Journal of Behavioral and Experimental Finance 37 (2023) 100776

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

Nudging debtors with non-performing loans: Evidence from three field experiments

Andris Saulītis *

Senior Researcher at the Institute of Philosophy and Sociology, University of Latvia, Latvia

A R T I C L E   I N F O

Article history:
Received 22 April 2022
Received in revised form 21 November 2022
Accepted 23 November 2022
Available online 30 November 2022

Keywords:
Debt collection
Field experiment
Behavioral insights
Loan repayment
Nudging
Reminders

A B S T R A C T

This study aims to explore how various nudges that have successfully increased the payment discipline among borrowers with performing loans affect the behavior of the defaulted debtors. In three field experiments involving 32,000 borrowers, debtors were randomly assigned to receive reminders that used personalized language, mentioned economic consequences, and prosocial motives. In one experiment, the design of the envelope varied. The experimental results show that simply nudging defaulted individuals does not work. Although every next reminder that debtors receive increases the payment rate, the effect is rather small. Moreover, sending reminders when the promise to make a payment on a debt has already been made can trigger a repeated default. I also find that a red envelope design backfires on collection efforts. The findings offer a fuller understanding of the behavior of defaulted debtors and suggest policy implications in debt repayment and recovery of non-performing loans.

1. Introduction

In the last decade, a growing number of studies have examined the so-called nudging approach as it pertains to loan repayment: sending subtle reminders and drawing attention to a particular piece of information or social cues to avoid late payments. The contents of such messages range from generic reminders to highlighting the economic consequences of nonpayment and foregrounding prosocial drivers of repayment. With some notable exceptions, nudging is an overall effective strategy to improve payment discipline among borrowers with performing loans (see Appendix A for a review). The question that drives this study is to explore if the effects remain the same on a particular set of debtors: those with non-performing loans (NPLs), i.e., with no payment of at least 90 days. I run three field experiments in cooperation with a debt-collecting company on more than 32,000 individuals that have either non-performing consumer debts or have just recovered from a default.

Defaulted debtors are more present-oriented and have less unfavorable attitudes toward debt than those with no arrears or short-term liquidity constraints (Lea, 2021; Webley and Nyhus, 2001). For this reason, debtors with NPLs might react differently to various nudging strategies than debtors with performing loans. Indeed, I find that most of the interventions do not work. The only successful nudging strategy is the repeated reminder that positively affects debt recovery. At the same time, there are backfiring effects to some of the interventions examined in this study. These findings highlight the differences in behavior for borrowers with NPLs compared to debtors with performing loans.

In the three experiments reported in this paper, I examine the effect of repeated communication, personalizing a message, priming individuals to a social norm, and the long-term economic consequences to debtors with NPLs. I also look at the effect of a noninformative dimension (i.e., a collection letter contained in a red envelope) on payment behavior. The effect of repeated generic reminders on NPLs is examined in all three experiments fielded in this study. For debtors with performing loans, sending generic reminders on scheduled payments is not a common practice and has been proven to have little or no effect on payment rates (Bursztyn et al., 2019; Homonoff et al., 2019; Karlan et al., 2015; Medina, 2020). For holders of NPLs, however, sending repeated requests to make a payment is a business-as-usual practice (Deville, 2015; Rock, 2013). The goal of a repeated reminder is to increase so-called "annoyance costs" (Damgaard and Gravert, 2018). Debt recovery will result if annoyance costs associated with a reminder are high enough relative

* Correspondence to: Institute of Philosophy and Sociology, University of Latvia, Kalpaka blv. 4, Riga, LV-1050, Latvia.
E-mail address: andris.saulitis@lu.lv.

https://doi.org/10.1016/j.jbef.2022.100776

to the costs of paying the debt. However, repeated reminders can backfire on collection efforts by triggering reactance when debtors purposefully choose nonpayment to punish the sender for sending a message (Brehm, 1966; Holzmeister et al., 2022; Steindl et al., 2015). I find repeated reminders are an effective nudging strategy vis-à-vis holders of NPLs, although the improvement in debt recovery is relatively small. However, once the debtor has restarted payments, additional reminders backfire on collection efforts and trigger repeated defaults.

