A personal touch: text message reminders and loan repayment

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Abstract

We report the results of an experiment sending weekly text message reminders to microfinance clients in two rural banks in the Philippines on late payment and loan default. We test three treatments: a personalization treatment, a framing treatment, and a timing treatment. We do not find an overall treatment effect. Rather, we find that the content of the message is important. The personalization treatment - a message that is signed from account officer reduces the probability a client makes a late weekly payment by 20% compared to the control group, and there is a 24% higher chance that the full balance of the loan is paid at the loan maturity date. We do not find any effects from a framing treatment or from a timing treatment, and so the results are not purely due to a reminder effect. We draw two main conclusions: firstly, there is evidence of ex post inefficiencies in the credit market. Our second conclusion speaks to the role of technology. We provide an example where, through personalization, technology is an effective and simple aid to finance in low income countries.

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1 Introduction

Information asymmetries in credit markets causes difficulties to fully contract between borrower and lender. Once the loan is made, the final outcome of a loan depends on many unobserved ex-post decisions, such as how much effort to put into repaying their loan. We examine this issue in the context of microfinance borrowers in the Philippines. We undertake a simple experiment where we send microfinance borrowers a text message reminder about their weekly repayment obligation, varying the timing and content of the messages across treatment groups. A text message does not change any contract terms between the borrower and bank, so any observed behavioral change must be the result of ex post, rather than ex ante, adjustment by the client. We test three treatments: a personalization treatment, a framing treatment, and a timing treatment. We do not find an overall treatment effect. Rather, we find that the content of the message is important. Text messages that contain the account officers name reduce late payment rates by 20%. This effect is not due to a pure reminder effect, as text messages that did not contain the account officers name had no effect on late payment. We draw two main conclusions: firstly, there is evidence of ex post inefficiencies in the credit market. Our second conclusion speaks to the role of technology. We provide an example where, through personalization, technology is an effective and simple aid to finance in low income countries.

There are several financial frictions present in the credit market. Banks cannot fully contract on effort, leading to issues of moral hazard. Banks cannot observe the type of agent, leading to issues of adverse selection. Additionally, in markets with limited enforcement of loans, borrowers can choose to strategically default if the benefit of doing so is larger than the costs. The presence of financial frictions may lead to inefficient allocation of capital across firms, and may explain much of the disparities in productivity across countries (Cooley et al. (2004); Amaral and Quintin (2010); Buera and Shin (2010)). Microfinance, small scale lending in developing countries, is as prone to these as to other more developed credit markets. Previous research shows that moral hazard is prevalent in microfinance (Karlan and Zinman (2009)).

In the context of our experiment, text messages do not change the contract terms between the client and the bank. Our observed results must therefore be coming from ex post adjustment in behavior. Our results illustrate the presence of ex post inefficiencies in loan repayment. These inefficiencies may be a combination of several financial frictions: moral hazard in effort, limited enforcement by the bank, and strategic default. We are not able to separately differentiate between these frictions, so refer to these ex post adjustments collectively as moral hazard in loan repayment. We find that clients can make a large amount of ex-post adjustment: clients who received text messages that contained their account officers name had late payment rates 20% lower than the control group not receiving messages. However, although this result is large, our results also suggest that such moral hazard may be fairly easily mitigated, for example through targeted text messages.

Our second conclusion relates to the role of technology in the banking sector, and for development more generally. We find that it is not technology in itself that leads to a change in behavior, but rather, receiving a text message that included the name of the account officer assigned to the loan that affects behavior. In finance, there is a debate between transactional based models of banking, where the interaction between the bank and the lender is a single transaction, compared to relationship models of banking, where there are repeated transactions between bank and client, and the bank invests in obtaining information about the client, such as monitoring savings and checking accounts, to inform other transactions (Boot (2000)). Theoretically, if banks can obtain private information about the clients unobserved type, and this can overcome many of the agency problems inherent in the credit market. Empirically, the effects of utilizing this additional information when making credit decisions results in lower rates of default and higher bank profits (Puri et al. (2010); Agarwal et al. (2010); Agarwal and Hauswald (2010)).

There is also an increase in the use of technology both for financial reasons and for other issues. Cell phone coverage across the developing world is high, providing a cheap and easily accessible communication channel that may provide large economic benefits (Aker and Mbiti (2010); Donner (2008)). Many services are provided through cellphones directly, such as mobile banking in Kenya (Jack and Suri (2010)). However, there is a debate again here about the interaction between technology and local institutions (Burrell and Toyama (2009)).

