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Behavioral messages and debt repayment

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Behavioral Messages and Debt Repayment*

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Abstract

We conduct a randomized experiment involving 7,063 late-paying clients of a large Colombian bank to compare the effects of text messages that leverage different behavioral motives on loan delinquency. Our results show that receiving a message decreases the likelihood of borrowers being late by 4%. The effects are more pronounced when messages leverage social norms. Using machine learning tools, we find that the effects are concentrated among borrowers with higher credit scores and unsecured loans. A second experiment shows that this type of message is ineffective in preventing on-time borrowers from falling into loan delinquency.

JEL: G51, D91.
Keywords: Loan Delinquency, Behavioral Messages, Personal loans, Field Experiments

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1 Introduction

A significant proportion of households worldwide are unable to meet their debt obligations on time. In 2020, 2% of households in the US were delinquent on their mortgage loans, and 2.5% defaulted on their credit card debt (FRED, Federal Reserve Economic Data, 2022a,b). In Colombia, 6.4% of borrowers were delinquent on their credit cards and 7% on their mortgages in the last quarter of 2020 (Transunion, 2021). Borrowers who fail to repay their loans on time, and those who default, face negative economic, financial, and social outcomes. These include lower credit scores, worsened access to credit in the future, loss of social benefits, and worsened mental health (Bos et al., 2018; Dobbie et al., 2020; de Roux, 2021; Gathergood, 2012). In the aggregate, low repayment rates may also exacerbate the financial sector's liquidity risk (Mian and Sufi, 2015). Therefore, interventions that promote good repayment behavior are important for the well-being of households and society as a whole.

Recently, the household finance literature has shown that behavioral biases, such as limited attention or the tendency to procrastinate, can have adverse effects on financial decisions (Stango and Zinman, 2014; Soll et al., 2013; Fernandes et al., 2014; Campbell, 2016). Repayment reminders and moral appeals have been tested as potential solutions to reduce indebtedness and default (Cadena and Schoar, 2011; Karlan et al., 2012; Bursztyn et al., 2019; Adams et al., 2021). However, none of this studies shows which intervention has the most significant impact on loan repayment and whether this impact varies across borrower characteristics. Doing so would require studying a large, homogeneous population and testing messages with different behavioral motivations in the same context.

In this paper, we address both challenges through a randomized intervention involving a sample of 7,063 households borrowing from a large Colombian financial services provider, hereafter referred to as "the Bank". The Bank offers customers a suite of financial products ranging from mortgage loans to credit cards. At the beginning of the study, all of these borrowers were late in repaying their loans, with an average delay of six days. Working within the Bank's existing processes, we designed six different messages that were randomly assigned at the individual level and sent weekly via text messages. The six treatments are: a "reminder" treatment that stresses the importance of repaying on time to avoid additional costs, a "reciprocity" treatment that touches upon the trust and reciprocity between the Bank and its customers, a "moral norms" treatment that leverages the moral appeal of debt repayment, a "social norms" treatment that highlights the good repayment behavior of other bank customers, and, finally, two treatments that emphasize the ability of a financially healthy bank to make socially responsible investments. All messages were positively framed and highlighted the benefits of repaying the loan for borrowers, the Bank, or society as a whole. By testing different treatments in the same context, our intervention allowed us to understand the relative importance of each behavioral message.

Five weeks after the start of the experiment, our results indicate that exposure to any of these message streams reduces the likelihood of being late by 4%, compared to a baseline likelihood of 59% in the control group. These effects are precisely estimated and consistent across different measures of loan delinquency. Among the message streams, only the moral and social norms messages significantly reduce the probability of late payment, with the social norms message having the strongest impact. Our findings suggest that nudging delinquent borrowers to repay can be particularly effective when messages emphasize the social value attached to loan repayment.

Using rich administrative data from the bank, we employ causal forest procedures in the spirit of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) to study heterogeneous treatment effects and explore potential mechanisms that may explain our results. We find that borrowers with higher credit scores, those with unsecured loans (such as consumption loans and credit cards), and those with loans with shorter maturities are more responsive to the messages. In contrast, we find no effect on borrowers with collateralized credit, particularly mortgages. Interestingly, we observe that the impact of behavioral messages on loan delinquency, while negative, is nonlinear across several characteristics including borrowers' age, size of debt, and interest rate. Furthermore, we find that some messages can have adverse effects for certain groups. For instance, messages leveraging the Bank' social responsible investing increase loan delinquency among low-income borrowers.

Our findings show that behavioral messages are particularly effective for delinquent borrowers of higher quality who have preferences for repayment. However, it remains unclear whether these messages have an impact on borrowers who are up to date with their payments. Answering this question can provide insight into whether behaviorally motivated messages can be effective for the borrowing population as a whole. Therefore, we conducted a second randomized controlled trial using the same set of treatment arms with 8,019 on-time paying borrowers of the Bank. The effects on this population are precisely estimated at zero, indicating that behavioral messages are not effective in preventing on-time borrowers from becoming late payers.

With this paper, we make four main contributions to the rich literature in household finance that documents how equipping borrowers with information can have a positive impact on borrowing, repayment, and saving decisions (Cadena and Schoar, 2011; Karlan et al., 2012; Soll et al., 2013; Agarwal et al., 2015; Seira et al., 2017; Stango and Zinman, 2014; Adams et al., 2021; Medina, 2021; Haran Rosen and Sade, 2022). First, our study represents one of the most comprehensive comparisons of the effects of different nudges on repayment in consumer finance, and shows that leveraging the social value of repayment has the largest impact on delinquency. Our findings also indicate that messages using a positive framing, in contrast with messages using a negative one (see, e.g., messages leveraging shaming in Perez-Truglia and Troiano, 2018), can perform well in reducing loan delinquency. This result aligns with Du et al. (2020), who show that messages emphasizing lenders' positive expectations towards borrowers increase repayments.

Secondly, while most of the existing literature focuses on providing information to credit card holders, our study examines the impact of behavioral messages on the repayment of a wide range of financial products. Our findings indicate that customers with unsecured credit are more likely to respond to the intervention, which supports the findings of Keys et al.

(2016) that information campaigns have little impact on homeowners' likelihood to refinance their mortgages. Our third contribution is the use of machine learning procedures to identify individual characteristics, taken from rich administrative data, that predict larger treatment effects. Our findings indicate that behaviorally-motivated messages can be particularly effective in reducing delinquency for late borrowers with higher credit scores.

Lastly, our paper adds to the literature on the adverse effects of poor credit scores caused by loan delinquency in consumer credit (Bos et al., 2018; Dobbie et al., 2020). While previous studies such as Dobbie and Song (2020), Liberman et al. (2021) and de Roux (2021) have explored potential sources of financial distress leading to repayment default and poor credit scores, we focus on the impact of simple, cost-effective messages to decrease repayment default and mitigate the negative effects on borrowers' access to employment, health services, and future credit (Mueller and Yannelis, 2019; Bernstein, 2017).

From a policy perspective, our findings imply that simple nudges like text messages could strengthen the impact of initiatives designed to prevent households from falling into delinquency or default. Examples of these programs include loan forbearance, such as the 2020 Coronavirus Aid, Relief, and Economic Security Act passed in the United States, and large-scale financial literacy programs, such as Indonesia's Financial Authority Services Digital Roadmap. However, results from the heterogeneity analysis indicate that some of these messages could increase, rather than mitigate, loan delinquency, particularly among borrowers with lower income. This calls for caution in the way debt-relief initiatives incorporate behaviorally motivated messages to increase their effectiveness.

2 Institutional Context and Experimental Design

The Bank offers customers a suite of financial products that range from mortgage loans to credit cards and consumer loans; customers may take multiple products. If borrowers are more than 30 days late on any of their loans, they are charged higher interest rates and they are reported by the Bank to the credit bureaus operating in Colombia, which proceed with the borrowers' credit score downgrading. When this happens, the Bank notifies the customer with an email that explains that they are being reported.

As part of the Bank's existing processes, a randomized intervention was designed to mitigate loan delinquency rates leveraging simple, short messages sent via SMS. These messages were sent to customers that were late by at least one day and in at least one product at the start date of the experiment – May 3rd, 2021. The experiment lasted three months. During these three months, the Bank did not contact customers except for these messages. However, because of regulatory requirements, the Bank could not avoid notifying customers if they were 30 days past due or reporting them to credit bureaus. To neutralize any potential confounding factors, the results we present in this paper refer to the first five weeks of our intervention. A timeline of the experiment can be seen in Figure 1. Clients in each treatment arm received the same behavioral message on a weekly basis until they repaid all their products; no further message was pushed to them afterward.

The text messages were pushed to customers on the phone number they indicated when they enrolled with the Bank.[1] We used the same provider the Bank partners with for home-banking services. Late-paying customers were identified through administrative records, which contain socio-demographic information like income, place of residency, and credit score for each borrower. Some customers are considered by the Bank as "central nodes" for information diffusion (Banerjee et al., 2014) based on an internal algorithm for social media analysis and were therefore excluded from the study to avoid spillover effects of the treatments – e.g., these customers could have posted the messages they received on Twitter or other social media platforms. Out of the clients who were late on May 3rd, 2021, we randomly selected 7,063 and sent the first set of messages to those who were still late on May 4th (7,029 borrowers). The final sample was stratified based on customers' credit scores and a segment variable that reflects the type of lending relationship with the client. Clients

[1] There may be cases in which clients' numbers changed since enrollment. The Bank regularly verifies clients' contact details to ascertain that clients can be successfully reached.

were assigned to 20 strata and randomly selected into each treatment and control group. Online Appendix C provides details on the construction of the strata.

2.1 Experimental Treatments

The experimental design is shown in Figure 2. Each treatment arm is associated with a different stream of messages that was pushed to 1,009 clients. In the control group, no message was pushed. Each experimental subject was uniquely assigned to either receive one of the treatments or to be in the control group. In this section, we present the exact wording of each message (translated from Spanish) and discuss the behavioral motivation behind it.

S1 (Reminder of financial implications of default): Clients assigned to S1 received the following message: *"The Bank reminds you that people who pay their loans on time take care of their money by not paying interest on arrears. Take care of your money by paying your financial products on time"*. This treatment arm speaks to the literature on financial sophistication and borrowing behavior (Lusardi and Tufano, 2015; Bertrand and Morse, 2011) and aims to test the role of limited attention in loan repayment (Stango and Zinman, 2014). By increasing the salience of the economic consequences of loan delinquency, borrowers should be moved to reduce defaults.

S2 (Reciprocity): Clients randomly assigned to S2 received the following message: *"At the Bank, we trusted you by giving you the money you needed. In the same way, we trust that your financial commitments will be paid on time"*. This message leverages the obligation/reciprocity relationship between the customer and the Bank. It could make borrowers feel an obligation towards the institution, which can increase their repayment efforts (Karlan et al., 2012; Charness and Dufwenberg, 2006).

S3 (Moral obligation of debt repayment): Clients randomly assigned to S3 received the following message: *"Nothing generates more peace of mind than a duty accomplished. By paying your financial products on time, you meet your commitments and live peacefully."* This message leverages the morality of *not* defaulting on one's debt, which in turn may enhance loan repayment (Guiso et al., 2013; Bursztyn et al., 2019).

S4 (Social norms): A fourth stream of messages leveraged social norms of repayment. The text message reads as follows *"Did you know that 8 out of 10 Colombians pay their loans on time? Be part of this group and keep up to date with your financial products."* This message appeals to two aspects of social norms: first, to the descriptive aspect of norms with salience to Bank clients' pool. Second, there is a clear reference to the minority versus majority norm, whereby borrowers are encouraged to be part of a majority that pays on time. While these types of messages are frequently used to encourage household savings (Beshears et al., 2015; Kast et al., 2018; Dur et al., 2021), tax compliance (Hallsworth et al., 2017; De Neve et al., 2021), and payment of TV licensing (Fellner et al., 2013), they have rarely been used to reduce repayment delinquency. Whether social norms positively affect repayment rates remains an empirical question that largely depends on the group (minority versus majority) our experimental subjects identify with.[2]

S5 and S6 (Socially Responsible Investments Concerns): Two streams of behavioral messages that leverage borrowers' concerns for the Socially Responsible Investments (SRI) carried out by the Bank were also included. Clients randomly assigned to S5 and S6 received the following message: *"With the payment of your financial products, the Bank invests in the country with projects that generate social and environmental benefits, such as access to decent housing and the fight against climate change. With your payment on time, you make a difference and support this transformation."*. Clients in S6 receive an additional portion of the message: *"Learn more about our investment here (weblink to the SRI page of the Bank)"*. So far, most of the literature on SRI has focused on how investors' preferences for SRI criteria affect investments (Pedersen et al., 2020; Krueger et al., 2020). We know little about how

[2]Individuals' preferences, choices, and self-image are shaped by their perception of the behavior of others. This fact should also apply to our bank clients. For example, knowing that the majority is paying on time should affect repayment rates, similar to how energy or water users respond to such social comparisons (Allcott, 2011). Related to this, Gathergood (2012) reports that the psychological costs of indebtedness are lower when bankruptcy rates are higher among the borrower's peers. Therefore, a perception of higher repayment rates in the social group should increase the psychological costs of delinquency and push the client to increase their effort to pay on time.

banks can leverage *debtors'* preferences for SRI to enhance repayment rates. The hypothesis behind S5 and S6 is that by leveraging borrowers' concerns for a specific set of public goods (i.e., the fight against climate change), the Bank makes borrowers feel more compelled to repay. The additional inclusion of a web link that allows borrowers' to verify the type of investments the Bank engages in, enables us to test whether a simple message on the Bank's SRI is sufficient, or if this type of message requires that the financial institution provides detailed information about the investment.

All messages we pushed in our experiment also gave the clients the possibility to reach out to the Bank by including the following sentence: "Do you want to communicate with us? Contact us at [number]".

3 Conceptual Framework

This experiment allows us to answer three key questions in the household finance literature: first, whether providing delinquent borrowers with behaviorally-motivated messages improves repayment behavior; second, which message is the most effective; third, which borrowers are more sensitive to behavioral messages. Several types of interventions, ranging from text reminders to messages with moral considerations, have shown positive effects on borrowing and repayment behavior (Agarwal et al., 2015; Stango and Zinman, 2014; Soll et al., 2013; Cadena and Schoar, 2011; Bursztyn et al., 2019; Medina, 2021). Yet, the mechanisms underlying their impact – which also depends on borrower characteristics – remain largely unexplored.

The behavioral literature has identified two conditions that are needed for behaviorally motivated messages to be effective (see Damgaard et al., 2020 for a review). First, individuals must have the potential and the motivation to improve their behavior (Allcott, 2011; Gravert and Kurz, 2021). Second, their decisions and actions must be constrained by the behavioral barrier targeted by the messages (Dinkelman and Martínez A, 2014).

In the context of debt repayment, these predictions imply that borrowers who have money to repay and whose credit score can still be "redeemed" should respond to messages encouraging repayment the most. If borrowers believe that, irrespective of their effort to repay, they will not have access to credit in the future, messages will hardly have an effect. At the same time, behavioral messages will have a greater impact on borrowers with higher preferences for repayment. This is the case if they obtain utility from being up to date for reasons unrelated to the direct economic consequences of being late, like the report to credit bureaus or overdue fees. For example, customers could obtain utility from being on time if they see a social or moral value in this or if being late negatively affects their self-image. Finally, another dimension that influence the effect of the messages is whether or not the customer is delinquent. Borrowers who are on time are not directly constrained by the specific behavioral barriers targeted by the messages, and hence they should be less sensitive to the text treatments.

We test the above predictions with rich, granular data on borrowers' characteristics from our partner Bank, which we use to carry out a machine learning based heterogeneity analysis. In addition, the results from a second experiment with on-time borrowers allows us to test whether behavioral messages improve the repayment behavior of all borrowers, or just that of delinquent ones.

4 Data and Empirical Approach

4.1 Summary Statistics

The data we use in the analysis mainly come from administrative records held by the Bank that were shared with us in anonymised form. For each credit product held by a borrower in our experimental sample, the Bank has shared daily information on the number of days past due.[3] Importantly, if a borrower repays during the intervention, this information allows us

[3]If the borrower's repayments for a specific financial product are up to date, this variable is equal to 0.

to know the exact day the payment was made. We also have socio-demographic information, including the gender of the borrower, monthly income, education, and occupation at the start of the intervention. Financial information like the total amount of outstanding debt and assets, as well as credit score, are also available. We also have measures of customers' engagement with the Bank (e.g., whether and when the client has reached out to the Bank's customer care).

