers assigned to the control group received their loan with standard conditions and received no incentives for repayment, all data was collected for them to compare their repayment behavior to that of the participants assigned to one of the treatments (incentives). For the duration of the implementation period, until mid-August 2008, every day, at selected branches, all approved MCC loan customers with a loan term up to 12 months came to the branch to meet with the loan administrator, receive the reimbursement and got assigned to one of the groups for the pilot test.

4. Data sources and sample

Sample construction: To analyze the repayment behavior across different treatment groups we constructed repayment data from different data extracts from the IT system at the bank, and complemented it with personal and business characteristics obtained from the loan application and loan appraisals forms and entered electronically by a team at Uganda Bureau of Statistics hired for this project. Building repayment data sets was a complicated process. During the period of analysis for the incentives for repayment program, UML went from being a Regulated Deposit Taking Institution in the Ugandan financial sector to being a Commercial Bank and became part of Equity Bank. The transition meant a lot of changes in procedures at UML including a change on banking software from Bakers Realm to Finacle. The migration process created a lot of problems and ultimately made impossible to track repayment in a consistent and flawless way using only loan accounts. Therefore we had to use information from the customers' deposit accounts and extract information for each of the loan payments that a customer made. In order to make a loan payment, customers are required to make a deposit to their savings account, and then that money deposited into the savings account will be transferred to their loan account which then is credited as a payment. This allowed us to reconstruct all the payments that borrowers had made over the term of their loans.

We obtained data from March 2008 until June 2009. We were able to build a data set to compare, on a monthly basis, cumulative payments made by each customer required for the duration of the loan. Because of the organizational strains on the bank from the transition to a deposit taking institution we terminated our experiment by June 2009. We therefore only include loans that had a final installment in June 2009 or before. This earlier cut of reduced our sample size from 1,467 subjects to 1,246. To ensure data quality we also drop customers that had additional concurrent loans. The resulting number of loans for the analysis is 1121.

Outcome Variables: We construct several indicators for repayment behavior for each of the customers in the program. These indicators include (1) number of installments paid on time for the duration of the loan (nonconsecutive), (2) number of installments paid on time consecutively before incurring any late payment (this variable is different from the first indicator since it takes into account the fact that once a customer pay late one installment may lose the incentive to continue paying on time, since the monetary incentives in the program are only for customer who paid perfectly on time every installment), (3) average days late across all the installments. We also have details of the loan characteristics such as the amount, term, cycle, and the location of the branch that issued the loan. Finally for most customers we also have details on their personal and business characteristics from the loan application and appraisal forms. These include gender, marital status, age, household size, if they are home or business owners, time in business, and repayment capacity.

Summary Statistics: Table 1 presents a summary of all the relevant variables for the analysis.[6] Panel A shows borrower and loan characteristics. The average loan size is about $800, although more than half of the borrowers have loans smaller than $500, the median is $450. The length of the loan maturity is concentrated around 7 months in fact 48% of loans in the sample had a 6 month maturity. The majority of borrowers have little experience with this type of loan, 75% of them are in their first or second loan series (cycle). 35% of the borrowers are women and 78%

[6] Appendix Table A1 includes a description of all variables.

are married. The average customer is 38 years old and lives in a household of 5 people. 58% own a home and while all of them have businesses that have been operating for 8 years on average, only 36% own the premises or the location in which the business operate. During the loan appraisal process, loan officers calculate the repayment capacity of the customer as the monthly surplus of the business discounting household expenses, on average $309. In Panel B of Table 1 we summarize selected repayment outcomes. 34% of people in the sample paid perfectly on time every installment of their loans, however, on average, people paid 62% of their installments on time. The repayment behavior differs substantially between borrowers, on average customers pay 8 days late every month however some customers never paid late while others were consistently late in all their payments.

Finally, Panel C in Table 1 displays the distribution of customers between different treatments (and the control group) and different branches. Consistent with the randomization design, the two treatments with monetary incentives for repayment had approximately 22% of the customers (245 and 241 for Cash Back and Future Interest Rate Reduction respectively). A larger fraction of borrowers, 34% (or 383 borrowers) were assigned to the SMS treatment. The reminding 22% of customers belong to the control group. The distribution between different braches aims to capture a large set of different branch types within the bank. Among other things we selected branches that had significant banking activity of MCC loans. Kajjansi, Kyengera and Nakawa are urban branches located in different neighborhoods around Kampala and together accounted for 55% of the loans, while Kiboga and Mityana, located in rural communities 2.5 and 1.5 hours drive away from Kampala respectively, accounted for 45% of the sample.

Random Assignment: The random assignment was successful in creating groups that are comparable on all observable dimensions at baseline. In Table 2 we present the means for loan and customer characteristics summarized in Table 1 for each one of the treatment (and control) groups in columns (1) to (4). Columns (5) to (7) show the p-values for the difference in means (t-test) and the difference in proportions tests. We cannot reject the null hypothesis of equality in any of the cases when we compare each of the treatment groups with the control group with a confidence level of 99%. However, when comparing different treatment groups we get some statistically significant differences in underlying characteristics. Although this may happen by chance when running several statistical tests it is worth noticing that loans assigned to the Cash

Back group are smaller than those assigned to the Future Interest Rate Reduction group. The difference is statistically significant at the 5% significance level. The same is true for household size; the difference between the group assigned to Future interest rate reduction and SMS reminder is significant at the same level.

