Supplemental Material

A personal touch in text messaging can improve microloan repayment

Dean Karlan, Melanie Morten, & Jonathan Zinman
Karlan, Department of Economics, Yale University; Morten, Department of Economics, Stanford University; Zinman, Department of Economics, Dartmouth College. Corresponding author's e-mail: dean.karlan@yale.edu

Methods

Study Sample and Randomization

We randomized 1,703 loans originated by Green Bank and Mabitac between May 2008 and March 2010. We could only randomize loans that were reported to us in timely fashion by the participating bank branches. We stopped randomizing in March 2010, after Green Bank changed its database and its reporting of loans to the research team for random assignment was disrupted. We dropped from the analysis 138 loans reported to us within two weeks of the end of their repayment cycle. Another 305 loans that did get random assignments were excluded because of bank reporting errors that made it impossible for us to randomize messaging or to match randomly assigned loans to bank data on loan repayment. Treatment assignment is uncorrelated with whether we could match loans to administrative data (p = .53). One loan was randomized twice, and 316 loans were subsequent loans to clients already in our study and hence dropped from the final analysis. This leaves a final sample of 943 loans.

The randomization was set to 33% for control and 66% to treatment, equally divided between the four treatment groups. The timing treatment was independently randomized, with each of three treatments equally likely. However, because of a coding error, the final breakdown of randomization was 34% control and then 12%, 25%, 14%, and 15% to each of the four treatments instead of 17% in each treatment group. There was no error in coding the independently randomized timing treatment.

Summary statistics for the loans in our sample are presented in Supplemental Table 1, which tests for balance across treatment arms in baseline loan characteristics. We find no evidence of imbalance. Assignment to treatment was orthogonal to key loan characteristics: loan size, loan term, and number of weeks the loan was part of the study (to verify there was not differential attrition). None of the pairwise comparisons between control and treatment produces a statistically significant difference. We also regress each of the eight different measures of treatment assignments on the three baseline loan variables and fail to reject equality at the 90% statistical significance threshold in only one of the eight regressions, which is about what would expect to find by chance (that is, one expects one false rejection for every 10 regressions).

Supplemental Table 1: Mean Baseline Loan Characteristics

	Log of loan size (peso)	Loan term (weeks)	Number of weeks in experiment	Number of loans	p-value of test for random assignment
Control (1)	9.7	19	10.6	310	
	(0.0)	(0.7)	(0.3)		
Treatment (2)	9.8	19.7	10.6	633	0.713
	(0.0)	(0.5)	(0.2)		
Content Treatments					
Positive Framing & Client Name (3)	9.8	19	10.2	116	0.432
	(0.1)	(1.0)	(0.4)		
Negative Framing & Client Name (4)	9.9	20.8	10.6	232	0.072
	(0.1)	(0.9)	(0.4)		
Positive Framing & Account Officer Name (5)	9.8	19	10.9	142	0.908
	(0.1)	(1.0)	(0.4)		
Negative Framing & Account Officer Name (6)	9.8	19	10.6	143	0.584
	(0.1)	(0.8)	(0.5)		
Timing Treatments					
Sent Day of Payment (7)	9.8	20.1	10.6	214	0.719
	(0.1)	(0.8)	(0.4)		
Sent 1 Day before Payment (8)	9.8	19.6	10.8	196	0.888
	(0.1)	(0.8)	(0.4)		
Sent 2 Days before Payment (9)	9.8	19.3	10.4	223	0.755
	(0.1)	(0.8)	(0.3)		

Notes: Standard errors in parentheses. In column 5 each cell shows the p-value from the joint test of statistical significance (F-test) for an OLS regression of the treatment variable in that row on the three baseline loan characteristics in Columns 1-3. Each regression also includes controls for account officer and month-year fixed effects, which are not shown the table.

We lack demographic data on the specific borrowers in our sample; however, a previous study with a different bank with similar microfinance operations suggests that borrowers are predominantly middle-aged female microentrepreneurs and about average with respect to education and household income (Karlan & Zinman, 2011). It is important to note that the bank in the previous study was located in urban and peri-urban Manila, versus the urban and rural setting of the two partner banks in this study.