Personalization is another behavioral trait that has the potential to improve the collection of NPLs and is examined in all three experiments in this study. Debtors prioritize repayment to creditors with whom they consider themselves in a close relationship (Polletta and Tufail, 2014). Debt collectors are rarely seen as friendly business partners, with debtors often reported as being threatened and treated impersonally or aggressively by the CMS firms (Mind, 2008, p. 16; Nettleton and Burrows, 2001; Papamichai and Mizamidis, 2015, p. 111; Walker et al., 2013). They find negotiations emotionally exhaustive and unfruitful (Krumer-Nevo et al., 2017; Tufail and Polletta, 2015). Debtors often avoid communicating with credit servicers rather than cooperating (Mann and Porter, 2009; Thorne and Anderson, 2006). CMS companies, on the other hand, resent that their practices are demonized by the media, as threats are rarely used (Deville, 2015; Pal, 2017). The result is that collection efforts become less effective for CMS firms than if carried out by the original lender (Wilkinson-Ryan, 2015). With this in mind, personalizing a message by including the recipient's name or debt collection agent might improve the collection efforts by signaling the commitment of the CMS firm to find an individual solution to the debt problem. Personalized messages have been proven effective in collecting delinquent fines (Haynes et al., 2013). However, I find that having a debtor or debt collection agent's name in the message is insufficient to minimize the social distance between debtor and collector and trigger a payment.

All three experiments in this study also include treatment with a social norm, as moral concerns often deter individuals from defaulting (Guiso et al., 2013; Wilkinson-Ryan, 2011). Among performing loans, these nudges can be as effective or even more effective than a message containing information on the economic consequences of default (Bursztyn et al., 2019; Du et al., 2019; Huang and Bao, 2020). However, disclosing to the recipient debtor information that he or she is in a better position than peers can trigger overconfidence and cause delinquencies (Bracha and Meier, 2014; Seira et al., 2017). Descriptive minority social norms that "characterize the perception of what most people do" (Cialdini et al., 1991, p. 203) have been effective in the collection of unpaid tax obligations (Alm, 2012; Carpio, 2014; Dwenger et al., 2016; Hallsworth, 2014). However, the use of descriptive minority social norms did not positively affect NPL recovery in any of the three experiments in this paper.

Experiment 2 includes a treatment message conveying reputational concerns. Such a message might affect debtors in default based on rational calculations (i.e., avoiding the costs of reputational damage) rather than on moral grounds or liquidity constraints. So-called strategic default occurs when servicing costs exceed those of defaulting, thus triggering nonpayment (Gerardi et al., 2018; Stiglitz and Weiss, 1981; Trautmann and Vlahu, 2013). The reputational concerns message in Experiment 2 reminds the debtor of the long-term economic costs of remaining in a status of default with an attempt to update the debtor's calculations vis-à-vis the costs of remaining in a default status. Priming for the long-term economic consequences is one of the most effective ways to reduce delinquencies among performing loans (Bursztyn et al., 2019; Homonoff et al., 2019; Huang and Bao, 2020). Such nudges come closest to financial incentives and might be why they tend to be effective, although in some cases, no effect or even negative effects have been found (Bracha and Meier, 2014; Karlan et al., 2015). I find that prompting on reputational risk is insufficient to reverse the decision to default. However, such messaging does not backfire on collection efforts, as observed in a study by Holzmeister et al. (2022).

Reminders in Experiment 2 were delivered via regular mail. Half of the letters in this experiment were sent in white envelopes, while the other half were in red envelopes. Posting materials in a non-white envelope is common in marketing communications (James and Li, 1993). A field study by Behavioural Insights Team (2018) revealed that a customized envelope (including but not limited to the color blue) enhances the quality of communication between the lender and debtors in mortgage arrears. I find the opposite for the red envelope: it backfires on collection efforts relative to a white envelope.

This study also contributes to an inquiry into a larger problem exposed by the NPLs. Defaults have become an important obstacle to economic growth, with an increasing number of households in long-term arrears (Balgova et al., 2016; European Commission, 2020; Tölö and Virén, 2021). In addition, banks have been under constant pressure from regulators to get NPLs off balance sheets and, as a result, are all-too-willing to sell them at a discount to credit management service (CMS) firms (Pal, 2017). Given this pressure, the debt collection industry has experienced rapid expansion. This study adds to the insights on the debt collection process and, particularly, broadens an understanding of how overindebtedness affects individual behavior.