Table 1 shows summary statistics for the sample of 7,029 borrowers who were still late the first day messages were sent, separated into control and treatment groups.[4] Half of the customers in our sample are women; they are on average 42 years old and have a monthly household income of around 4,200 thousand Colombian Pesos (approximately $1,124 USD).[5] Borrowers in our sample are fairly well educated, with almost 90% of them having completed higher education; most borrowers are employed and residing in the Central region of Colombia. Finally, borrowers are on average between 5 to 6 days late with their loan payment at the onset of the study. Table 1 also presents the p-value of a test of joint significance of the coefficients from a regression where the left-hand variable is the control listed in the first column and the right-hand variables are dummies for treatment assignment. The p-values reported in the table show that the control and the treatment groups are well balanced across all socio-demographic and financial characteristics, reassuring us that the randomization worked well.

4.2 Econometric Specification

We start by studying the effect on loan repayment of receiving any behavioral message for late borrowers. Individuals who completed all the repayment installments of the loan during the intervention are dropped out of the estimation sample in the week of their final repayment.

[4]Out of the clients who were late on the day we carried the randomization (May 3rd, 2021) we randomly selected 7,063 and sent the first set of messages to those who were still late on May 4th (7,029 borrowers).

[5]Throughout the paper we use an exchange rate of 3,735 Colombian Pesos per US Dollar, which was the average exchange rate in May 2021, the month of our intervention.

We estimate the following regression in a balanced panel at the individual-week level:

$$y_{iw} = \beta_0 + \beta_1 T_i + z_i + c_w + \varepsilon_{iw} \tag{1}$$

where y_{iw} is the probability that client i is late in week w in at least one product and T_i is a dummy that equals one if the subject is randomly assigned to receive any of the message streams. z_i is a vector of strata fixed effects, c_w denotes week fixed effects, and ε_{iw} is the error term. To account for individual heterogeneity, we also estimate equation (1) including in z_i a set of individual-level predetermined characteristic that we select with a double LASSO procedure (Belloni et al., 2014).[6] Standard errors are clustered at the individual level. Our main coefficient of interest is β_1, the Intent-to-Treat coefficient.[7]

In a second specification, we look at the impact of each individual treatment by estimating the following equation:

$$y_{iw} = \beta_0 + \sum_{j=1}^{6} \beta_j T_{ij} + z_i + c_w + \varepsilon_{iw} \tag{2}$$

where T_{ij} is a vector of dummies denoting random assignment, at the individual level, to any of the six message streams S_j discussed in Section 2.1. Equation (2) allows us to identify which message stream is the most effective in improving repayment rates. We estimate both equation (1) and equation (2) with administrative data from the Bank.

[6] We let the LASSO procedure select the relevant characteristics from the following list: income, age, value of outstanding debt, occupation and region dummies, and dummies for whether the borrower is a women, is a couple, or has children. Table 1 shows that some characteristics have missing values. We recode the missing values to 0 and define dummies that indicate if the corresponding covariate is missing. We include in the LASSO selection list both the recoded variable and the corresponding missing dummy and include both variables in the final regression if the characteristic is selected by the LASSO procedure.

[7] This is an intent-to-treat effect since we cannot guarantee that the borrowers actually read the text message. At the end of the intervention, we invited all the clients in our experiment to participate in a short survey via email. We obtained 234 answers, or a response rate of 3.3%. 70% of those who answered recall receiving a message from the Bank related to the importance of paying on time. This suggests that an important fraction of our customers were indeed reading the text messages of the intervention. Note also that non-compliance works against finding an effect of messages. In other words, with perfect compliance, that is if all the borrowers were to read the messages, we would expect a larger effect of messages on repayment than what is reported in this section.

5 Results

5.1 The Effect of Receiving Any Message

We study treatment effects by first examining the impact of receiving any type of message. Results from estimating equation (1) are shown in Panel of A of Table 2. Column (1) shows the results including as controls only strata fixed effects. Compared to the control group, receiving any message decreases the probability of a borrower being late by 2.3 percentage points – a decrease of 4% relative to a delinquency rate of 59% in the control group. Column (2) shows that this result is robust to the inclusion of week fixed effects and column (3) shows that it is robust to the inclusion of individual-level characteristics chosen with LASSO. The estimated coefficient is fairly stable across specifications, suggesting that the randomization was successful. The results from this table provide strong evidence that behavioral messages are effective at reducing loan delinquency.

To corroborate the results shown in Table 2, we estimate treatment effects on the intensive margin of loan delinquency, measured as the maximum number of days borrowers are late across all their products at the end of a given week. Results are shown in Panel A of Appendix Table A1. On average, borrowers in the control group are 6 days late in repaying their loans. Receiving a message reduces the number of days the debt is past due by almost 9%. This result holds both in significance and in magnitude in regressions with strata fixed effects (column (1)), strata and week fixed effects (column (2)), and strata, week fixed effects, and individual-level controls (column (3)), adding to the evidence that our behavioral messages positively impact repayment behavior.

5.2 The Effect of Individual Behavioral Messages

We dig deeper into our main result and study treatment effects for each individual message stream by estimating equation (2). Results are shown in Panel B of Table 2. We observe that treatment effects are particularly pronounced when borrowers are exposed to messages that leverage social norms for repayment: receiving a message that emphasizes social norms reduces the probability a borrower is late by around 4.5 percentage points (or about 7.7% relative to the mean delinquency rate of the control group). Appendix Table A2 presents p-values of tests that compare the coefficients of column (3) in Panel B of Table 2. The table shows that some of the effects of the individual messages can be distinguished from each other. In particular, the effect of the social norms message can be distinguished at the 10% level from the contract reminder and the social responsibility messages. The moral norms message reduces the delinquency rate by close to 2.7 percentage points (or about 4.6% relative to the control group mean). The messages that emphasize reciprocity between the borrower and the Bank, or that emphasize the Bank's Socially Responsible Investing (SRI) do not have a robust effect on borrowers' delinquency. Finally, we note that the treatment effect of the contract reminders are close to zero and not statistically significant.

Taken together, results from Table 2 indicate that messages appealing to social and moral norms work well to reduce loan delinquency. Importantly, these findings provide novel evidence in the context of personal loans on the effectiveness of messages that appeal to social comparisons. On the contrary, messages emphasizing the SRI carried out by the Bank, and also giving the borrower the possibility to verify these investments through a web link, do not have strong effects on repayment rates.

5.3 Survival Analysis

To asses the impact of behavioral messages over time, we conduct a survival analysis. The results are shown in Figure 3, where we plot the share of borrowers who have not yet repaid in a given day for each treatment group. We use a Kaplan-Meier estimate for the first 35 days of the intervention.

There are three main aspects to discuss. First, overall and as time passes, the share of delinquent borrowers decreases, with the largest drops occurring at the beginning of the time period. Second, the share of delinquent borrowers in the control group is consistently higher than in any treatment group at any point in time, in line with our main results. Finally, individuals assigned to the social norms treatment group display the highest propensity for loan repayment compared to any other treatment group at any point in time. Therefore, messages leveraging social norms are the most effective in reducing debt delinquency, regardless of time.

5.4 Robustness Checks

This section discusses several checks that were performed to ensure the robustness of our main results. The first relates to differences in lateness across borrowers. In our experimental design, the first text message was pushed to all treated borrowers (6,026 out of 7,029) on the exact same day (May 4th, 2021). Therefore, at the start of our intervention, borrowers were late to different extents – 50% of the borrowers at the start of the intervention were at least 4 days late, and 5% were at least 17 days late. Even if the number of days past due is balanced across treatment and control groups (see Table 1), one may wonder whether our results are affected by the extent of borrowers' lateness at baseline – and particularly by late-paying borrowers who at the start of the intervention found themselves relatively closer to the 30-days cutoff, after which the Bank has the obligation to report defaulting customers to credit bureaus. To ensure that our results are robust to this concern, we estimate equations (1) and (2) controlling for the number of days past due at the start of the intervention, in addition to the usual controls. For clients with multiple products, we use the average number of days past due across products. Results are reported in columns (1), (2) and (3) of Appendix Table A3. The treatment effects of receiving any message, as well as of individual messages, remain practically unchanged.

A second concern is that our effects could be confounded by regional, time-varying characteristics (e.g., some regions of Colombia could have been differently hit by the Covid-19 pandemic, thus affecting borrowers' ability to repay their loans). We run another robustness check including region×week fixed effects; results are shown in column (4) of Appendix Table

A3. Again, our main coefficients of interest remain very similar to those reported in Table 2.

Finally, we test whether behavioral messages also reduce delinquency if we consider the complete five-weeks time period. To do so, we estimate equations (1) and (2) in the cross-section of late borrowers and use as the outcome the maximum number of days past due (across products) in the five weeks after the start of the intervention. Results are reported in Appendix Table A4. Column (2) in Panel A shows that receiving any message reduces the maximum number of days past due by 0.97 days (or 7.5% relative to the mean of the control group). Individual messages also have an effect on reducing the maximum number of days past due. As before, the largest negative impact corresponds to the social norms message that reduces the maximum number of days past due in the month by 1.67 days (or 13% relative to the mean of the control group).

The results of Sections 5.1 to 5.4 show that behavioral messages improve repayment behavior. In the next section, we explore whether these effects are more pronounced for certain population groups.

5.5 Heterogeneous Treatment Effects

In this section and the following, we investigate which borrower and loan characteristics are associated with the largest reduction in repayment delinquency in response to the behaviorally motivated messages. We start by presenting results obtained with machine learning algorithms, and then compare them with those of traditional heterogeneity analysis. The use of machine learning tools to study heterogeneity allows us to stay agnostic as to the source of heterogeneous effects in our intervention, while identifying the groups of borrowers who are more likely to benefit from treatment.

We follow Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) to estimate Conditional Average Treatment Effects (CATE) using a causal forest. Similar to Appendix Table A4, the sample is the cross-section of borrowers and the outcome of interest is the maximum number of days past due in the first month of the intervention. We implement the procedure using all the available characteristics in the Bank's administrative data.[8] The procedure results in an estimate of the CATE and its variance for each observation in the sample. More details on how we implement the procedure are provided in Online Appendix B.

To present the results, we split the sample in two groups according to the median CATE: the group of borrowers with a low reduction in days past due and the group with a high reduction.[9] We are interested in the differences in characteristics between the two groups. Table 3 reports the results when the treatment is defined as receiving any message. Columns 1 and 2 report the average value of each characteristic in the low reduction and high reduction groups, respectively. Column (3) reports the standardized difference of the coefficients shown in column (1) and column (2). Finally, column (4) provides the p-value of the test of the null hypothesis that the average of the characteristic is the same in the two groups. We adjust the p-value in each table for multiple hypothesis testing (List et al., 2019; Carlana et al., 2022; Britto et al., 2022).

While most differences shown in column (4) of Table 3 are statistically significant due to the large sample size, we focus on those whose magnitude, as measured by the standardized difference, is large. The high-reduction group, as compared to the low-reduction group, comprises individuals who are more likely to be employed, have a higher credit score, and less debt exposure. Borrowers who reduced their debt delinquency to a higher extent are also more likely to posses a credit card or a consumption loan, and to hold products with shorter maturity. The differences in these characteristic are not only statistically significant but also

[8]These are gender, age, whether the borrower is married or not, number of children, education, occupation, region of residence, monthly income, total assets, total liabilities, monthly expenses, total equity, debt size, and credit score. We also include the following loan-level characteristics (averaged across the borrower's products): days past due (at the onset of the intervention), annual interest rate, maturity, installment amount, and a dummy equal to one for borrowers with at least one credit card or consumption loan at the beginning of the intervention.

[9]The group with a low reduction in days past due has a more *positive* CATE and the group with a high reduction has a more *negative* one. This approach to presenting the results follows, for example, Carlana et al. (2022) and Britto et al. (2022).

economically meaningful. On average, borrowers in the high-response group have a credit score that is 0.18 standard deviations higher, a proportion of credit cards or consumption loans that is 0.3 standard deviations higher, and a maturity and size of the debt that are 0.3 and 0.12 standard deviations lower, respectively.

Heterogeneous treatment effects for the messages leveraging social norms are presented in Table 4. The effects of the social norms messages are concentrated among borrowers who hold unsecured financial products with shorter maturities. Borrowers in the high response group have a credit score that is 0.1 standard deviations higher, on average. We also report the results for all other individual messages in Online Appendix Tables A6 to A10. We find substantial variation in the extent to which borrowers' characteristics explain treatment effects across message streams. The highlight of these tables is that borrowers with higher socioeconomic status and credit scores are generally more responsive to the messages. Additionally, borrowers with unsecured loans also appear to be more responsive, consistent with the findings of Keys et al., 2016, who show that information campaigns had little impact on homeowners' likelihood of refinancing their mortgages.

Next we examine non-linearities in the relationship between loan and individual characteristics and the treatment effects. Figure 4 shows how the effect of receiving any message varies across different quintiles of each of the individual characteristics available through the Bank's administrative records. The figure indicates that the impact of behavioral messages on loan delinquency, though negative, is non-linear along several characteristics, including borrowers' age, debt size, and interest rate. For example, borrowers with an interest rate in the first and fifth quintiles decrease their loan delinquency to a lower extent than borrowers with an interest rate in the middle of the distribution. The corresponding results for individual messages are shown in Appendix Figures A3 to A8. These figures reveal that non-linearities vary widely depending on the message.[10] This analysis also shows that

[10]For example, while the effects of the reciprocity message are not as strong for borrowers in the first and fifth quintiles of income (Appendix Figure A4), the reduction in delinquency from the moral norms message decreases sharply with income (Appendix Figure A5).

certain messages can *increase* delinquency for some groups of borrowers. This is the case for borrowers in the lower income quintile who receive the SRI message. These findings suggests that behavioral messages can have unintended consequences for certain segments of the population, and may exacerbate loan delinquency.

Finally, we can use the estimated CATEs to investigate how the treatment effects vary across borrower groups defined by pairs of characteristics. We focus on how the credit score interacts with other variables in explaining the size of the treatment effect. Figure 5 shows the treatment effect of receiving any message for borrowers across deciles of the credit score (y-axis) and the characteristic in the x-axis.[11] Interestingly, although borrowers with higher credit scores tend to respond more to the messages on average, there is heterogeneity in response across other dimensions withing credit score decile. This suggest that credit score may not capture all the factors that predict a strong message effect.

5.6 "Traditional" Heterogeneity Analysis

In addition to the machine learning heterogeneity analyses, we study heterogeneous treatment effects in a regression framework by estimating the following equation:[12]

$$y_{iw} = \beta_0 + \beta_1 T_i + \beta_2 X_i + \beta_3 T_i \times X_i + c_w + z_i + \varepsilon_i \tag{3}$$

where y_{iw} is the probability that client i is late in week w, T_i is a dummy equal to one if borrower i received any of the messages, X_i is a dummy indicating whether borrower i has a particular pre-specified characteristic, c_w denotes week fixed effects, and z_i denote individual controls that include strata fixed effects and individual characteristics selected using the double LASSO procedure. β_3 is our coefficient of interest; it captures how the effect of the treatment differs for individuals with different values of X_i. Given the results of the previous

[11] For individual messages, the corresponding figures are reported in Appendix Figures A9 to A14.

[12] For a comparison of machine learning heterogeneity analysis versus the more conventional methods, see: https://blogs.worldbank.org/impactevaluations/whats-new-analysis-heterogeneous-treatment-effects.

sections, we consider six sources of heterogeneity: gender, age, occupation, and borrower income, credit score, and type of product.

Table A5 reports results from estimating Equation 3. Panel A presents heterogeneity results for the effect of receiving any message. According to columns (1) to (4) of Panel A, there are no important heterogeneous effects by the gender, age, occupation, nor borrower income; all the coefficients of the interaction with X_i are precisely estimated zeros. By contrast, column (5) and (6) show that the negative effect on the probability of being late is concentrated in individuals with credit scores above the median or in individuals that hold at least a credit card or a consumption loan, while no significant effects were found for borrowers with mortgages. The heterogeneity results for the individual messages are reported in Panel B of Table A5. Most of the coefficients of the interactions are imprecisely estimated but the point estimates still suggest that the effects of the individual messages are concentrated among borrowers with *high* credit scores.

In sum, in comparison to the results from the machine learning approach, results from the traditional approach appear noisier and less conclusive. However, they do confirm that the treatment effects are concentrated among borrowers with higher credit scores and unsecured financial products.

5.7 An experiment with on-time borrowers

So far, our main results show that the most effective message leverages borrowers' desire to comply with social norms. At the same time, heterogeneous treatment effects show that the impact of messages on loan repayment is particularly pronounced for individuals with high credit scores and unsecured loans. But do behavioral messages improve repayment behavior at large – that is, are they also effective at keeping non-delinquent borrowers on time? Answering this question is key to our understanding of which segments of the population should be targeted with messages to mitigate loan delinquency, and whether other interventions may be more effective for other groups.

To cast light on this question, the Bank implemented a second randomized controlled trial where the same set of treatments were administered to approximately 8,000 borrowers of the Bank that at the onset of the study were on time with their repayments. Appendix Figure A1 shows the timeline of the intervention and Appendix Figure A2 shows the experimental design. We included an additional treatment group to which we send a message stream that congratulates the borrower for being on time.