Our results provide an example of how technology can be used effectively in contexts where personal relationships are also valued. This relates directly to the debate between relationship versus transactional models of banking, as well as to the debate for ICT for development about how to provide technology that is effective for the country-specific context.

Our paper is related to several other papers in the literature that use mobile technology to examine financial outcomes. Cadena and Schoar (2011) randomly send text message reminders to microfinance borrowers in Uganda and find that the text message reminders have the same effect on repayment rates as offering a change in the cost of capital of 25%. They interpret these results as a reminder effect. Our paper differs by varying the content of the text messages that clients received. We do not find reminder effects in general of our text messages, but we find that it is the specific content of the message that is important.

Karlan et al. (2010) set up a model of limited attention where consumers don't perfectly remember that they will face lumpy expenditure in the future to examine the effect of reminders on savings, and tested this model by sending randomized text message reminders about the savings product in two locations. The paper finds, consistent with the model of inattention, that the savings reminders increased savings, and that savings reminders with a specific savings goal have the largest effect.

The rest of the paper is as follows. Section 2 describes the setup of the experiment, undertaken in two rural banks in the Philippines. Section 3 presents the results and discussion, and Section 4 briefly concludes.

2 Experimental Design

The experiment was carried out in two rural banks in the Philippines over the period January 2009 to April 2010. We undertook a randomized experiment where we sent microfinance clients weekly reminder messages about their loan repayments. We varied the specific content of the message in three key ways: the framing, the degree of personalization, and the time the message was sent.

The Philippines is a suitable environment for this study. Anecdotally known as the texting capital of the world, cellphone use is widespread: 81% of the population had a cellphone subscription in 2009 [1] and texting is an especially popular method of communication owing to its low cost.

We received weekly reports of clients with payments due in the following week from each participating branches. We randomized clients the first time they appeared in these weekly reports into either treatment (receiving a text message reminder) or control (not receiving a text message reminder). Once randomized into treatment clients received weekly text messages until their loan maturity date. The text messages were automatically sent using SMS server software.

We undertook a cross-randomization design where each message contained both a framing and personalization treatment (resulting in four treatment groups) and an independently randomized timing treatment [2] . The framing treatment was either a positive message (to have a good standing...) or a negative message (to avoid penalty...). The per-

[1] Source: World Bank Development Indicators Database; accessed 8/27/201

[2] The randomization was set to 33% for control and 66% to treatment, equally divided between the 4 treatment groups. The timing treatment was independently randomized, with each three treatments equally likely. However, due to a coding error the final breakdown of randomization was 34% treatment, and then 12%, 25%, 14%, 15% to each of the four treatments instead of 17% each treatment group (note: these percentages for the 1703 ever randomized loans). There was no error in coding the independently randomized timing treatment. Tables 1 and Table 2 perform balanced randomization tests on the final sample used in the paper (which incorporates this coding error) and we find no evidence of an unbalanced randomization.

sonalization treatment was whether the client's name was included, or whether the account officer assigned to the loan's name was included. In both cases the name of the bank appeared in the message. The final treatment arm was the timing of messages. For this treatment arm we sent the text message either 2 days before the scheduled payment date, the day before the scheduled payment date, or the day of the scheduled payment date. For the specific wording of the messages please see Table 1.

The randomized loans were then matched to bank level administrative data to provide information on loan repayment.

In Bank A we randomized a total of 836 loans. Of these, 100 loans were randomized less than 2 weeks before the loan maturity date and so did not receive any text messages. A further 12 loans could not be matched to administrative data. This leaves a sample size of 724 loans.

In Bank B we randomized a total of 867 loans. In Bank B the situation was more complicated because the bank changed its database during the middle of the project and did not create an unique identifier between the two databases. This led to considerable difficulties in matching loans that we had received from one system to administrative records in the second system. We attempted to match all loans by hand based on client name. Despite this effort, we were unable to match 293 loans [3]. A further 38 loans were first randomized less than two weeks before the loan maturity date and so were not included in the sample, and one loan had been randomized twice so the duplicate was dropped. This left a final sample of 535 loans. Using the combined sample of loans from Bank A and Bank B yields 1259 loans.

Summary statistics for the final sample of 1257 loans are presented in Table 1. The first two columns present the statistics for the control group and the treatment group. The remainder of the table broken down by the three treatment arms: framing, personalization, and timing. We test for random assignment to each condition within treatment arm, omitting one category for each treatment arm, on the basis on the observable loan characteristics. The p value for the joint F test is reported in the final row of the table. The F test of balanced randomization is not rejected in either of the three treatment arms. We perform t-test for the equality of the group mean with the treatment mean for all loan characteristics and outcomes. The result of this t-test is indicated by significance stars in the table where appropriate. We do not find any evidence for unbalanced randomization

[3] The 293 loans that we were unable to match do not differ from the matched loans in treatment assignment: the p value of the joint F test for treatment assignment on dropped category is 0.5267. The unmatched loans did have a slightly larger term than the matched loans (p value: 0.069), the only loan characteristic we can directly verify for this sample. We verify the balanced randomization on observable loan characteristics for the final sample of 1257 loans in Table 1.

by any individual loan characteristic.