2. Overview of the experiments

Field experiments were conducted with a CMS company *Intrum* (previously called *Lindorff*). It is one of the largest CMS enterprises in Latvia. Individuals included in trials took out the debt with a range of entities, from traditional lenders (e.g., banks) to fast-credit companies and catalogue merchandisers, in the past but now have a liability with the CMS firm. Each debtor had received at least one simple reminder to repay the debt – either a call, a text or email message, or a letter sent by regular mail – before the start of the experiments. Fig. 1 provides an overview of the debt-recovery process and the timing of intervention in each of the experiments.

Experiment 1 examines the behavior of 24,950 defaulters with consumer debts. The messages were sent via mobile text messages and emails. Experiment 2 studies the behavior of 4,821 defaulters with consumer debts following an intervention carried out via regular mail. It consists of defaulters with consumer debts who could not be reached via mobile text message or email in Experiment 1 (i.e., were not treated in Experiment 1). Experiment 3 is carried out on a different sample of 2,497 debtors. The debts have been recently recovered, and debtors have started or promised to repay the debt. Typically, around half of the debtors who start or promise to repay their debt lapse repeatedly during the debt-repayment period. The interventions in this experiment are carried out via mobile text and email communication channels, similar to Experiment 1.

2.1. Sampling and randomization

Overall, many characteristics – such as the experimental conditions, debt type, delivery channel, and design type – are identical across the experiments. Table 1 summarizes the characteristics of each experiment, thus capturing both the commonalities and differences. As the sample consists of information on various characteristics of each individual, I use blocked randomization to reduce sampling variability (see Gerber and Green,

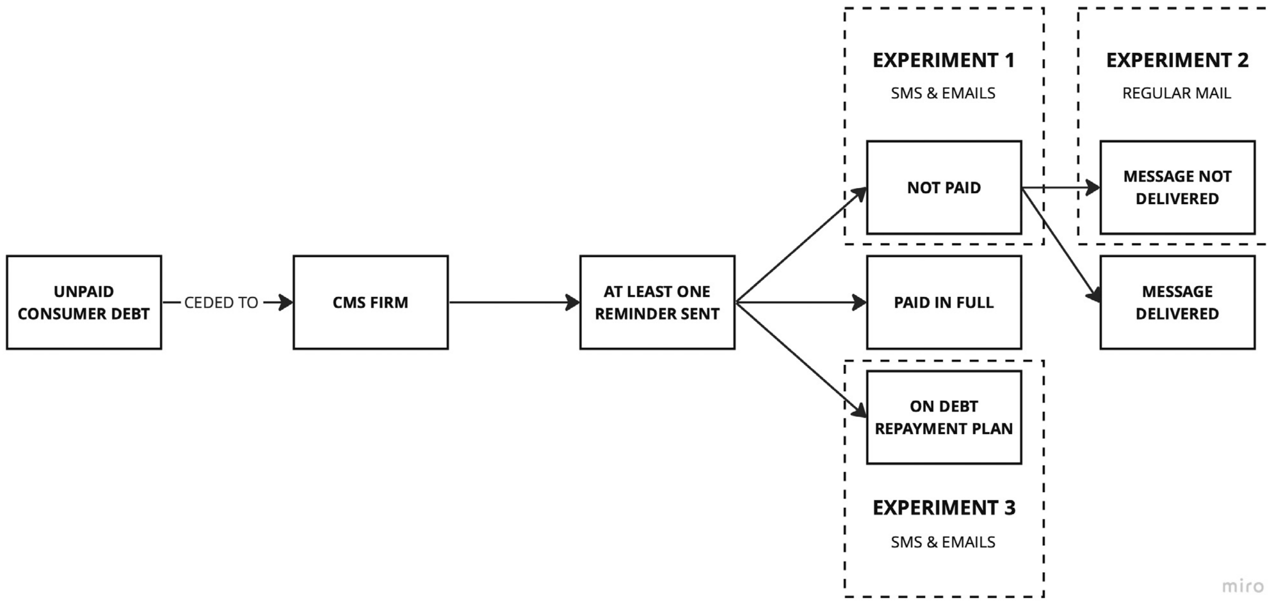

Fig. 1. Points within the debt-recovery process when the experiment took place

Table 1
Main characteristics of the study experiments.