Data, Analyses, & Results

Assessing Dimensions of Text Messaging Strategy on Loan Repayment Behavior

In our experiment, we tested the effects of three different dimensions of a messaging strategy. First, to examine the impact of receiving messages at all, borrowers were assigned to either a treatment (receive weekly messages for the entire loan term) or a control (no messages) condition.

The second dimension determined message content. Clients were randomly assigned to receive one of four different messages. All message variants included some boilerplate content: the bank name, text reading "pls pay your loan on time," and text reading "If paid, pls ignore msg. Tnx". Negatively framed messages started with "To avoid penalty." Positively framed messages started with "To have a good standing." The messages were also personalized with either the client's name ("From [bankname]: [client name]) or the account officer's name ("From [account officer's name] of [bankname]") in the beginning of the message.

The third dimension was message timing. We randomly and independently varied whether the borrower's messages were sent two days before the scheduled payment date, the day before the scheduled payment date, or the day of the scheduled payment date. Borrowers received the same content at the same time each week for the term of the loan.

The banks followed their standard procedures for late payments. Mabitac began actively following up on late payments three days after the due date, while Green Bank began after seven days. Bank staff at Mabitac communicated to us that their standard procedure was to call the client the day that the payment was missed, and the account officer notifies his or her supervisor. After three days, the account officer visits the client, accompanied by their supervisor. If the client cannot pay then, the first demand letter to the client is issued. For Green Bank, there is a seven-day grace period from when the payment is due. The account officer makes a follow-up visit after the payment is first missed. If the customer cannot pay, then the first demand letter is issued. For the second visit, the head account officer accompanies the account officer to the meeting, and then a second demand letter is issued. For the third visit, the branch manager accompanies the account officer, and then a third demand letter is issued.

Measuring Treatment Effects of Messaging on Loan Repayment

Supplemental Table 2 presents simple means comparisons for five different measures of late loan repayment. Asterisks indicate a pairwise significant difference between a treatment arm and the control group. These comparisons preview one of our main regression results: Only the positive messages containing the account officer's name reliably reduce delinquency relative to the control group.

Supplemental Table 2: Outcome variables by treatment arm: Simple means comparisons

	Proportion of weekly payments made late	Proportion of weekly payments made more than 1 day late	Proportion of weekly payments made more than 7 days late	Any unpaid balance at maturity	Any unpaid balance 30 days past maturity	Number of loans
Control	0.288	0.253	0.156	0.235	0.135	310
	(0.018)	(0.018)	(0.016)	(0.024)	(0.019)	
Any Treatment	0.295	0.251	0.152	0.216	0.098*	633
	(0.013)	(0.013)	(0.011)	(0.016)	(0.012)	
Content Treatments						
Positive Framing & Client Name	0.302	0.270	0.175	0.241	0.121	116
	(0.032)	(0.031)	(0.029)	(0.040)	(0.030)	
Negative Framing & Client Name	0.334	0.279	0.17	0.259	0.134	232
	(0.022)	(0.021)	(0.019)	(0.029)	(0.022)	
Positive Framing & Account Officer Name	0.231*	0.190**	0.110*	0.134**	0.035***	142
	(0.026)	(0.025)	(0.022)	(0.029)	(0.016)	
Negative Framing & Account Officer Name	0.291	0.249	0.148	0.21	0.084	143
	(0.027)	(0.026)	(0.024)	(0.034)	(0.023)	
Timing Treatments						
Sent Day of Payment	0.292	0.248	0.154	0.21	0.103	214
	(0.023)	(0.022)	(0.019)	(0.028)	(0.021)	
Sent 1 Day before Payment	0.300	0.256	0.156	0.209	0.082*	196
	(0.023)	(0.023)	(0.021)	(0.029)	(0.020)	
Sent 2 Days before Payment	0.293	0.249	0.148	0.229	0.108	223
	(0.023)	(0.021)	(0.020)	(0.028)	(0.021)	

Notes: Standard errors in parentheses. Stars indicate a statistically significant difference between a treatment arm and the control group: * 90%, ** 95%, *** 99%.

We also used an alternative measure of late payment: whether the client missed a payment in the calendar week, defined as Sunday–Saturday. If loan payments were made late, they were applied to the most outstanding installment first, so this alternative measure could capture whether a client made regular payments even if that client remained in arrears. Under this measure, no payment was made at all in 19% of weeks when a payment was due. The empirical results are robust using this alternative measure of late payment (see Supplemental Table 3).