The average loan size for the control group is 15,270 PHP (16,036 for the treatment group, not statistically different) which is equivalent to approximately 400 USD using an exchange rate of 40PHD = 1USD. The mean loan term is 4.4 months, and on average each loan spent 11 weeks in the experiment - if randomized into a treatment group these meant that they received 11 SMS message, or if randomized into treatment this means we have 11 weeks of repayment history of the loan. There is no statistical difference between any of the loan characteristics and whether the loan was assigned to treatment or control: the p value of a joint F-test for significance of loan characteristics is 0.918. T-tests on individual characteristics were performed comparing treatment group to the control group and the null hypothesis of no difference in the mean by group was not rejected for any characteristic.

The second and third panels of Table 1 present the outcome variables. We examine late payment of regular weekly installments, as well as loan default. There is a substantial amount of late payment. 29.1% of all weekly payments for the control group are made late, 25.7% are more than 1 day late, and 15.3% of all payments are more than 1 week late [4].

The third panel of Table 1 presents longer term repayment measures. The first measure is whether the loan was paid in full at loan maturity date. 22.0% of control loans were not paid in full at maturity. 11.9% of loans were not paid in full by 30 days after maturity date. 3.3% of loans have an outstanding balance and are coded as being in default.

3 Results

We now turn to our empirical results. Table 3 presents the results for the framing and personalization treatments, and Table 4 for the timing treatments. In all cases we only include the weekly loan repayments from when the loan was first randomized and included in the study.

We estimate the following general equation, where late is a measure of late payment for client i, T_i is a dummy indicating the treatment effect for client i, and we include an account officer fixed effect to account for unobserved effects of account officers on loan repayments (for example, an individual account officer's method of communicating with their clients). The account officer fixed effect controls for level differences between account

[4] We also defined an alternative measure of late payment which is whether the client missed a payment in the calendar week, defined as Sunday-Saturday. If loan payments are made late they are applied to the most outstanding installment first, so this alternative measure could capture whether a client is making regular payments even if they remain in arrears. Under this measure, no payment is made at all in 17.1% of weeks when a payment is due.

officers, incorporating the level difference between Bank A and Bank B. We cluster the standard errors by client.

$$late_{it} = \beta_0 + \beta_1 T_i + \gamma_{AO} + \epsilon_{it}$$

In Table 3 we present the results for the various indicators of late weekly payment, and then whether the loan was fully repaid at maturity. In the first column for each outcome variable we give the pure treatment effect the effect of receiving any text message compared to the control group. In the second column for each outcome variable we give the effect of the specific message template. We had 4 templates that crossed the personalization treatment with the framing treatment: positive framing with client personalization ('PosXClient'), negative framing with client personalization ('NegXClient'), positive framing with account officer personalization ('PosXAO') and negative framing with account officer personalization ('NegXAO'). The treatment effect is collinear with the full set of message templates so is omitted from the second column.

The treatment effect by itself does not affect late payment or final loan repayment. The coefficient on receiving any SMS is negative but is not statistically significant. However, the second column shows that the content of the text messages does affect loan repayment behavior. A message that contains the account officers name (the two categories 'PosXAO' and 'NegXAO') reduces the chance that the weekly loan payments are made late. Clients who received a 'PosXAO' message were 5.8 percentage points less likely to make a late payment than clients who did not receive a message, and clients who received a 'NegXAO' message were 4.7 percentage points less likely to make a late payment than treatment clients. These results are consistent and statistically significant for the alternative measures of late payment: more than 1 day late, and more than 7 days late.

This effect could be a pure reminder effect: the clients simply forget that they have a weekly payment due and receiving a text message reminds them of their payment deadline. The design of the experiment allows us to examine this hypothesis. We do not find a treatment effect of receiving a text message itself, but rather, a treatment effect only from receiving a text message that contains the account officers name. If it was a pure reminder effect then both text messages should have led to a decrease in late payment rates.