5. Treatment Effects

We estimate the effects of each of the treatments compared to the control group on different proxies for repayment outcomes. We select three outcome proxies that capture different dimensions of the borrower's repayment behavior. "Perfect Repayment" is a dummy variable which equals one if the customer paid on time in every single installment and zero otherwise. Monetary incentives provided in treatment groups A and B rely on a perfect payment profile. The second dependent variable we include is "Percentage of installments paid on time". This variable provides a more continue snapshot of a borrower's attempt of staying on time with their payments. Even if a borrower in the end did not have a perfect payment record and thus would not have received the reward, it shows us whether a borrower made an attempt of trying to do the right thing, even if they had to miss a few payments in the end. Finally, we look at the "Average number of days late per installment, which provides the most detailed image of a borrower's payment behavior. It tells us whether some customers were completely oblivious to their payment dates while others only fall late by a small margin.

We now estimate the impact of the three different treatments on these proxies for repayment outcomes. The general form of the equation is:

$$Y_i = \beta_0 + \beta_1 Cash\ Back_i + Future\ Interest_i + SMS_i + Z_i + X_i + \varepsilon_i \qquad (1)$$

Where Cash Back is a dummy that equals 1 for borrowers assigned to the cash back treatment and zero for all others, similarly for Future Interest Reduction and SMS treatments. In some specifications we control for loan characteristics (Z) including loan size and loan series and for the most complete ones we also add controls for borrower characteristics (X) like gender, age, and household and business characteristics.

The variables of interest are a set of dummy variables for each of treatment groups. We also include branch fixed effects in all estimations to account for differences in management and customer types across braches which may affect repayment. These include for example the ability of bank staff to induce good repayment practices, the quality of service at the branch, and the location or accessibility of the branch (including being urban or rural branch). We also include month of disbursement fixed effects. Since the project was implemented from April to August, we want to account for any changes in the economy that may impact loan repayment in the period.

In Table 3 we show the results from the main regressions. Columns 1 to 4 show results from a probit model with "perfect repayment" as the dependent variable. In column 1 we present results for the basic model that only includes treatment dummies as well as a set of branch and disbursement month fixed effects. The coefficients for all three treatment dummies are positive and statistically significant. The coefficients for the Cash back, Future Interest Reduction and SMS reminders incentives are 0.262, 0.225, and 0.274, respectively. The interpretation of these magnitudes imply that customers assigned to Cash back incentives had a probability of repaying perfectly that is 8.56 percentage points higher than customers in the control group. Customers assigned to Future reduced interest rate were 7.27 percentage points more likely to pay every installment on time than those in the control group, while interestingly, those without any monetary incentives but receiving SMS reminders had a probability of perfect repayment 9 points higher than the control group[7]. While each of the treatment groups has significantly better repayment behavior than the control group, we do not find a statistically significant difference between the different treatment groups. This means that we cannot rule out that the effect of the treatments is of similar magnitude. Columns 2 and 3 replicate the same estimation results but including loan characteristics and loan plus personal and business characteristics respectively. The impact of the treatment is robust to the inclusion of different sets of control variables. Coefficients for the treatment dummies across specifications are very similar and all in the range of 0.2 and 0.3 and statistically significant at the 5% or 10% significance level. The number of observations drops from 1121 to 1117 in column 2 and to 855 in column 3 because of the availability of covariates. In column 4 we reproduce the same regression as in column 2 but we drop the sample size to that used in the specification with the full set of control variables (as in column 3) in order to show that the results are not driven by changes in sample size. In fact

[7] Wald chi-squared tests for equality of coefficients for the three different treatments indicate that we cannot reject the null hypothesis of the coefficients being equal to each other.

coefficients are very similar, for Cash Back, Future Interest Reduction and SMS treatment they are 0.240, 0.316 and 0.254 respectively. The same robustness checks were run for all the other outcome variables and specifications, and the results are unchanged.

In columns 5 and 6 of Table 3 we now repeat the specification from columns (1) and (2) but using the percentage of installments paid on time as the dependent variable. The Cash Back incentive is the only one that has a significant effect on repayment and only when not including personal and business characteristics in the regression. People in the Cash Back treatment group had a percentage of installments paid on time 6 percentage points higher than customers in the control group, people in the Future Interest Reduction and the SMS treatments had a percentage of timely-paid installments that were about 4 percentage points higher that the control group, but the difference was not statistically significant. Finally, columns 7 and 8 show results when using the average days late per installment as a dependent variable. Customers assigned to the Cash Back incentive reduced by about 2 days their average lateness in repayment, a 22% reduction on average. The effects for the other treatments were between 0.7 and 1.1 reductions in days late, although not statistically significant at conventional levels.