Supplemental Table 3: Replication of Supplemental Table 2 with Three Additional Repayment Measures

	Weekly payment received late			Weekly payment received more than 7 days late			Any unpaid balance 30 days past maturity		
Panel A: Varying content of text messages									
Received any SMS	-0.006		0.023	0		0.023	-0.008		0.022
	(0.020)		(0.025)	(0.016)		(0.020)	(0.029)		(0.035)
Received Message with Positive Framing and Client Name		0.017			0.016			0.043	
		(0.034)			(0.027)			(0.047)	
Received Message with Negative Framing and Client Name		0.026			0.026			0.011	
		(0.028)			(0.022)			(0.040)	
Received Message with Positive Framing and Account Officer Name		-0.057**			-0.040*			-0.076**	
		(0.027)			(0.022)			(0.038)	
Received Message with Negative Framing and Account Officer Name		-0.024			-0.011			-0.011	
		(0.026)			(0.021)			(0.041)	
SMS signed by account officer			-0.063***			-0.048**			-0.065*
			(0.024)			(0.019)			(0.034)
Panel B: Varying timing of text messages									
Received any SMS	-0.006		0.023	0		0.023	-0.008		0.022
	(0.020)		(0.025)	(0.016)		(0.020)	(0.029)		(0.035)
Received Message Day Payment Due		-0.013			-0.005			-0.004	
		(0.027)			(0.022)			(0.039)	

Received Message 1 Day Before Payment Due		-0.009			-0.005			-0.011	
		(0.026)			(0.020)			(0.038)	
Received Message 2 Days Before Payment Due		0.002			0.009			-0.009	
		(0.026)			(0.021)			(0.037)	
SMS signed by account officer			-0.063***			-0.048**			-0.065*
			(0.024)			(0.019)			(0.034)
Mean of dependent variable for control group	0.253	0.253	0.253	0.185	0.185	0.185	0.235	0.235	0.235
Number of weekly repayments	9990	9990	9990	9990	9990	9990	.	.	.
Number of loans	943	943	943	943	943	943	943	943	943
N	9990	9990	9990	9990	9990	9990	943	943	943

Notes: OLS regressions with standard errors clustered at the loan level. Stars indicate statistical significance (* 90%, ** 95%, *** 99%). Dependent variables are dummy variables for measures of late payment or outstanding balance at maturity. Controls for account officer, month-year fixed effects, and baseline loan characteristics included. All treatment effects estimated relative to no-message control group.

We also estimated treatment effects using an ordinary least squares regression with the following specification: $Y_{it} = \alpha + \beta T_i + \delta \boldsymbol{X}_i + \varepsilon_{it}$ where Y is a measure of late payment for loan (or, equivalently, client) i at time t. T is either an indicator for whether messages were sent for this loan or the complete vector of treatment categories capturing assignment to one of the four content arms (Loss or Gain × Client Name or Account officer Name) and to one of the three timing arms. In either setup, the control group is the omitted category for T. X is a vector of account officer and month–year (of the Y observation) fixed effects. In specifications where we have multiple weekly observations per loan, we cluster the standard errors by loan to allow for correlation in payment activity for the same person.

Supplemental Tables 4 and 7 present results for three different measures of late repayment. *Weekly payment received late* and *more than 7 days late* are based on the timeliness of the required weekly payments; for these outcomes, the unit of observation is the loan week. We only include weeks starting with the week a bank first reported a loan to us and we randomly assigned that loan to treatment or control. The other outcome, *late 30 days after loan maturity*, is measured at a single point in time; hence, the unit of observation is the loan. *Late* is a dummy variable equal to 1 if the weekly payment was not received on the day it was due; *more than 7 days late* is a dummy equal to 1 if the weekly payment was not received by seven days after the weekly payment due; *late 30 days after loan maturity* is a dummy variable equal to 1 if the loan balance was not repaid was not fully repaid 30 days after the loan maturity date. Supplemental Table 3 presents results for three other outcome measures, with similar results.