Category	Experiment 1	Experiment 2	Experiment 3
Debt type	Defaulted consumer debts (bank loans, fast credits, catalogue merchants)		Recovered consumer debts on a repayment plan
Delivery channel	SMS and emails	Regular mail	SMS and emails
Period	Feb 11–March 1, 2016	May 5, 2016–July 5, 2018	Feb 11–March 31, 2016
Exposures	Max. 4 SMSs and 4 emails	One letter sent by regular mail	Max. 8 SMSs & 8 emails
Conditions	9	9	9
N	24,950	4,821	2,497

2012, pp. 71–77; John, 2017, pp. 38–39). Therefore, randomization is undertaken within the blocks (strata) of gender, ethnicity, the value of the loan, communication channel, and other covariates—depending on the available information in the sample. After blocked randomization, I assess any imbalance in my covariates in the sample. This is accomplished through pairwise comparisons of means with adjusting for multiple comparisons, using Dunnet's method (see Gerber and Green, 2012, pp. 431–432). If the difference in means for any covariate between experimental conditions is statistically significant ($p<0.05$), I repeat the blocked randomization procedure until there is no imbalance in covariates among the experimental conditions. Rerandomization allows better sampling properties in terms of variance and does not create any complications in assessing the treatment effect of an experimental study (Athey and Imbens, 2017, pp. 108–109). The results from the balance tests are reported in Appendix B, together with the descriptive statistics for each experiment.

The number of exposures to the treatment message differs from one experiment to another. For Experiment 3, the debtor might be exposed to the treatment message as many as eight times, while in Experiment 2, the individuals receive only one regular mail letter. Although the number of exposures differs, each individual is exposed to the same treatment message during the intervention period. Note that each debtor is included in one – and only one – of the three experiments.

2.2. Treatments and empirical strategy

The message for the control group is a generic reminder. As noted before, the effect of social norms and personalization is examined in all the experiments. Reputational concerns and envelope design (salience effect) are examined only in Experiment 2 (letters via regular mail). Table 2 summarizes which hypotheses and factors are examined in each experiment. I also combine several treatment texts in one message within a study. For instance, in Experiment 1, the personalization of the sender and receiver is examined separately and together in one message. Three different treatments in one message (social norm, reputational concerns, and personalization) are examined in Experiment 2. The treatment messages for each experiment can be found in Appendix C.

The variable of interest in all the experiments is whether an individual makes payment within the month following the final intervention. The study was double-blinded, as both the participants and the CMS employees who collected data were unaware of which treatments individuals received. Information collected at the individual level is then used to estimate the payment rate in each experimental condition.

The sharp null hypothesis in the experiments is that individuals are indifferent to any alternative messaging strategy relative to a generic reminder. The treatment effect estimation is accomplished by fitting a linear probability model using ordinary least

Table 2
Experimental conditions included in the experiments of the study.

Treatment	Factor	Experiment 1 (consumer debts; SMS and email)	Experiment 2 (consumer debts; regular mail)	Experiment 3 (Consumer debts on a repayment plan)
Control group: Generic reminder		✓	✓	✓
Communication effect (no message)		✓		✓
Personalization	Debtor name	✓		✓
	Agent name	✓	✓	✓
Social norm		✓	✓	✓
Reputational concerns			✓	
Salience	Red color		✓	

squares regression, as the variable of interest is binary (Freedman, 2008). The empirical method aims to identify the average treatment effect (ATE) between the control group and any of the treatment arms. This is accomplished by comparing the payment rate among the different experimental conditions. ATE is an unbiased estimator where all the treatment messages are delivered to the experiment participants. However, in field experiments, quite often, a substantial share of individuals targeted end up being so-called "noncompliers". These individuals are assigned to the treatment but are not treated for some reason. The ATE is not a proper estimate for an unbiased comparison in such cases.

To address this issue, the empirical method measures two different estimates: first, the average intention-to-treat (ITT) effect; second, the complier average causal effect (CACE) (Gerber and Green, 2012, pp. 131–166). I use separate regression models to calculate CACE for the No Message condition and other treatment arms assigned to receive a message. In the No Message condition, I use two-stage least squares regression, equal to an instrumental variable regression, with the delivery rate used as an instrument (Gerber and Green, 2012, pp. 157–160). To calculate CACE for any other treatment condition, I apply the same regression model used to calculate ATE by removing noncompliers from the sample. To address multiple hypotheses issues arising from having many treatment arms, I use the procedure proposed by List et al. (2019).