5.1.Heterogeneous Treatment Effects

It is interesting to note that in particular the size of the loan and the loan series variables when included in the regressions showed significant effects on repayment outcomes. Bigger loans seem to be performing worse than smaller loans although more experienced customers (with higher loan series) seem to repay better than less experienced ones. To further explore the interaction between the treatment effects and loan and customer characteristics, we turn to examine heterogeneous treatment effects. We conjecture that loan size could be an important covariate since it might be a proxy for the success of the business or the ambitions of the founder. In turn this could affect their willingness to respond to the different treatments, if they are already managing the business better than other firms. Similarly, we pick the series of the loan as a proxy for the experience of the borrower. It is possible that people who are starting their banking experience are more prone to respond to incentives, while more experienced customers may be already set in their ways and thus may be difficult to influence. In Tables 4 to 7 we explore these hypotheses further focusing on the more complete specifications that control for loan, personal and business observable characteristics.

In Table 4 we divided our sample in two groups according to loan size. Customers with median loan size and below (less than 1 Million UGX or $450) are part of the "small" sample. Customers with bigger than median loans, are classified as "big". The results show that the effects of the incentives on repayment were only significant for customers with relatively small loans. In general, the size of the coefficients for the incentives is higher and they are more significant for the sample of small loans relative to the whole sample. For example, the impact of the Cash Back incentive on the amount of days late improves by more than one day (the coefficient goes from -1.67 to -2.84, and it is 0.31 and not statistically significant for the bigger loans, see columns 5 and 6). The Cash Back incentive resulted in borrowers with a percentage of timely-paid installments 10 percentage points higher than similar customers in the control group (columns 3 and 4). It is interesting to note that for the probability of perfect repayment (columns 1 and 2) the significance of the Reduced Future Interest incentive is exclusively for bigger loans, the coefficient is 0.384 –probably customers who expect to get bigger loans in the future are particularly interested on receiving preferential rates going forward-, while the SMS Reminders seem to only work on customers with smaller loans. The effective results for the SMS reminders on improving the probability of perfect repayment seem to be driven by customers with smaller loans. The coefficient is more than 100 times as the coefficient for bigger loans.

In Table 5 we now repeat the same analysis by dividing the sample into customer's with and without experience with the MCC loan. The average and median customer is in the second loan series, and the effectiveness of the incentives seems to be a feature of customers with relatively little experience (loan series 1 and 2). Although the differences are not as big as between customers with small and big loans, it is clear that the size of the coefficients and the significance levels of all treatment dummies are higher for less experienced borrowers. In columns 1 and 2 for the probability of perfect repayment the coefficients for the treatment dummies are very similar and range between 0.31 and 0.34 all significant at the 5% significance level for the inexperienced customers, while for the experienced customers coefficients range between 0.21 and 0.27 and are not statistically significant at standard levels. In columns 3 to 6 we see that only the Cash Back incentive has significant effects on improving the percentage of installments paid on time and reducing the number of days late, both for inexperienced customers (coefficients are 0.07 and -2 respectively). It is important to note that the sample size for the more experienced customers is small. In Table 6 we examine heterogeneous effects for customers dividing the sample by age. The younger customers in columns 1, 3 and 5 are 30 years old or younger (25% percentile) and the older customers in columns 2, 4 and 6 are older than the average (36 years old). We see that in general for this reduced sample sizes significance of the incentives coefficients drops. However, Table 6 allows us to identify a very significant difference on the impact of the SMS reminders on younger customers. The coefficient for the perfect repayment outcome is five times bigger than for older customers (0.697 versus 0.137 in columns 1 and 2 respectively), and is highly significant.[8]

To further analyze the profile of the customer with the most sensitivity to the incentives we worked on dividing the sample in new subsamples with all possible combinations of loan size, loan experience and age. For that purpose we created 4 different subgroups for each of three categories: size and age, size and experience and age and experience[9]. Using our three main dependent variables, this resulted in 36 regressions that allowed us to identify the group of younger customers with relatively small loans as the driver of the main results. We report a simplified version of the results in Table 7 where the odd columns show the regressions for the sample of younger customers with small loans and the even columns put together the samples of younger customers with big loans and older customers with small and big loans. The coefficients for the impact on the probability of paying perfectly of Cash Back and SMS incentives are about 3 times bigger than for the whole sample and are highly significant. The incentives actually reduced the average amount of days late by 4 days for the younger customers with small loans (compared to two days for the whole sample), while the effects were small and insignificant for the rest.

6. Conclusions

The results of this study suggest that financial incentives in the form of either a cash back promise or a lower interest rate for the next loan cycle had a similar impact in terms of magnitude on customer repayment behavior than an SMS reminder service prior to each payment due date. Customers who received one of these treatments relative to the control group, had on average an 8% increase in the probability of paying all their installments on time and the average

[8] In fact, this is the only case for the different heterogeneous effects that we run in which a Wald test of equality of coefficients in seemly unrelated estimations allow us to reject the null hypothesis.