Supplemental Table 4: Treatment Effect Estimates for Message, Content, and Timing: OLS Regressions

	Weekly payment received late			Weekly payment received more than 7 days late			Any unpaid balance 30 days past maturity		
Panel A: Varying content of text messages									
Received any SMS (1)	-0.007		0.024	-0.001		0.023	-0.026		-0.002
	(0.021)		(0.025)	(0.018)		(0.023)	(0.023)		(0.027)
Received Message with Positive Framing and Client Name (2)		0.007			0.01			0.001	
		(0.036)			(0.031)			(0.035)	
Received Message with Negative Framing and Client Name (3)		0.032			0.029			-0.004	
		(0.029)			(0.026)			(0.031)	
Received Message with Positive Framing and Account Officer Name (4)		-0.062**			-0.040*			-0.077***	
		(0.028)			(0.024)			(0.025)	
Received Message with Negative Framing and Account Officer Name (5)		-0.024			-0.019			-0.03	
		(0.028)			(0.023)			(0.031)	
SMS signed by account officer			-0.067***			-0.052**			-0.051**
			(0.025)			(0.021)			(0.024)
p-value from t-test comparing rows (4) and (5)		0.222			0.41			0.105	
R-squared	0.13	0.134	0.133	0.157	0.161	0.161	0.17	0.176	0.174
Panel B: Varying timing of text messages									
Received any SMS	-0.007		0.024	-0.001		0.023	-0.027		-0.002
	(0.021)		(0.025)	(0.018)		(0.023)	(0.023)		(0.027)
Received Message Day Payment Due		-0.012			0.001			-0.013	
		(0.027)			(0.024)			(0.030)	
Received Message 1 Day Before Payment Due		-0.007			-0.008			-0.04	
		(0.027)			(0.023)			(0.027)	
Received Message 2 Days Before Payment Due		-0.002			0.002			-0.027	
		(0.027)			(0.024)			(0.028)	

SMS signed by account officer			-0.067***			-0.052**			-0.051**
			(0.025)			(0.021)			(0.024)
R-squared	0.13	0.13	0.133	0.157	0.157	0.161	0.17	0.171	0.174
Mean of dependent variable for control group (both panels)	0.292	0.292	0.292	0.158	0.158	0.158	0.135	0.135	0.135
Number of weekly repayments (both panels)	9990	9990	9990	9990	9990	9990	.	.	.
Number of loans (both panels)	943	943	943	943	943	943	943	943	943
N (both panels)	9990	9990	9990	9990	9990	9990	943	943	943

Notes: OLS regressions with standard errors clustered at the loan level. Stars indicate statistical significance (90%, ** 95%, *** 99%). Dependent variables are dummy variables for measures of late payment or outstanding balance at maturity. Controls for account officer, month-year fixed effects, and baseline loan characteristics included in all regressions but coefficients not reported. All treatment effects estimated relative to no-message control group.*

Columns 1, 4, and 7 in Supplemental Table 4 present the estimated treatment effect on each of the three outcomes after receiving any messaging. None of the point estimates is statistically significant, but all three are negative (indicating reduced delinquency), and the confidence intervals do not rule out economically meaningful effects (the control group means are reproduced near the bottom of the table for reference and scaling). Supplemental Table 5 groups the positively and negatively framed messages to test them relative to each other and to the control group. It shows a bit of evidence that negatively framed messages are more effective at reducing late payments, on average: The coefficient on negatively framed messages is more negative than the coefficient on positively framed messages for each of the three outcomes, and the *p* values on the difference between loss and gain frames are .09, .18, and .25.

Supplemental Table 5: Loss vs. Gain Frames

	Weekly payment received late	Weekly payment received more than 7 days late	Any unpaid balance 30 days past maturity
Message had positive framing	0.01	0.01	-0.015
	(0.023)	(0.021)	(0.026)
Message had negative framing	-0.032	-0.018	-0.042*
	(0.025)	(0.022)	(0.025)
p-value from F-test that coefficients are same for negative and positive framing	0.09	0.177	0.247
Mean of dependent variable for control group	0.292	0.158	0.135
Number of weekly repayments	9990	9990	.
Number of loans	943	943	943
N	9990	9990	943

Notes: OLS regressions with standard errors clustered at the loan level. Stars indicate statistical significance (* 90%, ** 95%, *** 99%). Dependent variables are dummy variables for measures of late payment or outstanding balance at maturity. Controls for account officer, month-year fixed effects, and baseline loan characteristics included. All treatment effects estimated relative to no-message control group.