We estimate equations (1) and (2) on this group and report the results in Table 5. Panel A shows no effect of receiving any behavioral message on the probability of loan delinquency. The coefficient of each specification is precisely estimated at zero. Panel B considers the effect of individual messages and shows that none of them have any effect on on-time borrowers. Results from this second experiment corroborate our hypothesis that interventions to improve repayments are effective tools when borrowers are marginally struggling to repay. On the contrary, behavioral messages do not appear to be equally effective in improving the behavior of very delinquent borrowers, who possibly would need a bigger “push”, for example through financial literacy training (Bertrand and Morse, 2011; Lusardi and Tufano, 2015), than a simple message. Similarly, they do not seem to be the right tool to prevent on-time borrowers from falling into loan delinquency.

5.8 Gains from the Intervention

In this final section, we provide a back-of-the-envelope calculation of the additional benefits to the Bank if it were to send the social norms message to the pool of late borrowers in a given month. We focus on the increase in profits that result from the time value of money. If a customer pays on time then the Bank can use that money to invest, for example by lending the proceeds to another customer. On the other hand, bank customers can gain from the intervention thanks to the reduction in late payment fees and additional interest rates.

Regarding the reduction of costs for the Bank from loan delinquency, recall that the social norms message leads to a reduction of 1.67 days past-due on average per month.[13] From Table 1, the yearly average interest rate (across products) is 22% or approximately 0.06% per-day (= 22/365%). Furthermore, from the Bank administrative data, we can recover the average amount our late borrowers had to pay at the beginning of the intervention and on which they were late. This number is around 652 thousand Colombian Pesos. Therefore the amount of money saved per month by the Bank on each borrower that receives the social norms message is around 653 pesos ($= 1.67 \times 652,000 \times 0.0006$). On May 4th, 2021 we selected our experimental sample of 7,000 late borrowers from a pool of late borrowers of around 120,000. Therefore, the total benefit of sending the social norms message to this group would have been $120,000 \times 653 = 78,360$ thousand COP (approximately 20,980 USD). This figure is considerable and corresponds to the benefits of applying the intervention to the population of late clients in a given month. This can be repeated month by month leading to even higher profits.

6 Conclusions

The idea that individuals respond to social and moral motivations is now widely recognized across various domains, including markets, communities, and interactions with the state. This principle should hold true in the financial and credit markets as well. In this study, we conduct a large-scale randomized controlled trial with a major Colombian bank to evaluate the effectiveness of behaviorally-motivated messages in improving the repayment behavior of delinquent borrowers. We randomly assign six different streams of text messages to a sample of 7,029 customers at the individual level.

Our setting allows us to push the frontier on behavioral interventions in consumer finance in two important ways. Firstly, we test multiple behavioral interventions on a large, homogeneous population of borrowers, which allows us to compare the effectiveness of

[13]See results obtained in the cross-section of borrowers reported in Appendix Table A4 and the discussion in Section 5.4.

different behavioral drivers of loan repayment such as reminders, reciprocity, moral norms, and social norms. Secondly, we use a rich set of administrative data from the Bank and employ machine learning algorithms to study the heterogeneity of treatment effects.

We find that receiving such messages has a positive and substantial impact on repayment behavior, with a 4% increase in repayment rates observed. Our results are precisely estimated and remain robust to the inclusion of time fixed-effects and individual-level controls. Importantly, we find that messages that reference social norms have the largest impact among delinquent borrowers, suggesting a social dimension to repayment decisions. Further heterogeneity analysis reveals that our results are concentrated among relatively better-off borrowers, with higher credit scores and unsecured loans. However, a second experiment with on-time borrowers finds no effects from these messages.

Our findings lead to the three important observations. First, the strong effect of the social norms message suggests that payment decisions are not influenced solely by financial concerns. Second, targeting individuals based on their individual characteristics can result in higher returns. When strategies to maintain a healthy debt portfolio fail, targeted campaigns with behavioral messages may prove to be promising and cost-effective tools to reduce loan delinquency. Finally, our results suggest that behaviorally-motivated messages may not always be the most effective intervention to reduce delinquency across all population segments. In some cases, certain messages may even exacerbate loan delinquency, and may be ineffective with borrowers who are currently on time but may become delinquent in the future. Taking these insights into account becomes especially important during times of economic downturn when marginally vulnerable borrowers seek additional or emergency credit. Policies that help these individuals maintain a good repayment behavior can ensure continued access to credit.

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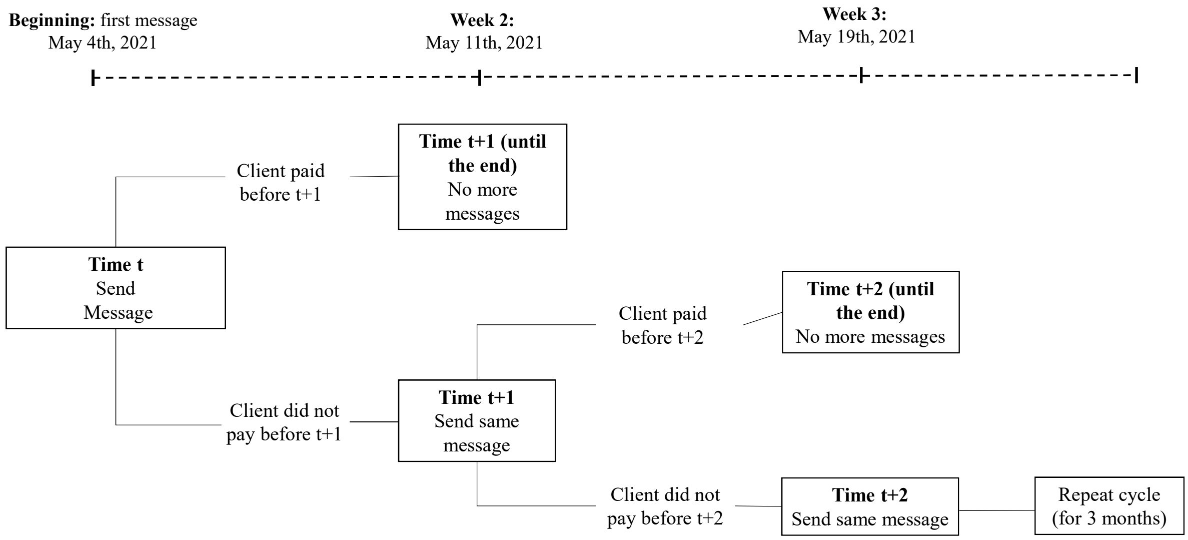
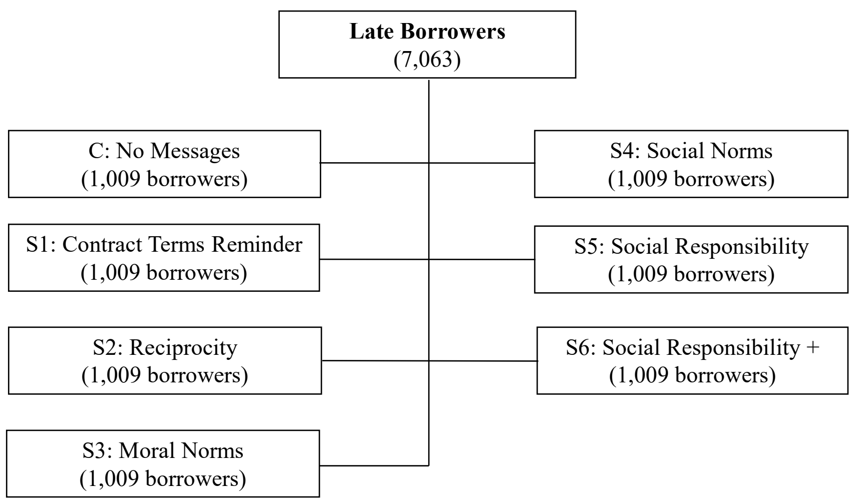
Figure 1: Intervention Timeline



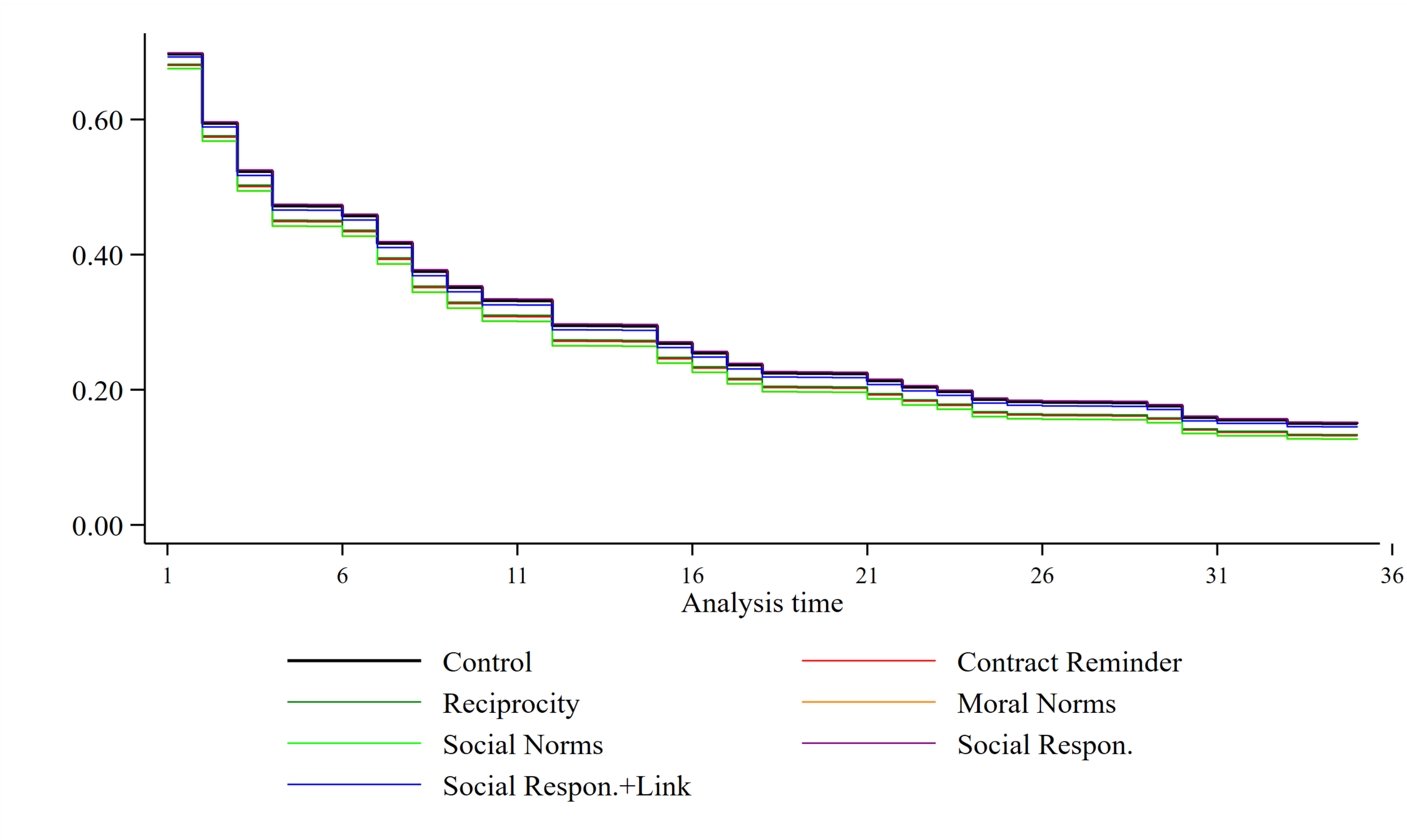
Notes: The figure shows the timeline of our intervention with late-paying borrowers. The first text message was pushed to all treated borrowers in the experiment on May 4th, 2021. Borrowers received messages on a weekly basis for 3 months until they fully repaid.

Figure 2: RCT design



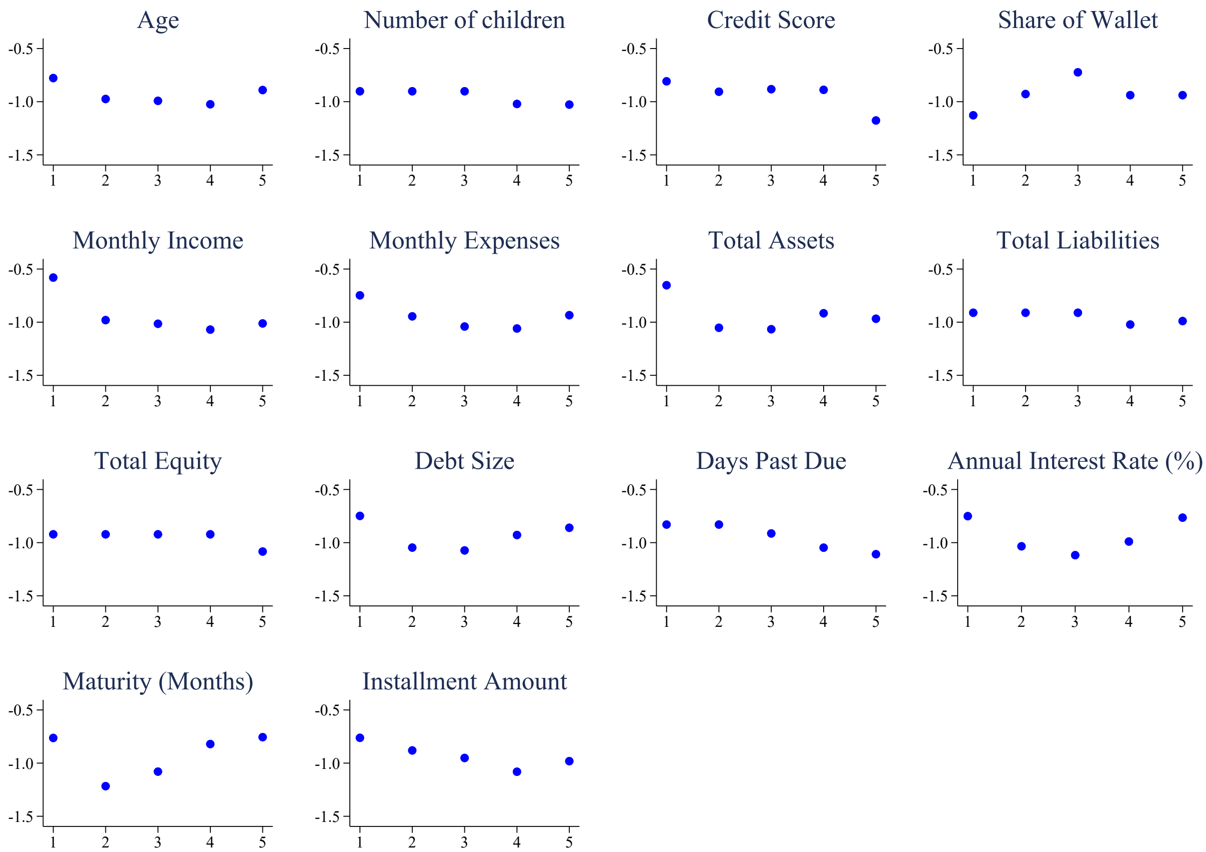
Notes: The figure shows the design of our intervention. We randomly selected 7,063 clients who were late on May 3rd, 2021, and sent the first set of messages to those who were still late on May 4th (7,029 borrowers). The 7,063 late-paying clients were randomly allocated with equal probability to either the control group or to one of six different message streams.