[9] For example, for age and size of the loan we had 4 groups: young and small, young and big, older and small, older and big

days late drop by 2 days per month. Interestingly the SMS treatment which is almost costless for the bank to implement has the same economic effect on late payments as a 25% reduction in the monthly interest rate. In addition we see some heterogeneity in the treatment impact, in particular less experienced borrowers and those with smaller loans respond more strongly to the treatments, especially the Cash Back and SMS treatments. If more experienced borrowers are already set in their ways, they might find it more difficult to change their behavior in response to new incentives. While in contrast more recent borrowers are still in the process of setting up a payment routine. Therefore, the estimated treatment incentives could be explained by newer borrowers still setting up their payment routines and thus might be more successful in helping them shape timely repayment routines. In fact, we find the strongest effects of the incentives on younger customers with relatively small loans.

We can also shed some light on the underlying behavior of borrowers. A large fraction of borrowers seem to pay late not for strategic reasons but because they previously seem to be unable to keep track of their payment schedules, without the help of simple reminders. This supports the idea that small businesses in developing countries suffer from lack of financial management which affects their ability to make payments on time. But this insight has broader implications for the design of credit products by financial institutions. The repayment behavior of a borrower is not only shaped by the financial dimensions of the credit, such as interest rate, late fees etc., but is also driven by what appears to be simple product details such as the ease with which the borrower can pay the loan, for example whether he remembers the payment due date. Any implementation which facilitates the payment for borrowers seems to have substantial implications for loan payment behavior and with it the assessment of credit risk. In fact, this simple implementation change is equivalent to an incentive of a 25% lower interest rate.

These findings suggest that we need to widen our concept of credit risk beyond strategic and economic default, and take into account the role of channel factors for loan repayment. The exact structure and channels through which borrowers pay their loan, may themselves have an impact on the credit risk of the borrower. Much more has to be done to understand the exact form of these channel factors, but our results suggest that the magnitude of these effects might be economically very significant. For example, in future work it would be very interesting to build on the heterogeneous treatment effects we found in this study and explore whether the different treatments can be optimally targeted to different subgroups of the borrower population. Another interesting extension would be to understand whether there are positive interaction effects between the pecuniary and non-pecuniary treatments such as SMS reminders.

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Annex

Table A1. Description of Variables

Variable	Description	Source
Age	Age of customer (in years)	Loan Application/ Appraisal
Average Days Late	Average number of days late per installment	Calculated from Accounts information
Business Owner	Customer owns the business location or premises	Loan Application/ Appraisal
Cash Back	(% of) Customer randomly assigned to Cash Back Incentive	Project Implementation
Control	(% of) Customer randomly assigned to Control group	Project Implementation
Female	(% of) Customer is female	Loan Application/ Appraisal
Future Interest Reduction	(% of) Customer randomily assigned to Reduced Future Interest Rate Incentive	Project Implementation
Homeowner	Customer own his/her home	Loan Application/ Appraisal
Household Size	Number of people living in the household	Loan Application/ Appraisal
Installments Paid on Time	Percentage of installments paid on time	Calculated from Accounts information
Kajjansi	(% of) Customer banks at Kajjansi (urban) branch	Project Implementation
Kiboga	(% of) Customer banks at Kiboga (rural) branch	Project Implementation
Kyengera	(% of) Customer banks at Kyengera (urban) branch	Project Implementation
Loan Series	Number of MCC loans the customer has had with the bank	Loan Application/ Appraisal
Loan Size	Loan amount in UGX	Project Implementation
Married	(% of) Customer is married or live with partner	Loan Application/ Appraisal
Mityana	(% of) Customer banks at Mityana (rural) branch	Project Implementation
Nakawa	(% of) Customer banks at Nakawa (urban) branch	Project Implementation
Perfect Repayment	(% of) Customer repay loans on time for every installment	Calculated from Accounts information
Repayment Capacity	Montly surpluss of the business discounting household expenses	Loan Application/ Appraisal
SMS Reminders	(% of) Customer randomily assigned to SMS Reminder Incentive	Project Implementation
Term	Term of the loan (in months)	Project Implementation
Year Business Created	Year of business creation, businesses have to be at least one year old to access loans	Loan Application/ Appraisal

Table 1. Descriptive Statistics

This table presents some descriptive statistics for the main variables included in the analysis. Panel A include loan and customer characteristics, Panel B repayment outcomes, and Panel C the distribution of customers between experimental groups and branches. N is the number of available observations. Detailed descriptions of variables can be found in Annex Table A1

	Mean	Median	Standard Deviation	N
Panel A: Loan and Customer Characteristics				
Loan Size (UGX)	1,786,084	1,000,000	2,296,619	1121
Loan Size (USD)	804	450	1,033	1121
Term	7.94	7	2.26	1121
Loan Series	1.98	2	1.29	1117
Female	34.88%		47.68%	1121
Married	77.61%		41.70%	1121
Age	38.14	36	10.10	992
Household Size	4.86	5	1.93	1013
Homeowner	58.34%		49.32%	1121
Business Owner	35.95%		48.01%	1121
Year Business Created	2000.91	2002	4.83	934
Repayment Capacitiy (UGX)	685,571	435,700	912,699	1024
Repayment Capacitiy (USD)	309	196	411	1024
Panel B: Repayment Outcomes				
Perfect Repayment	33.81%		47.33%	1121
Installments Paid on Time	62.36%	0.7	37.09%	1121
Average Days Late	8.25	3.33	9.95	1121
Panel C: Distribution of Treatments and Branches				
Treatment Groups				
Cash Back	22.66%		41.88%	254
Future Interest Reduction	21.50%		41.10%	241
SMS Reminders	34.17%		47.45%	383
Control	21.68%		41.22%	243
Branches				
Kajjansi	16.50%		37.14%	185
Kiboga	29.79%		45.76%	334
Kyengera	16.24%		36.89%	182
Mityana	14.72%		35.45%	165
Nakawa	22.75%		41.94%	255