Text messages do not change the contract terms between the client and the bank. The effect of text messages on late payment is not a selection effect, because all clients have selected into taking a loan before being randomized into the treatment. Rather, we can interpret the effect of the text message as affecting ex post adjustment. We take an agnostic stance of the precise ex post adjustment the client makes as a result of receiving the targeted text message. There are several explanations that could explain the change. The first is strategic default. Strategic default is when the client decides not to repay the loan because the benefits of doing so, and maintaining the relationship with the provider and not as high as the benefits of retaining the loan balance. If the text message adjusts the penalty to the client of not repaying the loan then it may be working through this angle. A second explanation is moral hazard. An example of moral hazard would be that the client optimizes the level of effort they put into repaying the loan: visiting the branch in person each week requires effort. If the text message conveys increased monitoring, then the level of effort that the client extends should increase, resulting in reduced late payment.

To examine if there is a long-term effect we look at the effect of text messages on an indicator for the loan being repaid in full at maturity. As with the short-term measure there is no overall treatment effect. The template 'PosXAO' has a strong and negative effect: clients who received this message were 7.4% more likely to have repaid their loan in full at maturity compared with clients in the treatment group. This result is consistent when we consider loans which are not paid in full by 30days after maturity: the coefficient is slightly smaller but is still statistically significant. The other AO treatment, 'NegXAO' has a negative coefficient but is not statistically significant for either measure of default. The content of the text message affects both long-term repayment and short-term repayment.

Table 4 presents the results for the timing treatments: whether the client received the message the day the payment was due (0 day), the day before (1 day) or 2 days prior (2 day). The timing treatment was independently randomized after the initial randomization into loan template. We do not find any statistically significant evidence that a specific timing treatment effects repayment rates for either of the short-term or long-term measures.

4 Conclusion

This paper presents the results of a simple randomized trial sending text messages to microfinance clients from two rural banks in the Philippines. We test three treatments: a personalization treatment, a framing treatment, and a timing treatment. We do not find an overall treatment effect. Rather, we find that the content of the message is important. The personalization treatment - a message that is signed from account officer reduces the probability a client makes a late weekly payment by 20% compared to the control group, and there is a 24% higher chance that the full balance of the loan is paid at the loan maturity date. The magnitude of this result is striking: the text message does not change any ex ante selection effects of the loan, but rather, is only affecting ex post decisions about repayment. The magnitude of the effect provides evidence of ex post inefficiencies in the credit market. On the other hand, it also gives a simple suggestion for easily mitigating such inefficiencies: targeted text message reminders can cheaply affect loan repayment outcomes.

The second conclusion is the role of information technology in both the banking sector and for development more generally. We provide an example where, through personalization, technology is an effective and simple aid to finance in low income countries. It does not appear there needs to be a trade-off between technology and personalization.

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Table 1. Wording of text messages

Personalization	Framing	Message
AO name	Positive	From [aoname] of [bankname]: To have a good standing, pls pay your loan on time. Amount P[amount] due [today/SendingDate]. If paid, pls ignore msg. Tnx.
	Negative	From [aoname] of [bankname]: To avoid penalty pls pay your loan on time. Amount P[amount] due [today/SendingDate]. If paid, pls ignore msg. Tnx.
Client name	Positive	From [bankname]: [name], to have a good standing, pls pay your loan on time. Amount P[amount] due [today/SendingDate]. If paid, pls ignore msg. Tnx.
	Negative	From [aoname] of [bankname]: To avoid penalty pls pay your loan on time. Amount P[amount] due [today/SendingDate]. If paid, pls ignore msg. Tnx.