Figure 3: Duration Analysis



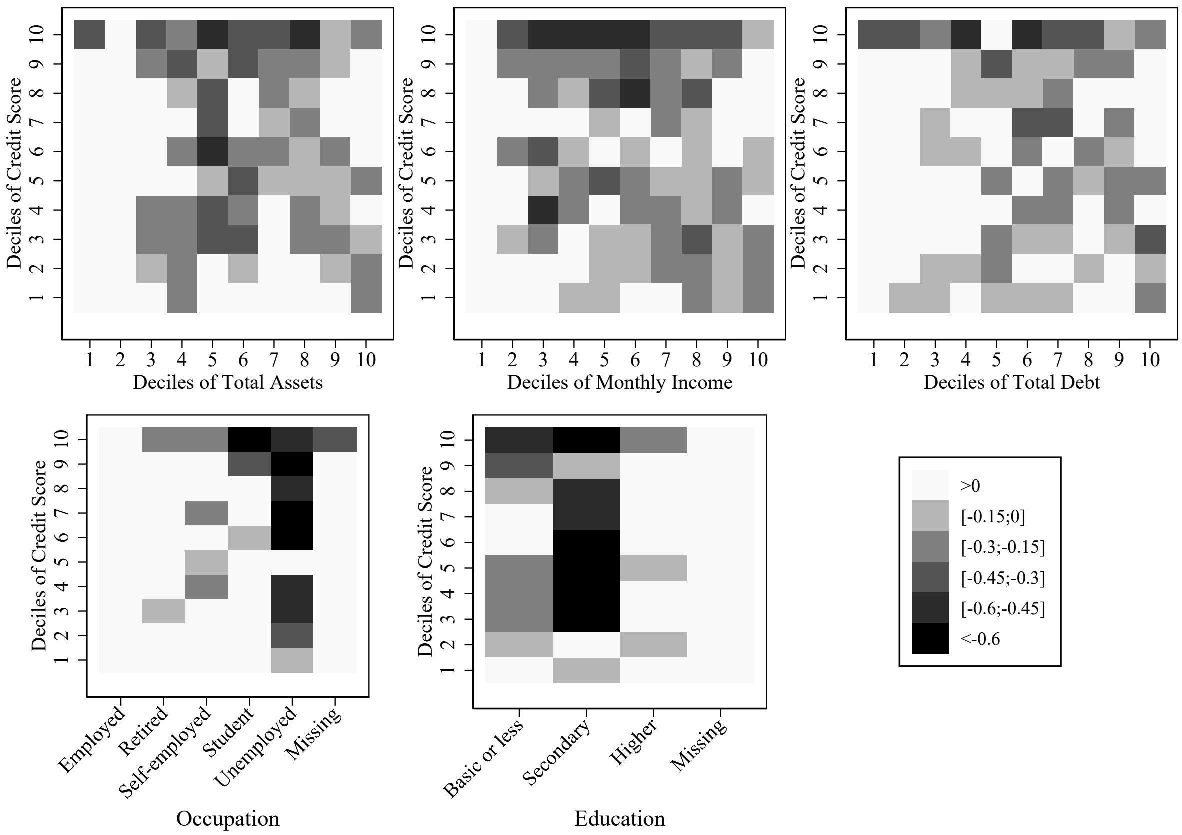
Notes: This figure shows Kaplan-Meir estimates of the survival probability of late borrowers, where survival is defined as having at least one late loan product. The y-axis shows the fraction of borrowers who have not yet repaid.

Figure 4: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Any Message



Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving any message.

Figure 5: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Any Message



Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving any message.

Table 1: Balance Checks – Late-paying Borrowers

	Control group			Treatment (pooled)			T-test
	N	Mean	Sd	N	Mean	Sd	(p-value)
A. Borrower Characteristics							
Female	1,003	0.50	0.50	6,026	0.51	0.50	0.61
Age	1,003	42.35	13.00	6,022	41.91	13.22	0.32
Couple	856	0.47	0.50	5,119	0.49	0.50	0.45
Number of children	1,003	0.46	0.99	6,025	0.47	1.00	0.82
Education: Basic or Less	377	0.10	0.30	2,230	0.10	0.30	0.98
Education: Secondary	377	0.89	0.32	2,230	0.88	0.32	0.64
Education: Higher	377	0.01	0.10	2,230	0.02	0.14	0.24
Occupation: Employed	950	0.83	0.38	5,722	0.83	0.38	0.89
Occupation: Retired	950	0.07	0.25	5,722	0.07	0.25	0.76
Occupation: Self-employed	950	0.07	0.26	5,722	0.07	0.25	0.70
Occupation: Student	950	0.03	0.16	5,722	0.03	0.18	0.21
Occupation: Unemployed	950	0.01	0.08	5,722	0.01	0.08	0.96
Region Amazonia (South)	970	0.01	0.08	5,832	0.01	0.10	0.45
Region Andina (Center)	970	0.65	0.48	5,832	0.64	0.48	0.51
Region Caribe (North)	970	0.13	0.34	5,832	0.14	0.35	0.51
Region Pacifico (West)	970	0.17	0.37	5,832	0.18	0.38	0.45
Region Orinoquia (East)	970	0.04	0.18	5,832	0.03	0.16	0.20
Region Outside	970	0.01	0.10	5,832	0.01	0.09	0.51
B. Financial Characteristics							
Credit Score	1,003	0.69	0.22	6,026	0.68	0.22	0.91
Share of Wallet	848	69.49	29.89	4,982	69.30	30.72	0.87
Monthly Income	1,003	4,388	6,513	6,026	4,165	5,907	0.28
Debt size	1,003	29,089	43,174	6,026	30,451	48,524	0.40
Days Past Due	1003	5.78	5.46	6,026	5.80	5.69	0.89
Annual Interest Rate (%)	979	21.78	9.13	5,867	22.14	9.28	0.26
Maturity (Months)	979	107.38	79.68	5,867	109.05	82.29	0.56

Notes: This table displays summary statistics of different borrower characteristics, separated between borrowers in the control group and borrowers in any of the treatment arms. N is the number of observations for which the variable is available. Couple is a dummy equal to one for borrowers in a couple. Share of wallet is the fraction of the debt that the Bank holds relative to the debt of the borrower from other banks (this information comes from credit bureaus). Monthly income and debt size are in thousands of Colombian pesos. Primary education or less, secondary education, and higher education are dummies for the corresponding educational attainment level. The occupation variables are dummies for the corresponding occupation level. The region variables are region dummies for the corresponding region of Colombia. To obtain days past due, annual interest rate, and maturity we average across all the loan products of each borrower.

Table 2: The Effect of Behavioral Messages

	Late in Week		
	A. Pooled Treatments		
	(1)	(2)	(3)
Any message	-0.0227**	-0.0228**	-0.0220**
	(0.0112)	(0.0112)	(0.0112)
Outcome mean (control)	0.593	0.593	0.593
Observations	34,781	34,781	34,781
	B. Separate Treatments		
Contract Reminder	-0.0159	-0.0159	-0.0148
	(0.0146)	(0.0146)	(0.0145)
Reciprocity	-0.0211	-0.0212	-0.0209
	(0.0145)	(0.0145)	(0.0144)
Moral Norms	-0.0252*	-0.0251*	-0.0247*
	(0.0145)	(0.0145)	(0.0144)
Social Norms	-0.0388***	-0.0388***	-0.0398***
	(0.0146)	(0.0146)	(0.0145)
Social Responsibility	-0.0135	-0.0137	-0.0118
	(0.0146)	(0.0146)	(0.0145)
Social Responsibility + Link	-0.0217	-0.0217	-0.0204
	(0.0146)	(0.0146)	(0.0146)
Outcome mean (control)	0.593	0.593	0.593
Observations	34,781	34,781	34,781
Stratum FE	Yes	Yes	Yes
Week FE	No	Yes	Yes
Controls (LASSO)	No	No	Yes

Notes: This table shows treatment effects of behavioral messages in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (3), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table 3: Conditional Average Treatment Effect (CATE), Any Message

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.53	0.48	-0.063	0.0003
Age	41.67	42.12	0.024	0.8053
Couple: No	0.46	0.41	-0.075	0.0003
Couple: Yes	0.36	0.47	0.048	0.0003
Couple: Missing	0.18	0.13	-0.098	0.0003
Number of children	0.41	0.52	0.079	0.0003
Education: Basic or Less	0.04	0.04	-0.002	0.9010
Education: Secondary	0.01	0.01	0.032	0.5737
Education: Higher	0.31	0.35	0.055	0.0003
Education: Missing	0.65	0.61	-0.058	0.0003
Occupation: Employed	0.73	0.84	0.178	0.0003
Occupation: Retired	0.08	0.05	-0.089	0.0003
Occupation: Self-Employed	0.06	0.07	0.03	0.6363
Occupation: Student	0.04	0.02	-0.081	0.0003
Occupation: Unemployed	0.01	0.01	-0.018	0.8970
Occup.: Missing	0.08	0.02	-0.199	0.0003
Region: Amazonia South	0.01	0.01	0.017	0.9007
Region: Andina Center	0.60	0.64	0.067	0.0003
Region: Caribe North	0.13	0.13	0.003	0.9807
Region: Pacifico West	0.17	0.16	-0.021	0.8677
Region: Orinoquia East	0.02	0.03	0.053	0.0267
Region: Outside	0.01	0.01	0.022	0.8610
Region: Missing	0.06	0.01	-0.215	0.0003
B. Financial Characteristics				
Credit Score	0.66	0.71	0.177	0.0003
Share of Wallet	75.31	66.71	-0.219	0.0003
Monthly Income	3,735.9	4,658.5	0.109	0.0003
Monthly Expenses	1,696.9	701.9	-0.019	0.9327
Total Assets	69,338.2	71,125.4	0.008	0.9640
Total Liabilities	8,960.3	7,247.0	-0.026	0.8063
Total Equity	7,643.8	10,827.6	0.027	0.7897
Debt Size	34,383.0	26,131.3	-0.123	0.0003
Days Past Due	5.22	6.38	0.145	0.0003
Annual Interest Rate(%)	22.25	21.78	-0.038	0.3173
Maturity (Months)	125.88	89.78	-0.323	0.0003
Installment Amount	861.92	897.55	0.012	0.9130
Credit Card or Consumption Loan	0.60	0.79	0.293	0.0003

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving any message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column (3) reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Table 4: Conditional Average Treatment Effect (CATE), Social Norms

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.53	0.47	-0.087	0.0650
Age	39.67	44.01	0.242	0.0003
Couple: No	0.42	0.44	0.018	0.9833
Couple: Yes	0.39	0.45	0.089	0.0610
Couple: Missing	0.19	0.12	-0.147	0.0003
Number of children	0.36	0.56	0.138	0.0003
Education: Basic or Less	0.02	0.05	0.142	0.0003
Education: Secondary	0.00	0.00	0.014	0.9683
Education: Higher	0.38	0.27	-0.158	0.0003
Education: Missing	0.60	0.67	0.097	0.0520
Occupation: Employed	0.77	0.80	0.048	0.7757
Occupation: Retired	0.04	0.08	0.115	0.0003
Occupation: Self-Employed	0.06	0.07	0.006	0.9813
Occupation: Student	0.03	0.03	-0.013	0.9927
Occupation: Unemployed	0.00	0.01	0.02	0.9937
Occup.: Missing	0.09	0.03	-0.206	0.0003
Region: Amazonia South	0.00	0.01	0.044	0.8680
Region: Andina Center	0.57	0.66	0.125	0.0003
Region: Caribe North	0.13	0.13	0	0.9927
Region: Pacifico West	0.18	0.16	-0.032	0.9760
Region: Orinoquia East	0.04	0.03	-0.02	0.9950
Region: Outside	0.01	0.00	-0.055	0.7633
Region: Missing	0.07	0.00	-0.244	0.0003
B. Financial Characteristics				
Credit Score	0.67	0.70	0.097	0.0130
Share of Wallet	69.74	71.49	0.045	0.8583
Monthly Income	4,954.2	3,377.6	-0.187	0.0003
Monthly Expenses	4,010.6	603.0	-0.036	0.9913
Total Assets	92,994.3	44,827.7	-0.227	0.0003
Total Liabilities	12,398.6	4,410.7	-0.131	0.0003
Total Equity	14,234.3	8,723.0	-0.05	0.7877
Debt Size	41,590.0	16,809.4	-0.389	0.0003
Days Past Due	5.23	6.43	0.147	0.0003
Annual Interest Rate (%)	21.27	22.26	0.077	0.2047
Maturity (Months)	133.11	83.01	-0.463	0.0003
Installment Amount	898.11	821.88	-0.026	0.9860
Credit Card or Consumption Loan	0.56	0.83	0.446	0.0003

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving the social norms message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column (3) reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Table 5: The Effect of Nudges, On-Time Borrowers

	Late in Week		
	A. Pooled Treatments		
	(1)	(2)	(3)
Any message	-0.00243	-0.00236	-0.0028
	(0.00736)	(0.00735)	(0.00735)
Outcome mean (control)	0.235	0.235	0.235
Observations	39,548	39,548	39,548
	B. Separate Treatments		
Contract Reminder	-0.00982	-0.00940	-0.00971
	(0.00964)	(0.00963)	(0.00963)
Reciprocity	-0.0117	-0.0117	-0.0133
	(0.00971)	(0.00970)	(0.00966)
Moral Norms	-0.0121	-0.0123	-0.0119
	(0.00964)	(0.00963)	(0.00961)
Social Norms	0.00504	0.00491	0.00506
	(0.00996)	(0.00995)	(0.00991)
Social Responsibility	0.0124	0.0123	0.0119
	(0.00971)	(0.00970)	(0.00968)
Social Responsibility + Link	0.00840	0.00855	0.00902
	(0.00995)	(0.00995)	(0.00995)
Congratulations	-0.00920	-0.00882	-0.00844
	(0.00964)	(0.00963)	(0.00958)
Outcome mean (control)	0.235	0.235	0.235
Observations	39,548	39,548	39,548
Stratum FE	Yes	Yes	Yes
Week FE	No	Yes	Yes
Controls (LASSO)	No	No	Yes

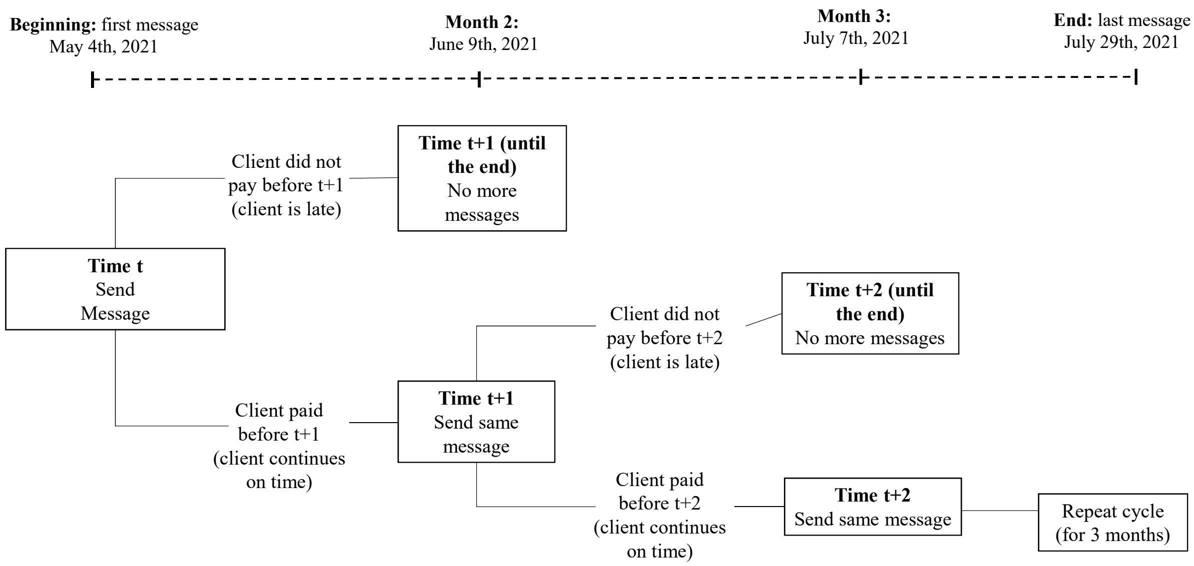
Notes: This table shows treatment effects of behavioral messages in a sample of 8,019 on-time borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (3), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

APPENDIX

(for online publication)

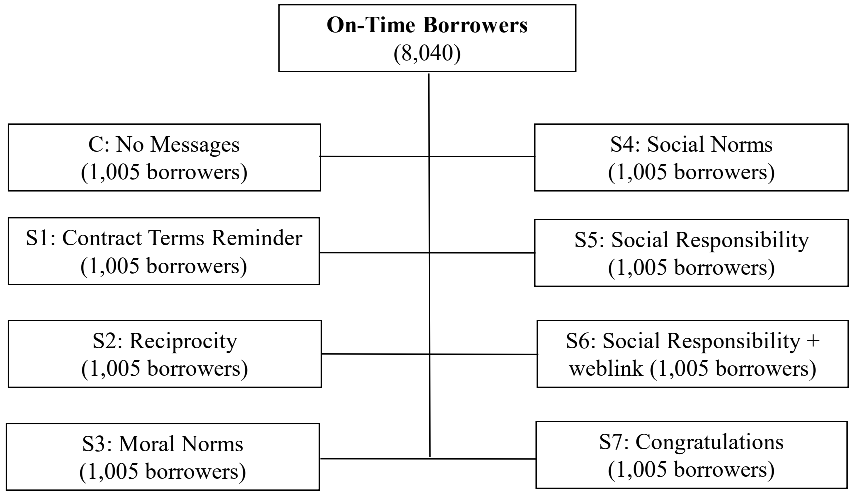
Appendix A Additional Figures and Tables