Table 2. Differences Across Groups

This table presents means and proportions for the main variables included in the analysis for each of the experimental groups (Columns 2 to 4) and for the control group. The description of the variables can be found in Annex Table A1. Columns 5 to 7 include the p-value associated to the t-test and the p-test for the difference in means and proportions respectively between each of the treatment groups and the control group.

	Control	**Cash Back**	**Future Interest Reduction**	**SMS Reminder**	**Test (1)-(2)= 0 P-Value**	**Test (1)-(3)= 0 P-Value**	**Test (1)-(4)= 0 P-Value**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Means							
Loan Size (UGX)	1,841,358	1,565,157	2,098,340	1,701,044	0.1283	0.3252	0.4087
Term	7.98	7.79	8.17	7.89	0.3402	0.3574	0.6095
Loan Series	1.91	1.99	2.08	1.96	0.4686	0.1441	0.6069
Age	38.23	38.35	38.91	37.47	0.8990	0.4862	0.3887
Houshold Size	4.81	4.93	5.07	4.73	0.5165	0.1602	0.6555
Year Business Created	2001.02	2000.71	2000.63	2001.16	0.5294	0.4553	0.7160
Log Repayment Capacity	13.09	13.07	13.13	13.04	0.7847	0.6435	0.4289
Proportions							
Female	33.33%	33.07%	36.10%	36.29%	0.9505	0.5227	0.4498
Married	79.84%	77.56%	76.76%	76.76%	0.5357	0.4123	0.3661
Home owner	57.61%	55.51%	60.17%	59.53%	0.6366	0.5682	0.6349
Business owner	34.16%	39.37%	35.68%	34.99%	0.2283	0.7244	0.8315

Table 3. Impact of Incentives on Repayment Behavior

This table reports regression results of the impact of different incentives on repayment behavior. We use three different outcome measures for repayment behavior. Perfect Repayment is a dummy variable that indicates a person who paid every installment on time, we also use the percentage of installments paid on time and the average number of days late per installment. Independent variables are described in Annex Table A1. Results are shown for different specifications, one basic model and models including loan charateristics and person and business characteristics respectively. The analysis uses repayment data built from the bank IT records and data entered from loan application forms and includes only loans that had their final installment on or before June 2009 and for customers with no concurent loans at the bank. Regressions (1)-(4) are estimated using Probit, and all others using OLS, all include branch and time of disbursement fixed effects. Robust Standard Errors are in parentheses. *, ** and *** indicate statistical significance for 10%, 5% and 1% significance levels, respectively.

	Perfect Repayment (Probit)				Percentage of installments paid on time		Average number of days late per installment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cash Back	0.262**	0.242**	0.261*	0.240*	0.0625**	0.0591	-1.780**	-1.671*
	(0.119)	(0.121)	(0.140)	(0.139)	(0.0313)	(0.0361)	(0.866)	(0.992)
Future Interest Reduction	0.225*	0.218*	0.331**	0.316**	0.0340	0.0412	-0.865	-0.715
	(0.121)	(0.124)	(0.140)	(0.140)	(0.0329)	(0.0372)	(0.901)	(1.020)
SMS Reminders	0.274**	0.261**	0.262**	0.254**	0.0465	0.0375	-1.150	-1.063
	(0.110)	(0.111)	(0.130)	(0.129)	(0.0296)	(0.0341)	(0.812)	(0.940)
Log Loan Size		-0.159***	-0.00324	-0.171***	-0.0657***	0.00143	1.829***	-0.0981
		(0.0516)	(0.106)	(0.0595)	(0.0140)	(0.0275)	(0.382)	(0.750)
Loan Series		0.214***	0.258***	0.263***	0.0574***	0.0670***	-1.254***	-1.324***
		(0.0326)	(0.0409)	(0.0393)	(0.00885)	(0.00939)	(0.225)	(0.257)
Female			0.101			0.0314		-1.099
			(0.113)			(0.0300)		(0.809)
Married			0.0453			-0.00826		0.353
			(0.133)			(0.0360)		(0.961)
Age			-0.00326			-0.000895		0.0281
			(0.00534)			(0.00140)		(0.0379)
Household Size			-0.0341			-0.00613		0.114
			(0.0310)			(0.00776)		(0.208)
Homeowner			0.0669			0.0299		-0.820
			(0.111)			(0.0285)		(0.785)
Year Business Created			-0.0157			-0.00508*		0.126*
			(0.0103)			(0.00260)		(0.0702)
Business Owner			0.0761			-0.000270		0.544
			(0.0991)			(0.0266)		(0.735)
Log Repayment Capacitiy			-0.233*			-0.0884***		2.285**
			(0.125)			(0.0327)		(0.903)
Constant	-0.760***	1.200*	33.47	1.157	1.337***	11.77**	-12.87**	-269.9*
	(0.164)	(0.707)	(20.78)	(0.826)	(0.196)	(5.256)	(5.374)	(142.0)
Observations	1121	1117	855	855	1117	855	1117	855
R-squared					0.092	0.113	0.070	0.078