Columns 2, 5, and 8 of Supplemental Table 4, Panel A, present the results for the content treatments for each of the three outcome measures. Neither of the client name messages (whether positively or negatively framed) produced statistically significant effects, and four of the six coefficients on these variables were actually positive (indicating increased delinquency). Conversely, the account officer name messages have negative point estimates in each of the six cases, with the positively framed message in particular producing statistically significant reductions in each of the three delinquency measures.

In columns 2, 5, and 8 of Supplemental Table 4 (but not the other columns), some adjustment for multiple-hypothesis testing is in order: With 12 cells, one would expect to find about one significant result purely by chance. A conservative way to do this would be to simply inflate each *p* value by 12, thereby reducing the likelihood that any individual treatment variable is statistically significant by a factor of 12. This correction would move the *p* values on the *positive frame-account officer name* from .025 to .3 in column 2, from .091 to 1 in column 5, and from .002 to .022 in column 8. This correction is too conservative, in our view, because each of the three outcomes is meant to measure the same thing: loan default as a proxy for bank profits. In that sense, we are closer to running a single regression with four treatment variables—forced to choose, we surmise that the best proxy outcome is probably the books-closing measure in column 8—than we are to running three separate regressions with 12 treatment variables.

Hence Supplemental Table 6 aggregates our three outcomes into a single outcome—a *summary index* in statistical parlance—and reruns the specification used in Supplemental Table 4, columns 2, 5, and 8. Supplemental Table 6 has three columns of its own to show results for three different aggregation rules. We find results similar to those shown in Supplemental Table 4: a statistically significant result on *positive frame–account officer name* in each case and no other statistically significant results. The one difference from Supplemental Table 4 is that in Supplemental Table 6, we find statistically significant differences between positively and negatively framed account officer messages.

Supplemental Table 6: Replication of Supplemental Table 4 with summary index measures of late payment

	Index: Late, More 7 Days Late, Bal 30 Days Past Maturity		Index: More 7 Days Late, Bal 30 Days Past Maturity		Index: Late, Bal 30 Days Past Maturity	
Panel A: Varying content of text messages						
Received any SMS (1)	-0.011	0.047	-0.018	0.026	-0.018	0.018
	(0.056)	(0.067)	(0.039)	(0.047)	(0.038)	(0.046)
Received Message with Positive Framing and Client Name (2)		0.046		0.023		0.024
		(0.092)		(0.063)		(0.062)
Received Message with Negative Framing and Client Name (3)		0.046		0.027		0.014
		(0.077)		(0.054)		(0.052)
Received Message with Positive Framing and Account Officer Name (4)		-0.164**		-0.130***		-0.111**
		(0.069)		(0.047)		(0.045)
Received Message with Negative Framing and Account Officer Name (5)		0.004		-0.014		-0.012
		(0.080)		(0.054)		(0.054)

SMS signed by account officer			-0.125*			-0.097**			-0.079*
			(0.065)			(0.044)			(0.043)
p-value from t-test comparing rows (4) and (5)		0.045			0.037			0.069	
R-squared	0.215	0.221	0.218	0.197	0.204	0.202	0.194	0.199	0.197
Panel B: Varying timing of text messages									
Received any SMS	-0.011		0.047	-0.018		0.026	-0.018		0.018
	(0.056)		(0.067)	(0.039)		(0.047)	(0.038)		(0.046)
Received Message Day Payment Due		0.004			-0.009			0.001	
		(0.076)			(0.053)			(0.052)	
Received Message 1 Day Before Payment Due		-0.006			-0.018			-0.027	
		(0.071)			(0.048)			(0.047)	
Received Message 2 Days Before Payment Due		-0.029			-0.027			-0.028	
		(0.073)			(0.050)			(0.049)	
SMS signed by account officer			-0.125*			-0.097**			-0.079*
			(0.065)			(0.044)			(0.043)
R-squared	0.215	0.215	0.218	0.197	0.197	0.202	0.194	0.194	0.197
Mean of dependent variable for control group (both panels)	0.58	0.58	0.58	0.424	0.424	0.424	0.292	0.292	0.292
Number of weekly repayments (both panels)	.	.	.	.	.	.	.	.	.
Number of loans (both panels)	943	943	943	943	943	943	943	943	943
N (both panels)	943	943	943	943	943	943	943	943	943