Figure A1: Intervention Timeline, On-time Borrowers



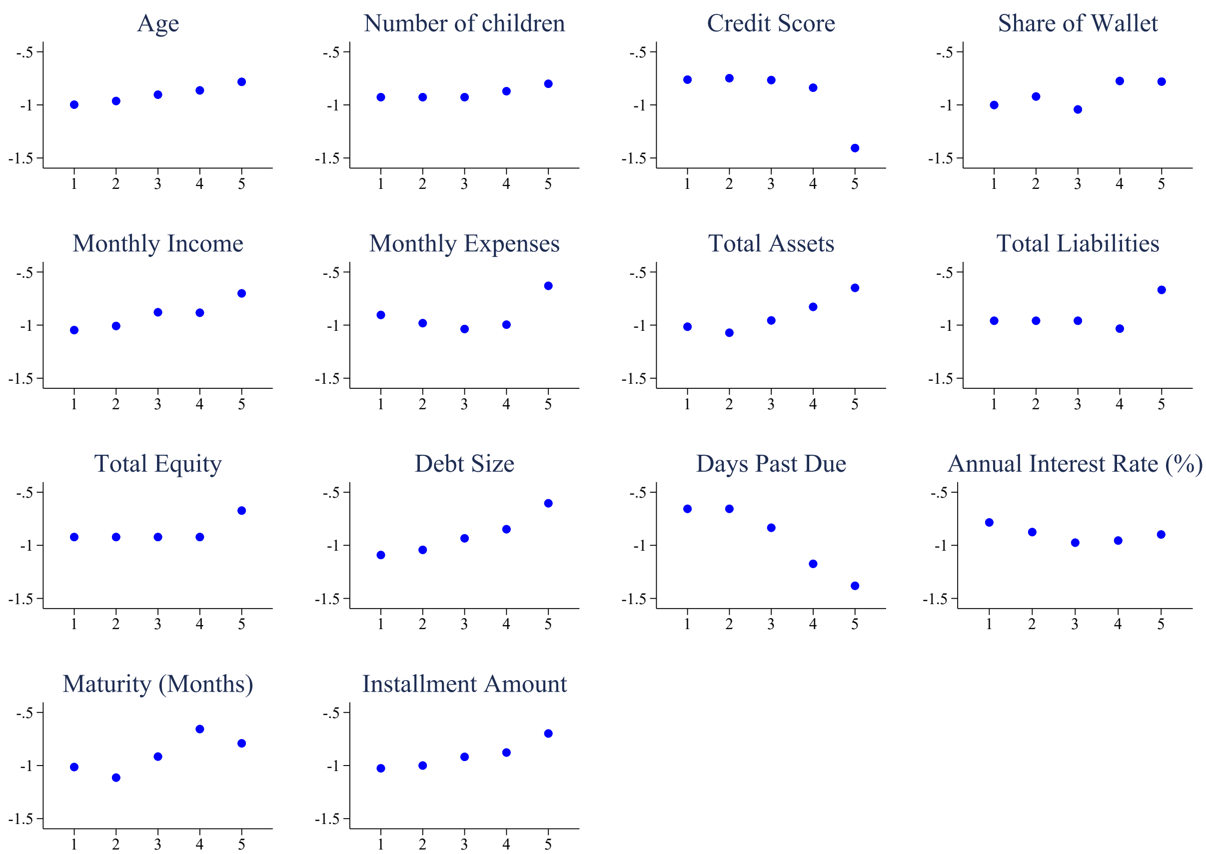
Notes: The figure shows the timeline of our intervention with on-time borrowers. The first text message was pushed to all treated borrowers in the experiment on May 4th, 2021. Borrowers received messages on a monthly basis for 3 months until they became delinquent.

Figure A2: RCT design, On-time Borrowers



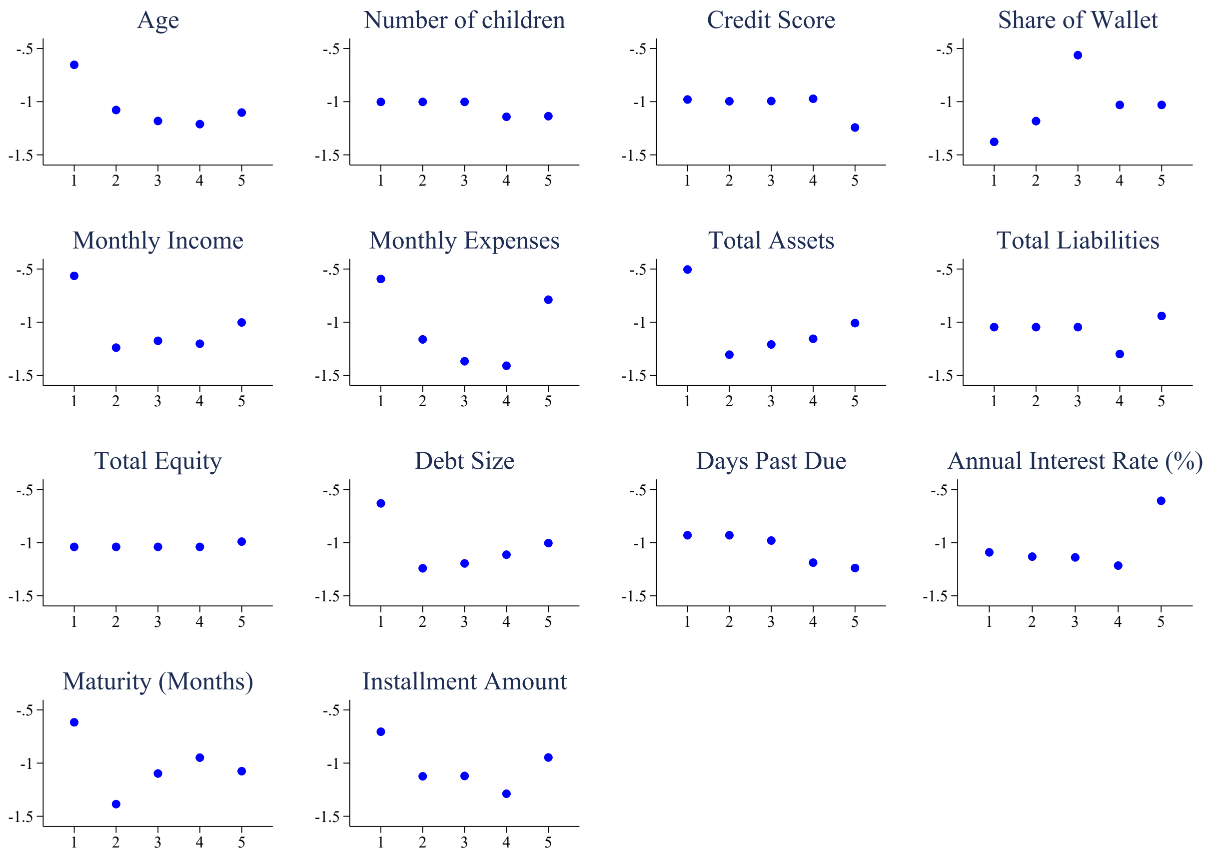
Notes: The figure shows the design of our intervention with on-time borrowers. We randomly selected 8,040 clients who were up to date with their payments on May 3rd, 2021, and sent the first set of messages to those who were still up date on May 4th (8,019 borrowers). The 8,040 clients were randomly allocated with equal probability to either the control group or to one of seven different message streams.

Figure A3: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Contract Reminder



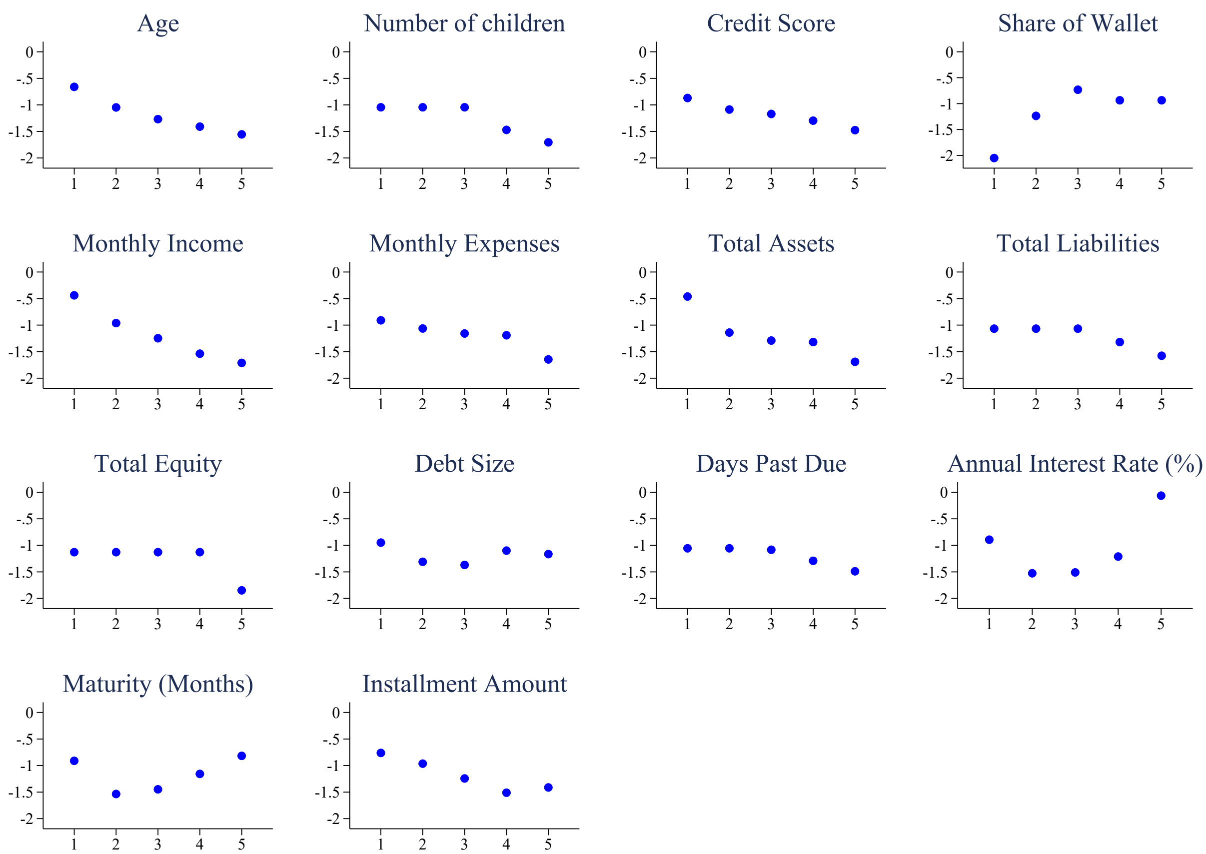
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving the contract reminder message.

Figure A4: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Reciprocity



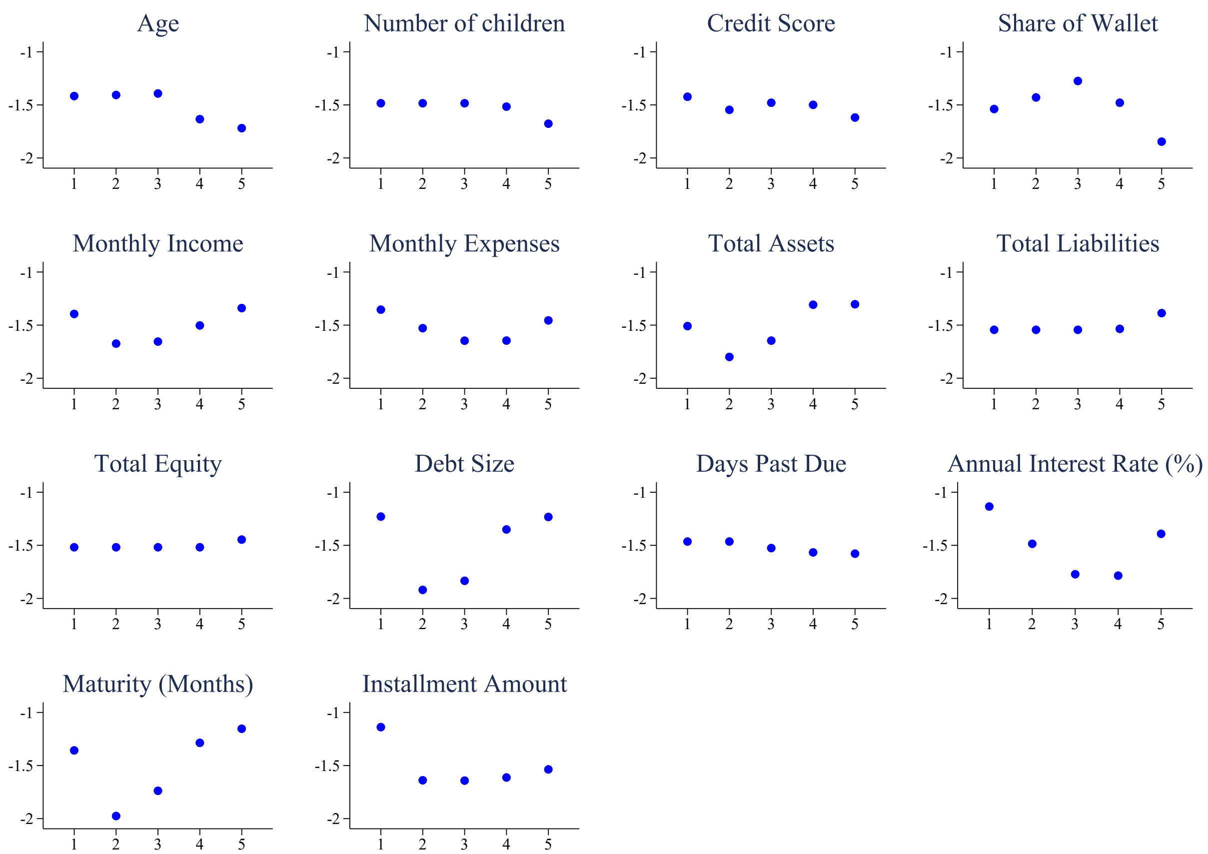
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving the reciprocity message.

Figure A5: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Moral Norms



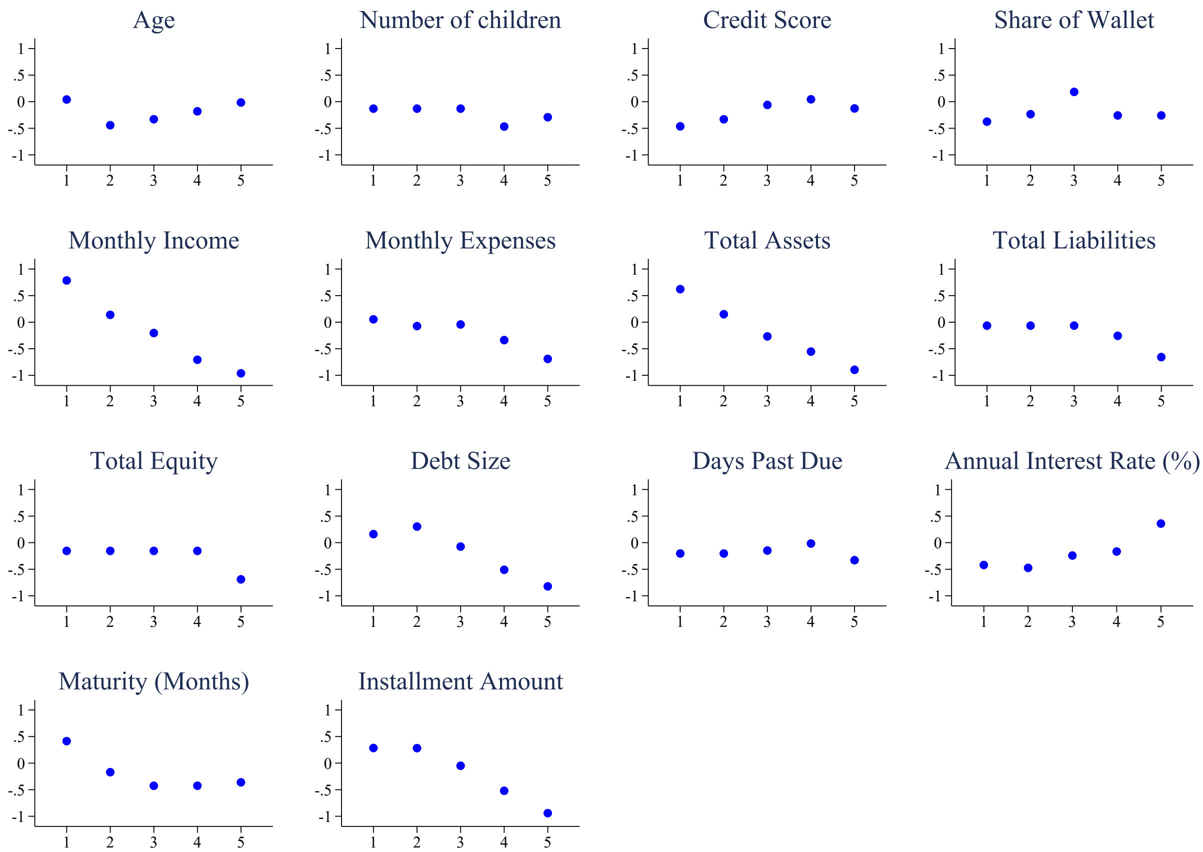
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving the moral norms message.