Table 4. Impact of Incentives on Repayment Behavior by Loan Size

This table reports regression results of the impact of different incentives on repayment behavior. We use three different outcome measures for repayment behavior. Perfect Repayment is a dummy variable that indicates a person who paid every installment on time, we also use the percentage of installments paid on time and the average number of days late per installment. Independent variables are described in Annex Table A1. Results are shown for different samples: customers with small loans under or equal to USD450 (UGX1,000,000) and for customers with big loans higher than USD450 (UGX1,000,000). The analysis uses repayment data built from the bank IT records and data entered from loan application forms and includes only loans that had their final installment on or before June 2009 and for customers with no concurent loans at the bank. Regressions (1) and (2) are estimated using Probit, and all others using OLS, all include branch and time of disbursement fixed effects. Robust Standard Errors are in parentheses. *, ** and *** indicate statistical significance for 10%, 5% and 1% significance levels, respectively

	Perfect Repayment (Probit)		Percentage of installments paid on time		Average number of days late per installment	
Loan Size is:	Small	Big	Small	Big	Small	Big
	(1)	(2)	(3)	(4)	(5)	(6)
Cash Back	0.380**	0.0364	0.0997**	-0.00415	-2.843**	0.308
	(0.180)	(0.230)	(0.0455)	(0.0600)	(1.259)	(1.666)
Future Interest Reduction	0.287	0.384*	0.0589	0.0212	-1.055	-0.109
	(0.189)	(0.214)	(0.0512)	(0.0551)	(1.426)	(1.514)
SMS Reminders	0.384**	0.00363	0.0349	0.0379	-0.802	-1.351
	(0.167)	(0.213)	(0.0452)	(0.0519)	(1.236)	(1.454)
Loan Series	0.300***	0.218***	0.0639***	0.0633***	-1.194***	-1.349***
	(0.0597)	(0.0588)	(0.0144)	(0.0129)	(0.384)	(0.349)
Female	-0.127	0.519***	0.00107	0.0866*	-0.669	-1.976
	(0.141)	(0.186)	(0.0386)	(0.0461)	(1.045)	(1.224)
Married	-0.0256	0.220	-0.00650	-0.0203	0.193	0.471
	(0.174)	(0.224)	(0.0496)	(0.0522)	(1.295)	(1.432)
Age	0.000199	-0.00887	-3.70e-05	-0.00261	0.00796	0.0715
	(0.00689)	(0.00909)	(0.00191)	(0.00212)	(0.0523)	(0.0575)
Household Size	-0.0644	0.000720	-0.00712	0.00251	0.0909	0.0297
	(0.0415)	(0.0475)	(0.0106)	(0.0114)	(0.282)	(0.313)
Homeowner	0.0639	0.0139	0.0152	0.0258	-0.867	-0.334
	(0.147)	(0.180)	(0.0387)	(0.0451)	(1.035)	(1.302)
Year Busniess Created	-0.0146	-0.0156	-0.00524	-0.00445	0.127	0.136
	(0.0139)	(0.0169)	(0.00365)	(0.00394)	(0.102)	(0.103)
Business Owner	0.0824	0.118	-0.00190	-0.00467	0.370	0.949
	(0.128)	(0.165)	(0.0353)	(0.0423)	(0.964)	(1.173)
Log Repayment Capacitiy	0.00194	-0.469***	-0.0351	-0.147***	1.301	3.410***
	(0.160)	(0.131)	(0.0437)	(0.0316)	(1.169)	(0.871)
Constant	28.16	36.58	11.42	11.44	-259.3	-309.9
	(28.29)	(34.15)	(7.433)	(7.960)	(207.4)	(208.8)
Observations	498	357	498	357	498	357
R-squared			0.083	0.198	0.061	0.135

Table 5. Impact of Incentives on Repayment Behavior by Experience with loans at the bank

This table reports regression results of the impact of different incentives on repayment behavior. We use three different outcome measures for repayment behavior. Perfect Repayment is a dummy variable that indicates a person who paid every installment on time, we also use the percentage of installments paid on time and the average number of days late per installment. Independent variables are described in Annex Table A1. Results are shown for different samples: customers without much previous experience with loans at the bank (in their first or second loan series), and more experienced customers that are on their third or higher loan. The analysis uses repayment data built from the bank IT records and data entered from loan application forms and includes only loans that had their final installment on or before June 2009 and for customers with no concurent loans at the bank. Regressions (1) and (2) are estimated using Probit, and all others using OLS, all include branch and time of disbursement fixed effects. Robust Standard Errors are in parentheses. *, ** and *** indicate statistical significance for 10%, 5% and 1% significance levels, respectively