Table 2. Summary Statistics by Type of Treatment: Pooled

	Received SMS		Framing		Personalization		Timing		
	No	Yes	Positive	Negative	Client	AO	0 Day	1 Day	2 Days
	mean/se	mean/se	mean/se	mean/se	mean/se	mean/se	mean/se	mean/se	mean/se
Loan Characteristics									
Loan Size (peso)	15270	16036	16688	15633	14788	17614	16685	15591	15784
	(1104)	(855)	(1286)	(1133)	(978)	(1488)	(1285)	(1361)	(1739)
Loan Term (months)	4.4	4.5	4.4	4.5	4.5	4.4	4.6	4.5	4.4
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)
Number SMS sent	10.7	10.8	10.6	11.0	10.8	10.8	10.9	10.8	10.8
	(0.2)	(0.2)	(0.3)	(0.2)	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)
Outcome variables: proportion of all payments									
Late	0.291	0.283	0.269	0.291	0.305	0.255	0.270	0.305	0.275
	(0.016)	(0.011)	(0.018)	(0.014)	(0.015)	(0.016)	(0.019)	(0.021)	(0.019)
More 1 Day Late	0.257	0.240	0.229	0.246	0.262	0.212**	0.225	0.265	0.232
	(0.016)	(0.011)	(0.017)	(0.014)	(0.015)	(0.015)	(0.018)	(0.020)	(0.018)
More 7 Days Late	0.153	0.142	0.137	0.145	0.160	0.120*	0.131	0.158	0.139
	(0.014)	(0.010)	(0.015)	(0.012)	(0.013)	(0.013)	(0.015)	(0.018)	(0.017)
Outcome variables: not fully paid									
Not paid in full at due date	0.220	0.205	0.171*	0.225	0.235	0.167*	0.189	0.211	0.215
	(0.020)	(0.014)	(0.021)	(0.018)	(0.020)	(0.019)	(0.023)	(0.025)	(0.024)
Not paid in full at + 30 days	0.119	0.093	0.072**	0.106	0.126	0.051***	0.079*	0.092	0.108
	(0.016)	(0.010)	(0.014)	(0.014)	(0.015)	(0.011)	(0.016)	(0.018)	(0.018)
Loan in default	0.033	0.036	0.031	0.039	0.053	0.013*	0.024	0.023	0.059
	(0.009)	(0.006)	(0.010)	(0.008)	(0.010)	(0.006)	(0.009)	(0.009)	(0.014)
Number loans	419	840	321	519	469	371	291	261	288
p value: random assignment on loan chars		0.954	0.557		0.552		0.514	0.957	

Table reports mean and standard error. Significance stars indicate cell is statistically different to control group. P value of F test for random assignment on loan characteristics. Missed week defined as missing a payment over a calendar week.

Table 3. Payment Results

	Late		More 1 day late		More 7 days late		Missed week		Unpaid at maturity		Unpaid at mat + 30day	
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Received any SMS	-0.020		-0.020		-0.011		-0.010		-0.010		-0.016	
	(0.018)		(0.017)		(0.015)		(0.013)		(0.024)		(0.019)	
PosXClient		0.009		0.018		0.017		0.018		0.008		0.009
		(0.031)		(0.030)		(0.027)		(0.024)		(0.039)		(0.030)
NegXClient		0.005		0.001		0.009		0.006		0.017		0.015
		(0.023)		(0.023)		(0.020)		(0.018)		(0.032)		(0.025)
PosXAO		-0.058**		-0.055**		-0.043**		-0.035*		-0.074**		-0.072***
		(0.024)		(0.023)		(0.020)		(0.018)		(0.033)		(0.020)
NegXAO		-0.047**		-0.050**		-0.036**		-0.032*		-0.010		-0.035
		(0.023)		(0.021)		(0.018)		(0.017)		(0.034)		(0.023)
Constant	0.282***	0.282***	0.243***	0.243***	0.143***	0.143***	0.166***	0.166***	0.216***	0.216***	0.112***	0.112***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)	(0.013)	(0.011)	(0.011)	(0.020)	(0.020)	(0.015)	(0.015)
AO Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number repayments	13586	13586	13586	13586	13586	13586	13586	13586	.	.	.	.
Number loans	1259	1259	1259	1259	1259	1259	1259	1259	1259	1259	1259	1259

Standard errors clustered at the loan level. Stars indicate statistical significance (* 10%, ** 5%, *** 1%). Paid in full is a dummy variable indicating whether loan has been fully repaid at maturity or 30 days after maturity. Missed week var considers a calendar week (Sunday-Saturday).

TABLE 4. PAYMENT RESULTS: TIMING

	Late	More 1 day late	More 7 days late	Missed week	Unpaid at maturity	Unpaid at mat + 30day
	b/se	b/se	b/se	b/se	b/se	b/se
0day	-0.029	-0.030	-0.021	-0.023	-0.015	-0.023
	(0.022)	(0.022)	(0.019)	(0.017)	(0.031)	(0.023)
1day	-0.014	-0.013	-0.009	-0.006	-0.010	-0.021
	(0.023)	(0.023)	(0.020)	(0.017)	(0.032)	(0.023)
2day	-0.017	-0.016	-0.003	0.001	-0.005	-0.005
	(0.023)	(0.022)	(0.020)	(0.018)	(0.031)	(0.024)
Constant	0.282***	0.243***	0.143***	0.167***	0.216***	0.112***
	(0.015)	(0.015)	(0.013)	(0.011)	(0.020)	(0.015)
AO Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number repayments	13586	13586	13586	13586	.	.
Number loans	1259	1259	1259	1259	1259	1259

Standard errors clustered at the loan level. Stars indicate statistical significance (* 10%, ** 5%, *** 1%). Paid in full is a dummy variable indicating whether loan has been fully repaid at maturity or 30 days after maturity. Missed week var considers a calendar week (Sunday-Saturday).