Figure A6: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Social Norms



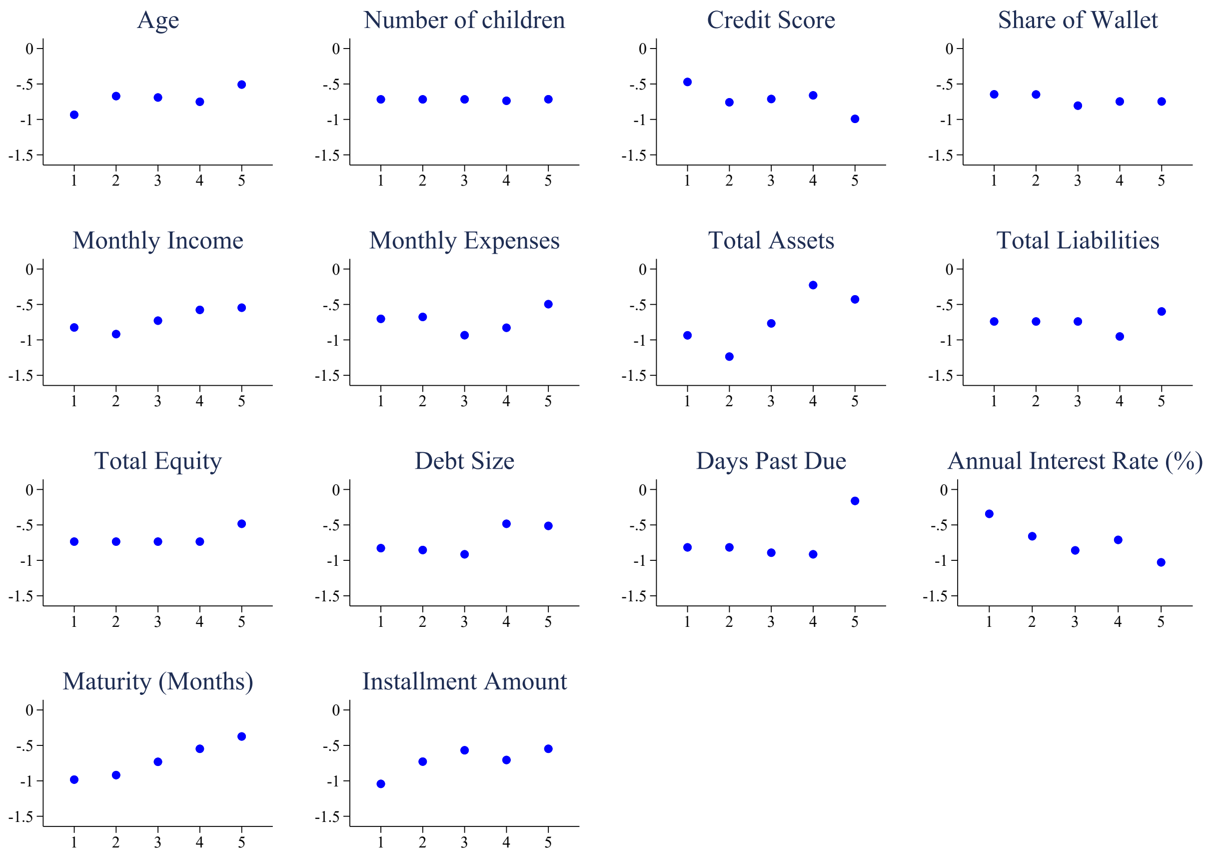
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving the social norms message.

Figure A7: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Social Responsibility



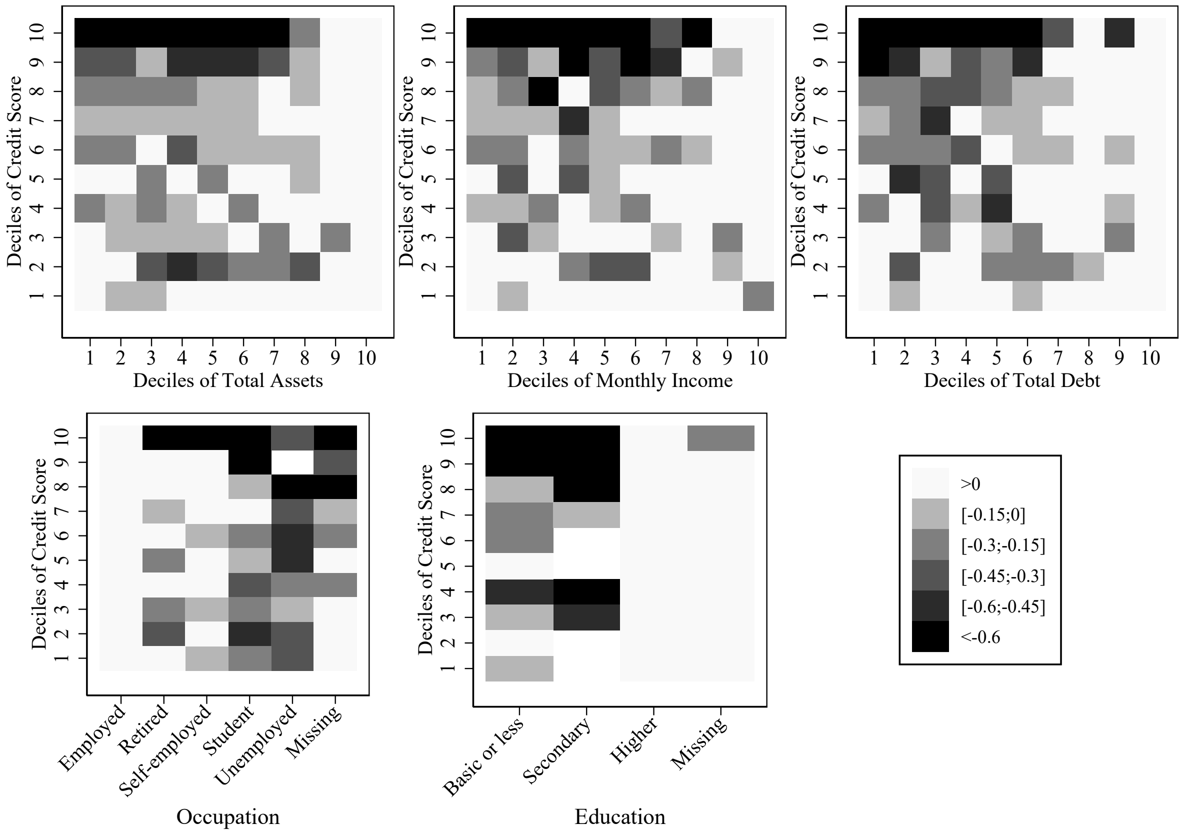
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving the social responsibility message.

Figure A8: Conditional Average Treatment Effects by Quintiles of Borrower characteristics, Social Responsibility + Link



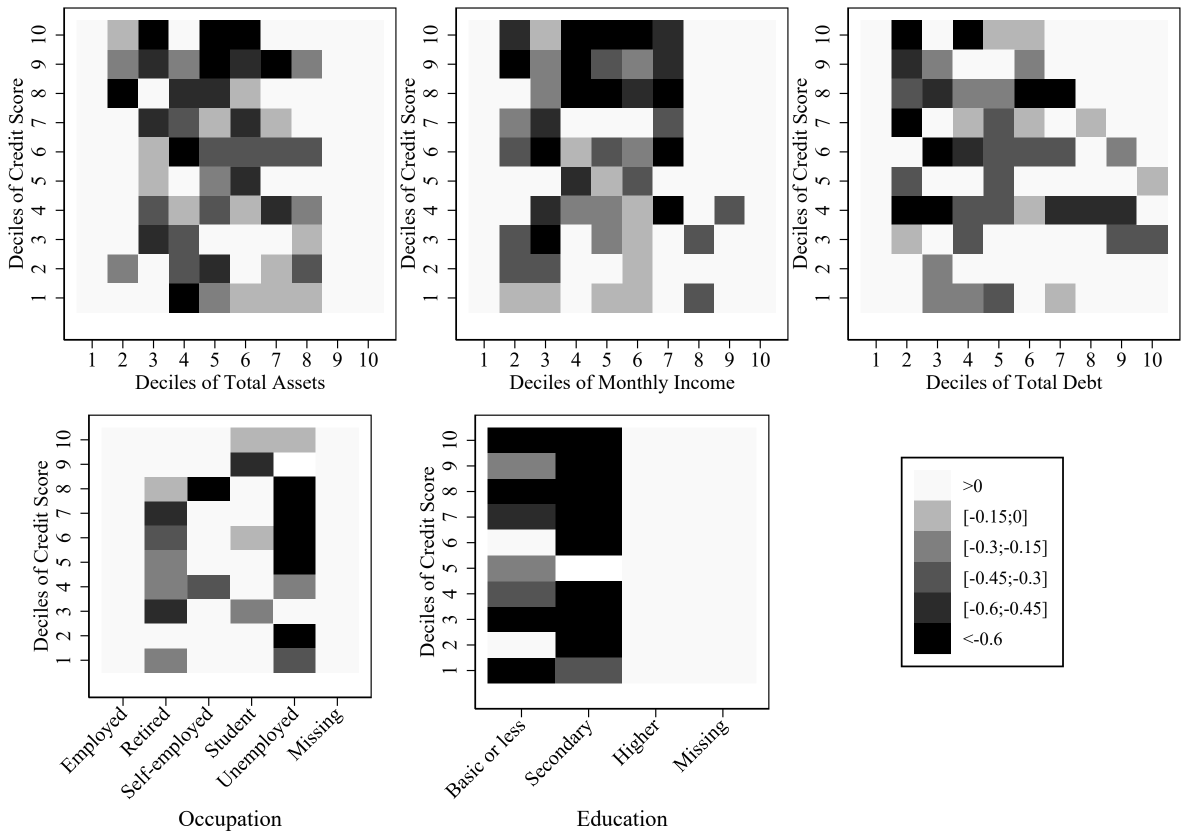
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) by quintiles of different individual characteristics. The treatment group consists of individuals receiving the social responsibility + link message.

Figure A9: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Contract reminder



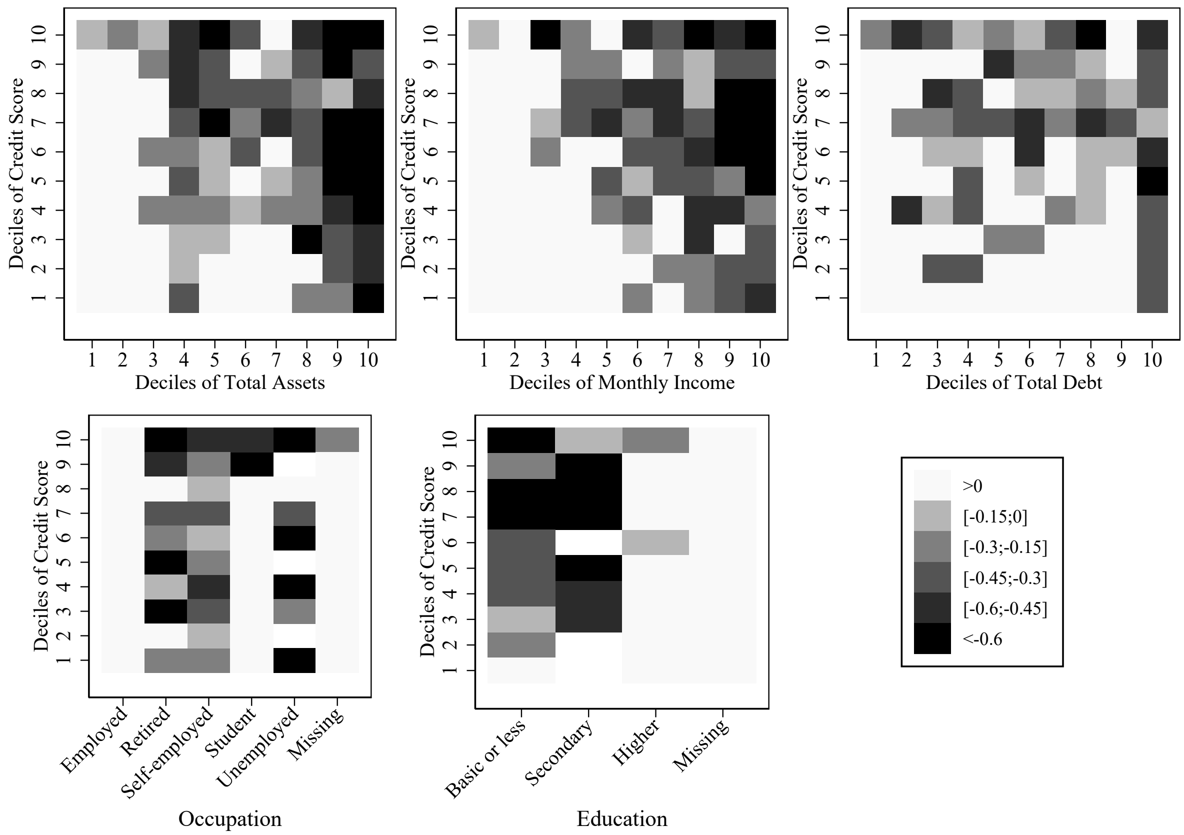
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving the contract reminder message.

Figure A10: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Reciprocity



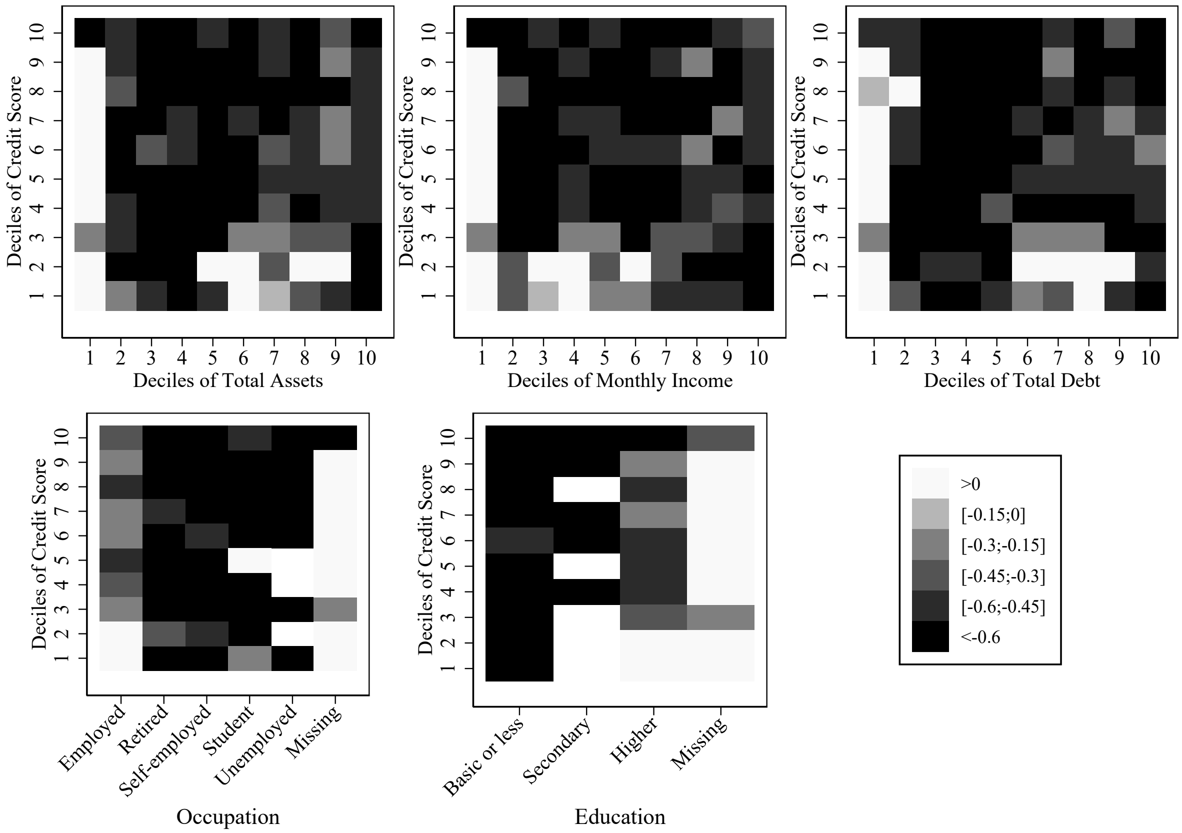
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving the reciprocity message.