	Perfect Repayment (Probit)		Percentage of installments paid on time		Average number of days late per installment	
Loan Series is:	Inexperieced	Experienced	Inexperieced	Experienced	Inexperieced	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)
Cash Back	0.341**	0.242	0.0705*	0.0730	-1.998*	-1.770
	(0.162)	(0.281)	(0.0426)	(0.0718)	(1.183)	(1.862)
Future Interest Reduction	0.355**	0.272	0.0309	0.0916	-0.386	-2.222
	(0.160)	(0.287)	(0.0441)	(0.0722)	(1.215)	(1.915)
SMS Reminders	0.306**	0.212	0.0288	0.0966	-0.839	-2.480
	(0.145)	(0.276)	(0.0394)	(0.0732)	(1.090)	(1.989)
Log Loan Size	0.0382	0.161	-0.00721	0.0811*	0.454	-2.664**
	(0.129)	(0.205)	(0.0342)	(0.0480)	(0.900)	(1.305)
Female	0.0534	0.418*	0.0257	0.0762	-0.883	-2.274
	(0.129)	(0.252)	(0.0361)	(0.0643)	(0.960)	(1.744)
Married	0.145	-0.167	0.00929	-0.0500	-0.387	2.216
	(0.154)	(0.302)	(0.0435)	(0.0667)	(1.161)	(1.644)
Age	-0.00230	-0.00212	-0.000671	-0.000234	0.0275	0.0129
	(0.00634)	(0.0114)	(0.00173)	(0.00255)	(0.0463)	(0.0723)
Household Size	-7.84e-05	-0.0786	-0.00203	-0.0100	0.00561	0.268
	(0.0372)	(0.0525)	(0.0101)	(0.0123)	(0.270)	(0.328)
Homeowner	0.117	-0.00821	0.0535	-0.0302	-1.427	0.418
	(0.131)	(0.218)	(0.0353)	(0.0536)	(0.973)	(1.410)
Year Busniess Created	-0.0200	-0.0224	-0.00692*	-0.00609*	0.167*	0.146
	(0.0123)	(0.0184)	(0.00366)	(0.00364)	(0.0988)	(0.0966)
Business Owner	0.0390	-0.0390	-0.0151	-0.0121	0.895	0.555
	(0.115)	(0.206)	(0.0321)	(0.0517)	(0.873)	(1.461)
Log Repayment Capacitiy	-0.364**	-0.0152	-0.0963**	-0.0837*	2.040*	3.233**
	(0.156)	(0.231)	(0.0423)	(0.0482)	(1.133)	(1.309)
Constant	43.30*	42.69	15.75**	12.75*	-358.1*	-289.5
	(24.88)	(37.13)	(7.404)	(7.316)	(200.1)	(193.8)
Observations	658	197	658	197	658	197
R-squared			0.068	0.119	0.053	0.119

Table 6. Impact of Incentives on Repayment Behavior by Age

This table reports regression results of the impact of different incentives on repayment behavior. We use three different outcome measures for repayment behavior. Perfect Repayment is a dummy variable that indicates a person who paid every installment on time, we also use the percentage of installments paid on time and the average number of days late per installment. Independent variables are described in Annex Table A1. Results are shown for different samples: young customers who are 30 or younger, and older customers who are older than 36. The analysis uses repayment data built from the bank IT records and data entered from loan application forms and includes only loans that had their final installment on or before June 2009 and for customers with no concurent loans at the bank. Regressions (1) and (2) are estimated using Probit, and all others using OLS, all include branch and time of disbursement fixed effects. Robust Standard Errors are in parentheses. *, ** and *** indicate statistical significance for 10%, 5% and 1% significance levels, respectively