Notes: OLS regressions with standard errors clustered at the loan level. Stars indicate statistical significance (90%, ** 95%, *** 99%). Dependent variables are borrower-level indices of late payment. Col (1)-(3) is an index composed of the average of the three late payments: mean number of payments late, the borrower-level mean number of payments more than 7 days late, and any unpaid balance 30 days past maturity. Each component has a maximum value of 1, so the overall index takes a value between 0 (no late payment of any kind at any point in the loan) to 3 (every weekly payment more than 30 days late (and hence also every payment received late), with balance unpaid 30 days past maturity). Col (4)-(6) constructs an index with two measures of late payment (more than 7 days late and balance more than 30 days past maturity), and Cols (7)-(9) constructs an index with two measures of late payment (late payment and more than 30 days past maturity). Controls for account officer, month-year fixed effects, and baseline loan characteristics included in all regressions but coefficients not reported. All treatment effects estimated relative to no-message control group.*

Supplemental Table 7 explores whether the content messages perform differently for new versus veteran clients. There are competing hypotheses here. On the one hand, new borrowers know less about account officer monitoring than experienced borrowers do, and hence new borrowers may infer more from the account officer message than experienced borrowers would about how closely account officer's will monitor the client. On the other hand, two theories suggest that the messages will be more effective on prior borrowers. First, if the messages heighten sentiments of reciprocity, the more experienced borrowers may be more responsive to messages, as they have built up more of a relationship with the account officer than the new borrowers. Second, past borrowers may see these messages as a signal of an increased diligence to enforce repayment given that no such text messages have been sent before, whereas new borrowers had no prior experience against which to compare.

Supplemental Table 7 shows that the account officer–signed text messages are effective only for the prior borrowers. The difference between prior and first-time borrowers is significant for all three dependent variables (see the p values at the bottom of Supplemental Table 7).

Supplemental Table 7. First-Time Clients vs Pre-Prior Clients: OLS Regressions (same as Supplemental Table 4 but splitting the sample)

	Weekly payment received late			Weekly payment received more than 7 days late			An
Panel A: Clients who are first-time borrowers from the bank							
Received any SMS (1)	0.019		0.031	0.024		0.036	-0.01
	(0.031)		(0.036)	(0.028)		(0.033)	(0.03
Received Message with Positive Framing and Client Name (2)		-0.049			-0.03		
		(0.051)			(0.041)		
Received Message with Negative Framing and Client Name (3)		0.065			0.064*		
		(0.040)			(0.037)		
Received Message with Positive Framing and Account Officer Name (4)		-0.029			-0.025		
		(0.045)			(0.036)		
Received Message with Negative Framing and Account Officer Name (5)		0.032			0.036		
		(0.042)			(0.035)		
SMS signed by account officer			-0.028			-0.029	
			(0.038)			(0.031)	
p-value from t-test comparing rows (4) and (5)		0.234			0.118		
R-squared	0.173	0.178	0.174	0.238	0.244	0.239	0.27
Mean of dependent variable for control group	0.336	0.336	0.336	0.178	0.178	0.178	0.12
Number of weekly repayments	4654	4654	4654	4654	4654	4654	.
Number loans	476	476	476	476	476	476	476
N	4654	4654	4654	4654	4654	4654	476
Panel B: Clients who have borrowed from the bank before							
Received any SMS (1)	-0.027		0.019	-0.028		0.009	-0.05
	(0.027)		(0.033)	(0.025)		(0.031)	(0.03
Received Message with Positive Framing and Client Name (2)		0.051			0.022		
		(0.046)			(0.044)		
Received Message with Negative Framing and Client Name (3)		0			0.001		
		(0.037)			(0.035)		

Received Message with Positive Framing and Account Officer Name (4)		-0.083**			-0.064*		
		(0.036)			(0.033)		
Received Message with Negative Framing and Account Officer Name (5)		-0.066*			-0.070**		
		(0.034)			(0.029)		
SMS signed by account officer			-0.095***			-0.076***	
			(0.031)			(0.029)	
p-value from t-test comparing rows (4) and (5)		0.651			0.87		
R-squared	0.14	0.148	0.147	0.13	0.139	0.139	0.17
p-value "SMS signed by account officer" coefficient same across panels			0.007			0.077	
Mean of dependent variable for control group	0.248	0.248	0.248	0.137	0.137	0.137	0.15
Number of weekly repayments	5336	5336	5336	5336	5336	5336	.
Number of loans	467	467	467	467	467	467	467
N	5336	5336	5336	5336	5336	5336	467