Figure A11: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Moral Norms



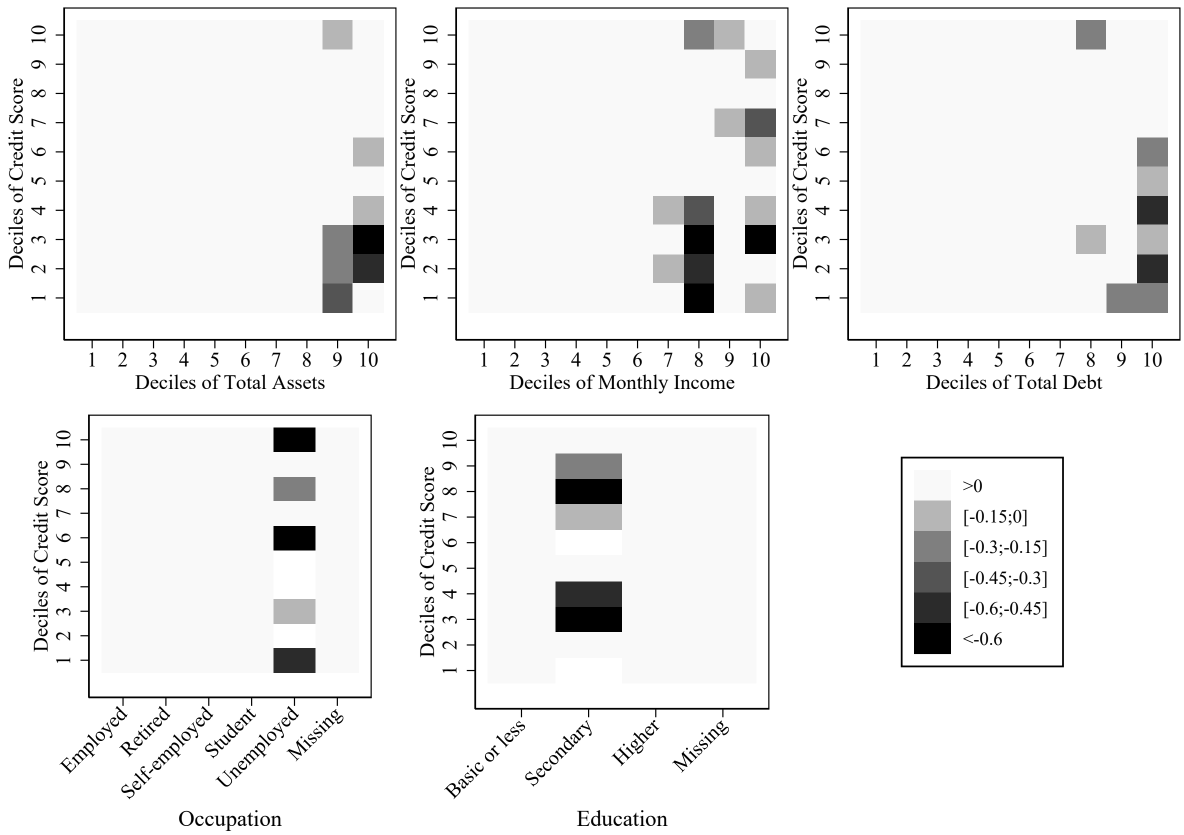
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving the moral norms message.

Figure A12: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Social Norms



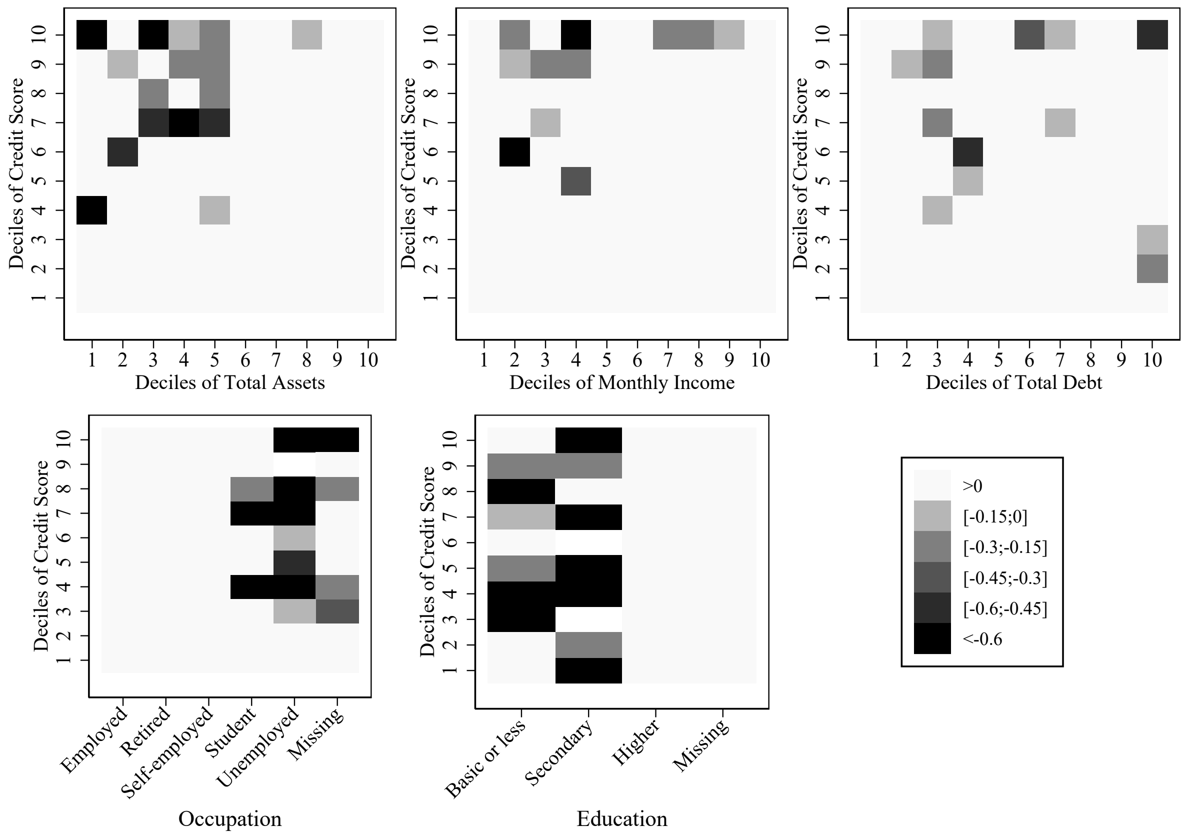
Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving the social norms message.

Figure A13: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Social Responsibility



Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving the social responsibility message.

Figure A14: Conditional Average Treatment Effects by Credit Score and Other Characteristics, Social Responsibility + Link



Notes: This figure shows the average predicted Conditional Average Treatment Effect (CATE) for groups of borrowers defined by credit score decile and different values of the characteristic listed in the x-axis of each plot. The treatment group consists of individuals receiving the social responsibility + link message.

Table A1: The Effect of Behavioral Messages, Days Past Due

	Days Past Due		
	A. Pooled Treatments		
	(1)	(2)	(3)
Any message	-0.554*	-0.555*	-0.567*
	(0.313)	(0.313)	-0.312
Outcome mean (control)	6.43	6.43	6.43
Observations	34,781	34,781	34,781
	B. Separate Treatments		
Contract Reminder	-0.639	-0.640	-0.630
	(0.393)	(0.393)	(0.391)
Reciprocity	-0.601	-0.601	-0.611
	(0.403)	(0.403)	(0.400)
Moral Norms	-0.653	-0.652	-0.664*
	(0.401)	(0.401)	(0.399)
Social Norms	-0.921**	-0.922**	-0.991**
	(0.396)	(0.396)	(0.394)
Social Responsibility	-0.141	-0.145	-0.133
	(0.408)	(0.408)	(0.406)
Social Responsibility + Link	-0.368	-0.368	-0.375
	(0.436)	(0.436)	(0.434)
Outcome mean (control)	6.43	6.43	6.43
Observations	34,781	34,781	28,937
Stratum FE	Yes	Yes	Yes
Week FE	No	Yes	Yes
Controls (LASSO)	No	No	Yes

Notes: This table shows treatment effects of behavioral messages in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is the number of days past due at the end of the week. For borrowers with multiple products, we take the maximum number of days past due at the end of the week across products. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (3), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A2: Differences Across Treatment Effects, p-values

	Contract Reminder	Recipro.	Moral Norms	Social Norms	Social R.	Social R. + link
Contract Reminder		0.6724	0.4882	0.0812	0.8316	0.6986
Reciprocity	0.6724		0.7847	0.1830	0.5241	0.9758
Moral Norms	0.4882	0.7847		0.2894	0.3639	0.7643
Social Norms	0.0812	0.1830	0.2894		0.0502	0.1792
Social R.	0.8316	0.5241	0.3639	0.0502		0.5497
Social R. + Link	0.6986	0.9758	0.7643	0.1792	0.5497	

Notes: This table presents p-values of tests that compare the effect of each individual message on the probability of being late in a given week, as reported in column (3), Panel B, Table 2. For each comparison, we report the p-value of a test where the null hypothesis is that the effect of the message listed on the line is equal to the effect of the message listed in the column.

Table A3: The Effect of Behavioral Messages, Additional Controls

	Days Past Due			
	A. Pooled Treatments			
	(1)	(2)	(3)	(4)
Any message	-0.0227**	-0.0228**	-0.0221**	-0.0244**
	(0.0112)	(0.0112)	(0.0112)	(0.0114)
Outcome mean (control)	0.593	0.593	0.593	0.591
Observations	34,781	34,781	34,781	33,686
	B. Separate Treatments			
Contract Reminder	-0.0158	-0.0158	-0.0148	-0.0171
	(0.0146)	(0.0146)	(0.0145)	(0.0148)
Reciprocity	-0.0215	-0.0215	-0.021	-0.0257*
	(0.0145)	(0.0145)	(0.0144)	(0.0147)
Moral Norms	-0.0253*	-0.0253*	-0.0248*	-0.0245*
	(0.0145)	(0.0145)	(0.0144)	(0.0147)
Social Norms	-0.0389***	-0.0389***	-0.0398***	-0.0439***
	(0.0146)	(0.0146)	(0.0145)	(0.0148)
Social Responsibility	-0.0128	-0.0131	-0.0115	-0.0118
	(0.0146)	(0.0146)	(0.0145)	(0.0147)
Social Responsibility (Link)	-0.0218	-0.0219	-0.0205	-0.0227
	(0.0146)	(0.0146)	(0.0146)	(0.0149)
Outcome mean (control)	0.593	0.593	0.593	0.591
Observations	34,781	34,781	34,781	33,686
Stratum FE	Yes	Yes	Yes	Yes
Week FE	No	Yes	Yes	No
Controls (LASSO)	No	No	Yes	Yes
Region-week FE	No	No	No	Yes

Notes: This table shows treatment effects of behavioral messages in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. All columns include as an additional control the number of days past due of the borrower at the beginning of the intervention. All columns include week fixed effects except for column (4) that includes week fixed effects interacted with region fixed effects. In columns (3) and (4), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A4: The Effect of Behavioral Messages, Cross Section

	Max Days Past Due	
	A. Pooled Treatments	
	(1)	(2)
Any Message	-0.952**	-0.967**
	(0.458)	(0.455)
Outcome mean (control)	12.93	12.93
Observations	7,029	7,029
	B. Separate Treatments	
Contract Reminder	-0.849	-0.825
	(0.599)	(0.596)
Reciprocity	-1.061*	-1.075*
	(0.600)	(0.596)
Moral Norms	-1.196**	-1.210**
	(0.599)	(0.596)
Social Norms	-1.570***	-1.672***
	(0.599)	(0.596)
Social Responsibility	-0.229	-0.212
	(0.600)	(0.596)
Social Responsibility + Link	-0.804	-0.807
	(0.599)	(0.596)
Outcome mean (control)	12.93	12.93
Observations	7,029	7,029
Stratum FE	Yes	Yes
Controls (LASSO)	No	Yes

Notes: This table shows treatment effects of behavioral messages in a cross-section of 7,029 late borrowers. The dependent variable is the maximum number of days past due of the borrower (across products) in a five-week time window after the start of the intervention. In Panel A, the variable of interest is a dummy equal to one if the borrower was assigned to receive any of the message streams. In Panel B, the outcomes of interest are dummies indicating the message stream to which the borrower was assigned. Stratum fixed effects are dummies to denote the stratum of the borrower, which is defined by the interaction between quintiles of a credit score computed by the Bank and the Bank segment. In column (2), we use PDS Lasso to select covariates (Belloni et al., 2014). Standard errors are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A5: Heterogeneous Effects, Traditional Approach

	Late in Week					
	A. Pooled Treatments					
	X_i: Female (1)	X_i: Age > median (2)	X_i: Employed (3)	X_i: High Score (4)	X_i: Inc. > median (5)	X_i: C.Card C.Loan (6)
Any Message	-0.024	-0.0278*	-0.0129	-0.00346	-0.011	0.0144
	(0.0152)	(0.0162)	(0.0240)	(0.0160)	(0.0158)	(0.0204)
Any Message $\times X_i$	0.00381	0.0109	-0.0115	-0.0371*	-0.0228	-0.0556**
	(0.0223)	(0.0224)	(0.0271)	(0.0223)	(0.0223)	(0.0238)
Outcome mean (control)	0.593	0.593	0.593	0.593	0.593	0.593
Observations	34,781	34,781	34,781	34,781	34,781	34,781
	B. Individual Treatments					
Contract Reminder	0.00934	-0.0329	0.00748	0.0106	-0.00473	0.024
	(0.0203)	(0.0210)	(0.0313)	(0.0207)	(0.0204)	(0.0264)
Contract Reminder $\times X_i$	-0.0464	0.0344	-0.0283	-0.0508*	-0.0204	-0.0571*
	(0.0290)	(0.0291)	(0.0353)	(0.0290)	(0.0290)	(0.0310)
Reciprocity	-0.0430**	-0.0386*	0.0113	0.00108	-0.0192	0.00563
	(0.0200)	(0.0211)	(0.0311)	(0.0207)	(0.0203)	(0.0268)
Reciprocity $\times X_i$	0.0443	0.0331	-0.041	-0.0438	-0.00409	-0.0431
	(0.0288)	(0.0289)	(0.0351)	(0.0288)	(0.0289)	(0.0312)
Moral Norms	-0.0326	-0.0117	-0.0124	-0.000558	-0.00935	0.0329
	(0.0199)	(0.0206)	(0.0309)	(0.0207)	(0.0200)	(0.0272)
Moral Norms $\times X_i$	0.0159	-0.0249	-0.0158	-0.0482*	-0.0316	-0.0887***
	(0.0289)	(0.0289)	(0.0350)	(0.0289)	(0.0289)	(0.0316)
Social Norms	-0.025	-0.0515**	-0.0501*	-0.0171	-0.0313	-0.0035
	(0.0198)	(0.0213)	(0.0303)	(0.0206)	(0.0203)	(0.0267)
Social Norms $\times X_i$	-0.0291	0.0226	0.0132	-0.0452	-0.0177	-0.0544*
	(0.0289)	(0.0290)	(0.0345)	(0.0289)	(0.0290)	(0.0311)
Social Responsibility	-0.00646	-0.0166	-0.0180	-0.00175	0.0130	0.0111
	(0.0200)	(0.0207)	(0.0315)	(0.0207)	(0.0206)	(0.0264)
Social Responsibility $\times X_i$	-0.0103	0.00904	0.00756	-0.0197	-0.0498*	-0.0315
	(0.0290)	(0.0290)	(0.0354)	(0.0290)	(0.0290)	(0.0309)
Social Responsibility (Link)	-0.0446**	-0.0155	-0.0174	-0.0137	-0.0143	0.0167
	(0.0203)	(0.0211)	(0.0325)	(0.0210)	(0.0203)	(0.0277)
Social Responsibility (Link) $\times X_i$	0.0481*	-0.00984	-0.00344	-0.0139	-0.0132	-0.0583*
	(0.0292)	(0.0293)	(0.0363)	(0.0292)	(0.0292)	(0.0321)
Outcome mean (control)	0.593	0.593	0.593	0.593	0.593	0.593
Observations	34,781	34,781	34,781	34,781	34,781	34,781

Notes: This table shows heterogeneous effects of behavioral messages according to predetermined characteristics at the beginning of the intervention, in a sample of 7,029 late borrowers. The sample is a panel at the individual-week level and includes five weeks after the start of the intervention. The dependent variable is a dummy equal to one if the borrower is late on any product in the week. The heterogeneity variable is a dummy denoted by X_i. In column (1), X_i is a dummy for women, and in column (2) a dummy for borrowers with age above the median. In column (3), X_i is dummy for employed individuals and in column (4) a dummy equal to one if the credit score is above the median score. In column (5) X_i is dummy if the income of the borrower is above the median income. In column (6), X_i equals 1 if the borrower has a credit card or consumption loan and zero otherwise. Panel A shows heterogeneous effects for the effect of receiving any message while Panel B shows estimates for each individual message. All columns include stratum fixed effects (defined by quintiles of the credit score interacted with the Bank segment), week fixed effects, and individual characteristics selected with a double Lasso procedure (Belloni et al., 2014). Standard errors clustered at the individual level are reported in parenthesis. *p<0.1, **p<0.05, ***p<0.01.