	Perfect Repayment (Probit)		Percentage of installments paid on time		Average number of days late per installment	
Age is:	Younger	Older	Younger	Older	Younger	Older
	(1)	(2)	(3)	(4)	(5)	(6)
Cash Back	0.421	0.183	0.0623	0.0544	-1.639	-1.629
	(0.280)	(0.201)	(0.0690)	(0.0533)	(1.873)	(1.491)
Future Interest Reduction	0.495*	0.319	0.0463	0.0721	-1.497	-1.789
	(0.284)	(0.197)	(0.0728)	(0.0527)	(1.969)	(1.417)
SMS Reminders	0.697***	0.137	0.0889	0.0269	-2.742	-0.673
	(0.261)	(0.185)	(0.0665)	(0.0494)	(1.736)	(1.374)
Log Loan Size	0.156	0.0183	0.0557	-0.0116	-1.438	0.578
	(0.204)	(0.148)	(0.0501)	(0.0395)	(1.247)	(1.117)
Loan Series	0.532***	0.218***	0.0880***	0.0638***	-1.679***	-1.380***
	(0.122)	(0.0521)	(0.0253)	(0.0133)	(0.645)	(0.380)
Female	-0.254	0.254	0.00984	0.0831*	-0.242	-2.553**
	(0.220)	(0.175)	(0.0579)	(0.0456)	(1.566)	(1.217)
Married	0.118	0.141	-0.0209	0.0326	0.435	-0.558
	(0.249)	(0.211)	(0.0727)	(0.0529)	(2.046)	(1.342)
Household Size	-0.128*	-0.0346	-0.0180	-0.00736	0.306	0.123
	(0.0749)	(0.0395)	(0.0183)	(0.00992)	(0.460)	(0.267)
Homeowner	-0.192	0.205	-0.0265	0.0497	1.203	-1.344
	(0.246)	(0.163)	(0.0562)	(0.0399)	(1.501)	(1.119)
Year Busniess Created	-0.0279	-0.0209*	-0.0105	-0.00466	0.303	0.0961
	(0.0321)	(0.0120)	(0.00799)	(0.00312)	(0.213)	(0.0833)
Business Owner	0.287	0.00518	0.0418	-0.00150	-1.104	0.473
	(0.232)	(0.137)	(0.0613)	(0.0363)	(1.596)	(0.990)
Log Repayment Capacitiy	-0.321	-0.262	-0.100	-0.0673	2.768*	1.638
	(0.251)	(0.168)	(0.0643)	(0.0445)	(1.640)	(1.268)
Constant	56.56	43.59*	21.99	10.74*	-611.6	-207.5
	(64.33)	(24.05)	(16.15)	(6.284)	(430.9)	(168.1)
Observations	222	409	222	409	222	409
R-squared			0.112	0.131	0.080	0.112

Table 7. Impact of Incentives on Repayment Behavior by Loan Size and Age

This table reports regression results of the impact of different incentives on repayment behavior. We use three different outcome measures for repayment behavior. Perfect Repayment is a dummy variable that indicates a person who paid every installment on time, we also use the percentage of installments paid on time and the average number of days late per installment. Independent variables are described in Annex Table A1. Results are shown for different samples: Small & Younger are young customers who are 30 or younger with small loans under or equal to USD450 (UGX1,000,000), and "Other" is the combination of young customers with bigger that USD 450 loans, and older customers (older than 36) with eaither small or big loans. The analysis uses repayment data built from the bank IT records and data entered from loan application forms and includes only loans that had their final installment on or before June 2009 and for customers with no concurent loans at the bank. Regressions (1) and (2) are estimated using Probit, and all others using OLS, all include branch and time of disbursement fixed effects. Robust Standard Errors are in parentheses. *, ** and *** indicate statistical significance for 10%, 5% and 1% significance levels, respectively.

	Perfect Repayment (Probit)		Percentage of installments paid on time		Average number of days late per installment	
	Small & Younger	Other	Small & Younger	Other	Small & Younger	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Cash Back	0.765**	0.140	0.170**	0.0246	-4.670**	-0.785
	(0.354)	(0.186)	(0.0858)	(0.0488)	(2.270)	(1.343)
Future Interest Reduction	0.503	0.334*	0.124	0.0511	-4.216*	-1.109
	(0.361)	(0.183)	(0.0906)	(0.0484)	(2.402)	(1.299)
SMS Reminders	0.939***	0.167	0.123	0.0302	-4.112*	-0.794
	(0.325)	(0.171)	(0.0851)	(0.0449)	(2.150)	(1.240)
Loan Series	0.539***	0.224***	0.0737**	0.0617***	-1.116	-1.310***
	(0.148)	(0.0507)	(0.0283)	(0.0127)	(0.695)	(0.353)
Female	-0.334	0.177	-0.00545	0.0556	-0.161	-1.727*
	(0.276)	(0.155)	(0.0769)	(0.0390)	(2.033)	(1.031)
Married	0.634*	0.0143	0.0381	-0.0148	-1.171	0.637
	(0.356)	(0.181)	(0.101)	(0.0447)	(2.802)	(1.161)
Household Size	-0.216**	-0.0440	-0.0196	-0.00967	0.173	0.199
	(0.101)	(0.0369)	(0.0267)	(0.00911)	(0.673)	(0.245)
Homeowner	-0.236	0.0940	-0.0213	0.0253	0.615	-0.535
	(0.323)	(0.147)	(0.0829)	(0.0367)	(2.262)	(1.015)
Year Busniess Created	0.0150	-0.0167	-0.00491	-0.00328	0.160	0.0617
	(0.0422)	(0.0116)	(0.0109)	(0.00297)	(0.297)	(0.0796)
Business Owner	0.453	0.00143	0.0252	0.00239	-0.704	0.399
	(0.295)	(0.128)	(0.0858)	(0.0335)	(2.228)	(0.911)
Log Repayment Capacitiy	0.229	-0.265***	0.0207	-0.0802***	-0.871	2.163***
	(0.393)	(0.0920)	(0.105)	(0.0241)	(2.766)	(0.674)
Constant	-34.49	35.74	9.865	8.087	-291.3	-141.4
	(85.42)	(23.22)	(22.35)	(5.963)	(607.1)	(160.1)
Observations	147	484	147	484	147	484
R-squared			0.141	0.123	0.130	0.098