Notes: OLS regressions with standard errors clustered at the loan level. Stars indicate statistical significance (* 90%, ** 95%, *** 99%). Dependent variab measures of late payment or outstanding balance at maturity. Controls for account officer, month-year fixed effects, and baseline loan characteristics in the coefficients are the same for first-time and pre-existing clients, computed by estimating a pooled model with an interaction term. Experience with th of the experiment, because the experiment only covers one loan. All treatment effects estimated relative to no-message control group.

The evidence on whether framing matters for the account officer message is mixed. In the full sample (see Supplemental Table 4), only the positively framed account officer message is statistically significant, but the p values on the difference between the negatively versus positively framed account officer messages are .22, .41, and .11 for our three main outcomes. In Supplemental Table 7, the p values between the negatively versus positively framed account officer messages are .23, .12, .04, .65, .87, and .91 for the interactions between our three main outcomes and the prior client and first-time client subsamples. But when we measure delinquency using the summary index variables (see Supplemental Table 6), the positively framed account officer message does have a stronger effect than the negatively framed one does (p values of .05, .04, and .07).

Supplemental Table 8. Treatment Effects Over the Course of the Loan: OLS

	Weekly payment received late		Weekly payment received more than 7 days late	
Weeks in experiment	0.004	0.004	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Received any SMS X Weeks in experiment	-0.002	0.001	-0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Received message with account officer name X Weeks in experiment		-0.006**		-0.006**
		(0.003)		(0.003
R-squared	0.131	0.133	0.161	0.164
Mean of dependent variable for control group	0.292	0.292	0.158	0.158
Number of weekly repayments	9990	9990	9990	9990
Number loans	943	943	943	943
N	9990	9990	9990	9990

Notes: OLS regressions with standard errors clustered at the loan level. Stars indicate statistical significance (* 90%, ** 95%, *** 99%). Installments since loan start measures the length of time since the loan was disbursed. Weeks in experiment measures the length of time the loan was enrolled in our study and began receiving text messages if assigned to treatment. Messages start one or more weeks after loan disbursement due to lags in bank reporting to the research team, since the research team administered the random assignments. Dependent variables are dummy variables for measures of late payment or outstanding balance at maturity. Controls for account officer, month-year fixed effects, and baseline loan characteristics included. All treatment effects estimated relative to no-message control group.

Returning to Supplemental Table 4, panel B presents treatment effect estimates for the timing treatments relative to the control condition. Clients assigned to messages were sent them every week, on either the day the payment was due, the day before, or two days before. This timing treatment was independently randomized after the initial randomization to either the control group or one of the four message scripts. We did not find any statistically significant evidence that a specific timing treatment was effective relative to the control condition or relatively effective compared with the other timing treatments.

We then looked whether treatment effects vary over the course of the loan by calculating the interaction between the number of weeks the loan is in the experiment (and the number of weeks the borrower is receiving text messages, if assigned to treatment) and our two key treatment variables. The account officer message effect became slightly stronger over the course of the loan (coefficient = -0.06); we found no evidence that the overall effect of receiving messages changed over the loan. We show regression results in Supplemental Table 8.

Additional Notes about Data Interpretation

Some previous work has suggested that receiving regular messages may help mitigate limited attention on the part of the borrower. Our results could be consistent with a limited-attention interpretation if messages mentioning the borrower's name reduce the likelihood of repayment relative to getting a message with no one's name mentioned (we did not test a nameless message) and if mentioning the account officer's name is no more effective than sending a nameless message. These outcomes might indicate that mentioning the borrower's name is somehow off-putting to the borrower but that messages serve as effective reminders otherwise. However, this does not seem especially plausible, given that bank correspondence typically addresses a borrower by name.

Another way our results could support a limited-attention interpretation is if text messages are viewed as a stronger signal of increased monitoring when they come from a recognizable individual employee of the bank. Repeat borrowers are more likely to recognize and pay attention to the name of their account officer.