Table A6: Conditional Average Treatment Effect (CATE), Contract Reminder

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.45	0.57	0.175	0.0003
Age	43.63	40.42	-0.178	0.0003
Couple: No	0.43	0.45	0.029	0.9307
Couple: Yes	0.45	0.38	-0.101	0.0067
Couple: Missing	0.13	0.17	0.099	0.0213
Number of children	0.54	0.37	-0.121	0.0063
Education: Basic or Less	0.04	0.03	-0.05	0.6857
Education: Secondary	0.00	0.01	0.029	0.9190
Education: Higher	0.37	0.29	-0.119	0.0003
Education: Missing	0.59	0.68	0.131	0.0003
Occupation: Employed	0.72	0.84	0.196	0.0003
Occupation: Retired	0.09	0.04	-0.144	0.0003
Occupation: Self-Employed	0.08	0.06	-0.046	0.7003
Occupation: Student	0.03	0.03	-0.026	0.8840
Occupation: Unemployed	0.01	0.00	-0.09	0.1127
Occup.: Missing	0.07	0.04	-0.099	0.0273
Region: Amazonia South	0.01	0.01	-0.008	0.9697
Region: Andina Center	0.66	0.58	-0.11	0.0117
Region: Caribe North	0.13	0.14	0.031	0.9377
Region: Pacifico West	0.13	0.20	0.143	0.0003
Region: Orinoquia East	0.03	0.03	0	0.9960
Region: Outside	0.01	0.01	0.021	0.8883
Region: Missing	0.04	0.03	-0.063	0.3947
B. Financial Characteristics				
Credit Score	0.65	0.72	0.244	0.0003
Share of Wallet	74.01	66.96	-0.18	0.0003
Monthly Income	5,230.1	3,543.9	-0.186	0.0003
Monthly Expenses	1,017.4	476.4	-0.218	0.0003
Total Assets	94,096.3	46,396.2	-0.228	0.0003
Total Liabilities	12,028.8	2,693.1	-0.193	0.0003
Total Equity	16,787.6	6,203.9	-0.104	0.0200
Debt Size	40,199.4	20,667.3	-0.298	0.0003
Days Past Due	4.12	7.34	0.447	0.0003
Annual Interest Rate (%)	21.61	22.24	0.05	0.6560
Maturity (Months)	114.78	99.77	-0.134	0.0003
Installment Amount	1037.99	642.51	-0.145	0.0003
Credit Card or Consumption Loan	0.67	0.71	0.064	0.4133

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving the contract reminder message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column 3 reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Table A7: Conditional Average Treatment Effect (CATE), Reciprocity

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.52	0.47	-0.076	0.2390
Age	40.99	43.55	0.141	0.0003
Couple: No	0.48	0.38	-0.133	0.0003
Couple: Yes	0.37	0.48	0.158	0.0003
Couple: Missing	0.16	0.14	-0.034	0.9827
Number of children	0.47	0.51	0.032	0.9763
Education: Basic or Less	0.04	0.04	0.033	0.9767
Education: Secondary	0.01	0.01	-0.017	0.9940
Education: Higher	0.34	0.33	-0.015	0.9887
Education: Missing	0.62	0.62	0.004	0.9897
Occupation: Employed	0.69	0.87	0.306	0.0003
Occupation: Retired	0.06	0.07	0.02	0.9897
Occupation: Self-Employed	0.08	0.06	-0.075	0.2883
Occupation: Student	0.06	0.00	-0.226	0.0003
Occupation: Unemployed	0.01	0.00	-0.107	0.1103
Occup.: Missing	0.09	0.01	-0.296	0.0003
Region: Amazonia South	0.01	0.01	0.007	0.9990
Region: Andina Center	0.59	0.68	0.125	0.0003
Region: Caribe North	0.14	0.11	-0.069	0.3820
Region: Pacifico West	0.17	0.17	0.002	0.9547
Region: Orinoquia East	0.03	0.03	-0.021	0.9947
Region: Outside	0.01	0.01	-0.007	0.9927
Region: Missing	0.06	0.01	-0.203	0.0003
B. Financial Characteristics				
Credit Score	0.67	0.70	0.077	0.2653
Share of Wallet	77.02	65.78	-0.289	0.0003
Monthly Income	4,458.0	4,202.8	-0.029	0.9867
Monthly Expenses	847.2	512.2	-0.198	0.0003
Total Assets	72,336.5	67,755.0	-0.023	0.9957
Total Liabilities	9,365.4	4,432.0	-0.104	0.0227
Total Equity	11,011.0	8,142.8	-0.034	0.9830
Debt Size	33,604.9	25,938.1	-0.121	0.0003
Days Past Due	5.11	6.72	0.198	0.0003
Annual Interest Rate (%)	22.72	20.89	-0.148	0.0003
Maturity (Months)	110.82	101.97	-0.079	0.2043
Installment Amount	928.14	802.48	-0.043	0.9350
Credit Card or Consumption Loan	0.68	0.72	0.065	0.4667

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving the reciprocity message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column (3) reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Table A8: Conditional Average Treatment Effect (CATE), Moral Norms

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.53	0.46	-0.094	0.0393
Age	38.19	46.15	0.453	0.0003
Couple: No	0.52	0.40	-0.172	0.0003
Couple: Yes	0.30	0.50	0.287	0.0003
Couple: Missing	0.18	0.11	-0.151	0.0003
Number of children	0.23	0.69	0.337	0.0003
Education: Basic or Less	0.04	0.05	0.024	0.9397
Education: Secondary	0.01	0.01	0.041	0.7907
Education: Higher	0.26	0.38	0.174	0.0003
Education: Missing	0.69	0.57	-0.186	0.0003
Occupation: Employed	0.79	0.79	0	0.9873
Occupation: Retired	0.03	0.10	0.182	0.0003
Occupation: Self-Employed	0.05	0.08	0.072	0.2170
Occupation: Student	0.04	0.01	-0.127	0.0003
Occupation: Unemployed	0.01	0.00	-0.032	0.9093
Occup.: Missing	0.09	0.03	-0.174	0.0003
Region: Amazonia South	0.01	0.01	-0.008	0.9947
Region: Andina Center	0.59	0.68	0.125	0.0003
Region: Caribe North	0.13	0.12	-0.007	0.9723
Region: Pacifico West	0.18	0.14	-0.072	0.2257
Region: Orinoquia East	0.03	0.04	0.044	0.7920
Region: Outside	0.01	0.01	0.023	0.9280
Region: Missing	0.06	0.01	-0.226	0.0003
B. Financial Characteristics				
Credit Score	0.65	0.72	0.227	0.0003
Share of Wallet	82.52	59.62	-0.632	0.0003
Monthly Income	2,665.1	5,958.9	0.375	0.0003
Monthly Expenses	485.5	1,055.4	0.151	0.0427
Total Assets	37,731.4	106,348.8	0.326	0.0003
Total Liabilities	2,455.7	12,504.8	0.216	0.0003
Total Equity	1,133.8	18,906.0	0.199	0.0003
Debt Size	28,518.9	31,152.8	0.042	0.7963
Days Past Due	5.45	6.29	0.107	0.0003
Annual Interest Rate (%)	23.22	20.88	-0.184	0.0003
Maturity (Months)	119.69	93.37	-0.234	0.0003
Installment Amount	739.98	1107.22	0.117	0.0003
Credit Card or Consumption Loan	0.63	0.77	0.211	0.0003

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving the moral norms message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column (3) reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Table A9: Conditional Average Treatment Effect (CATE), Social Responsibility

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.53	0.48	-0.063	0.3760
Age	42.85	41.37	-0.081	0.1623
Couple: No	0.45	0.45	-0.003	1.0000
Couple: Yes	0.34	0.46	0.175	0.0003
Couple: Missing	0.21	0.09	-0.237	0.0003
Number of children	0.44	0.47	0.026	0.9590
Education: Basic or Less	0.05	0.02	-0.119	0.0003
Education: Secondary	0.01	0.01	-0.01	0.9990
Education: Higher	0.22	0.45	0.358	0.0003
Education: Missing	0.72	0.52	-0.297	0.0003
Occupation: Employed	0.76	0.81	0.086	0.1287
Occupation: Retired	0.08	0.06	-0.076	0.2410
Occupation: Self-Employed	0.05	0.08	0.097	0.0190
Occupation: Student	0.03	0.03	0	1.0000
Occupation: Unemployed	0.00	0.01	0.02	0.9807
Occup.: Missing	0.08	0.02	-0.194	0.0003
Region: Amazonia South	0.01	0.01	0	0.9993
Region: Andina Center	0.58	0.66	0.106	0.0003
Region: Caribe North	0.14	0.13	-0.027	0.9670
Region: Pacifico West	0.19	0.15	-0.06	0.3970
Region: Orinoquia East	0.02	0.04	0.071	0.2897
Region: Outside	0.01	0.01	0.054	0.5543
Region: Missing	0.06	0.00	-0.228	0.0003
B. Financial Characteristics				
Credit Score	0.71	0.66	-0.187	0.0003
Share of Wallet	72.44	69.68	-0.071	0.2767
Monthly Income	1,919.6	6,587.1	0.592	0.0003
Monthly Expenses	461.5	979.3	0.239	0.0003
Total Assets	30,632.4	112,477.5	0.299	0.0003
Total Liabilities	4,105.7	12,145.9	0.092	0.2283
Total Equity	5,637.2	16,602.7	0.08	0.2740
Debt Size	13,295.5	46,826.4	0.534	0.0003
Days Past Due	5.35	5.75	0.056	0.4977
Annual Interest Rate (%)	24.33	19.17	-0.427	0.0003
Maturity (Months)	95.19	121.72	0.236	0.0003
Installment Amount	318.70	1399.93	0.399	0.0003
Credit Card or Consumption Loan	0.73	0.64	-0.131	0.0003

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving the social responsibility message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column (3) reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Table A10: Conditional Average Treatment Effect (CATE), Social Responsibility + Link

	Low Overdue Reduction (1)	High Overdue Reduction (2)	Std. diff. High - Low (3)	MHT p-value (4)
A. Borrower Characteristics				
Female	0.52	0.48	-0.047	0.8520
Age	43.84	40.22	-0.202	0.0003
Couple: No	0.43	0.47	0.056	0.7210
Couple: Yes	0.43	0.38	-0.078	0.2773
Couple: Missing	0.14	0.15	0.03	0.9370
Number of children	0.45	0.46	0.008	0.9617
Education: Basic or Less	0.03	0.05	0.076	0.3260
Education: Secondary	0.00	0.01	0.048	0.8260
Education: Higher	0.40	0.27	-0.19	0.0003
Education: Missing	0.57	0.67	0.148	0.0003
Occupation: Employed	0.77	0.82	0.077	0.2370
Occupation: Retired	0.09	0.04	-0.152	0.0003
Occupation: Self-Employed	0.08	0.06	-0.065	0.4593
Occupation: Student	0.02	0.04	0.067	0.4443
Occupation: Unemployed	0.01	0.01	0.034	0.9527
Occup.: Missing	0.04	0.05	0.034	0.9393
Region: Amazonia South	0.01	0.01	0.051	0.8050
Region: Andina Center	0.65	0.60	-0.082	0.1467
Region: Caribe North	0.11	0.16	0.102	0.0237
Region: Pacifico West	0.16	0.17	0.007	0.8170
Region: Orinoquia East	0.03	0.02	-0.026	0.8613
Region: Outside	0.01	0.01	-0.028	0.9267
Region: Missing	0.03	0.04	0.027	0.9030
B. Financial Characteristics				
Credit Score	0.66	0.72	0.194	0.0003
Share of Wallet	69.32	72.46	0.078	0.2653
Monthly Income	4,724.2	3,701.5	-0.12	0.0003
Monthly Expenses	1,036.4	561.7	-0.072	0.9293
Total Assets	94,213.1	49,670.7	-0.179	0.0003
Total Liabilities	8,949.9	6,271.0	-0.048	0.8357
Total Equity	12,649.1	10,804.2	-0.012	0.9710
Debt Size	35,259.3	23,411.8	-0.188	0.0003
Days Past Due	7.15	4.53	-0.329	0.0003
Annual Interest Rate (%)	20.03	23.89	0.315	0.0003
Maturity (Months)	125.43	87.59	-0.344	0.0003
Installment Amount	944.25	826.33	-0.04	0.9257
Credit Card or Consumption Loan	0.56	0.83	0.434	0.0003

Notes: This table presents the average of the individual characteristics (Panel A) or loan characteristics (Panel B) listed in the rows, for two groups split by the median Conditional Average Treatment Effect (CATE). The treatment group comprises borrowers receiving the social responsibility + link message. In column (1), the group comprises individuals whose CATE implies a low reduction of days past due in response to the treatment. For this group the CATE is more positive (above the median). In column (2), the group comprises borrowers with a high reduction in overdue days in response to the treatment. For this group, the CATE is more negative (below the median). Column 3 reports the standardized difference between columns (2) and (1), and column (4) reports p-value of a test of the null hypothesis that this difference is different from zero, adjusted for multiple-hypothesis testing. We estimate the CATE using a causal forest following the approach of Athey and Imbens (2016), Wager and Athey (2018), and Athey et al. (2019) in a cross section of borrowers, using as outcome the maximum number of days past due in the first five weeks of the experiment. See Appendix B for details.

Appendix B Heterogeneous Treatment Effects Using Causal Forest

To estimate heterogeneity in the causal treatment effects of our intervention, we used a machine learning algorithm called causal forest. This approach is becoming a more common way to estimate heterogeneous treatment effects in the context of randomized controlled trials (Carlana et al., 2022; Davis and Heller, 2017). Specifically, causal forest allows us to estimate Conditional Average Treatment Effects (CATE), defined as $E(Y_{1i} - Y_{0i} \mid X_i = x)$, where Y is the outcome of interest and X is a vector of observable baseline characteristics.

We include all baseline characteristics available to us; each categorical variable could also take on a missing value if data were unavailable to us. Demographic characteristics include: female (binary), age (continuous), currently a couple (binary), number of children (continuous), education (categorical variable with three values: basic education or less, secondary education higher education), occupation (categorical variable with five values: employed, retired, self-employed, student, unemployed), and home region (categorical variable with six values: South, Central, North, West, East, outside Colombia). Financial characteristics include: credit score (binary), share of wallet (continuous), monthly income (continuous), monthly expenses (continuous), total assets (continuous), total liabilities (continuous), total equity (continuous), debt size (continuous), average days past due across all loan products (continuous), average annual interest rate across all loan products (continuous), average days until maturity across all loan products (continuous), installment amount (continuous), and if the borrower holds a credit card or consumption loan (binary).

We follow a very similar procedure as the one outlined in Carlana et al. (2022)[14]. We use an honest approach to train a causal forest, using 100,000 trees for the individual message estimates and 50,000 for the any message estimates (due to computational constraints) and setting the minimum number of treatment and control observations allowed in a leaf to the

[14] This process uses the causal_forest command in R of the package grf (generalized random forest). This procedure closely mimics that suggested by Athey et al. (2019) and Wager and Athey (2018)

default value (5). Essentially, this means the training sample is split in two equal halves, and observations are used either for growing the tree or for estimating treatment effects within each leaf, but not both. Our next step is to calculate the out-of-bag predicted CATE and variance estimates. The CATE tells us the expected treatment effect on delinquency for each individual in the sample, given all the included covariates. Using these predictions, we divide the sample into two groups - those with CATE values in the top 50% and those in the bottom 50%.

Appendix C Stratification Details

We computed quintiles according to the Bank's internal credit score distribution which reflects the probability that a late client meets their repayment obligations in the next month. This probability is calculated with a machine learning algorithm that takes into account both the historical and the recent repayment behavior of the client. Regarding the segment variable, the Bank classifies clients into different segments that dictate the type of relationship it maintains with the customer. This classification, though not directly related to repayment outcomes, covers different socioeconomic characteristics of the borrower. A different segment results in a different type of customer service, which in turn can affect the client's perception of the bank.

From each stratum in the population of late clients, customers were randomly selected and sent to the strata of the experimental sample, so that the proportion of each stratum in the sample corresponds to the proportion in the population. Then, within each stratum in the sample, clients were randomly assigned to either the control group or one of the six treatment groups. The bank performed this process several times until the final sample fulfilled the balance tests made by the research team.