The coefficients are reported after adjusting for covariates. Heterogeneity is particularly important where the treatment effect is relatively small (Gerber and Green, 2012, p. 295). After reporting on the variable of interest, I analyze covariates to move the study from confirmatory objectives to exploratory ones. On the one hand, it proposes future confirmatory studies. On the other, it serves the purpose of gathering broader behavioral insights on defaulted individuals and provides a deeper understanding and explanation of the treatment effects.

Although I look at the covariates in my interpretation, it has to be noted that the relation between the covariates and the dependent variable has no causal explanation (Gerber and Green, 2012, pp. 102–105). Also, they do not reveal whether there is an interaction effect in an experiment. Theoretically, there might be a possibility that individual characteristics (such as gender, age, place of residence, etc.) can influence the treatment effect. A separate analysis of subgroups in which the so-called conditional ATE is measured helps to investigate this issue (see Gerber and Green, 2012, pp. 299–303). In each experiment, I examine the interaction effects of gender, age, and debt size on the treatment effect. Just as when covariates are introduced into a regression, caution has to be taken when studying interaction effects. Overall, the exploratory part of the experimental results are predictions without causal relation and are merely descriptive.

3. Experiment 1: NPL via SMS and email messages

The sample for Experiment 1 consists of unsecured consumer loans taken out with banks, payday loan companies, and catalogue merchants. In total, there were 24,950 individuals with unpaid liabilities ranging from €1 to approximately €40,000 with a median loan size of €310. On average, debtors had been on the CMS firm's books for around 7.7 years when the experiment was launched. Throughout this time, each debtor has been contacted regularly by the credit servicer via all the available channels: phone calls, mobile text messages, emails, and regular mail at least once a year. However, these various attempts to collect money via simple reminders have not succeeded. Therefore, the generic message sent by the CMS firm is deemed unlikely to induce the debtors in this experiment to make a payment on the debt.

Each debtor was randomly assigned either to a group that did not receive any message throughout the experiment or to one of the eight treatment messages. The experiment was launched on February 11, 2016. The CMS firm sent the randomly assigned message on Monday via its automated software. Every subsequent Monday, the CMS firm's software monitored the delivery status of each message and the payment status of each case. The following report was used to update the list of debtors for future communication. If both email and mobile text messages were not delivered, no further communication was carried out. Additionally, if the debtor agreed on a repayment plan or paid back the debt in full in the meantime, no additional messages were sent. If none of those mentioned above has been registered, the same assigned message was resent to the debtor the following day.

The procedure was repeated for three consecutive weeks. As a result, the debtor received the same treatment text a maximum of four times via one channel or eight times if both communication channels were available. The last message was sent out on March 1, 2016. The final update on all cases – whether payment had been made – was carried out 30 days after the last message was sent.

3.1. Experiment 1: results

In total, only 1.8% of individuals included in the experiment changed their behavior and started to repay the debt (see Appendix D). Around 45% of messages were not delivered, and the repayment rate among those who received any message is 3.2%. The difference between generic reminders and any of the alternative messages is no larger than 0.6 percentage points and not statistically significant. At the same time, there is a positive communication effect ($p<0.05$), as sending a generic reminder is more effective than not sending a message at all (see Appendix E). Hence, it is not the content, but the reminder per se, which improves the repayment rate by 1.3 percentage points from a baseline payment rate of 1.1%. It suggests that behavioral change among the defaulted individuals can be enacted by increasing the annoyance costs by sending a repeated reminder, as the treatment messages were followed after individuals received at least one initial reminder from the CMS company.

Regression models with all control variables show some statistically significant covariates which correlate with the repayment rate (see Appendix E, Model (2)). On average, the repayment rate among women is 0.6 percentage points higher than among men ($p<0.01$). The collection fees as a share of the total loan value positively affect the repayment rate. Notably, every 10 percentage-point increase in the share of collection fees increases the probability of repayment by 0.3 percentage points. A likely explanation for this non-intuitive effect is that collection fees grow with each additional reminder sent to the debtor. It is another indication that increasing the annoyance costs is the most effective way to recover NPLs.

Among the covariates, loan value has a statistically significant ($p<0.05$) negative effect on the repayment rate. In other words, the larger the loan, the lower the probability of recovering debt. Taking into account the significance of the communication effect and the nature of the annoyance costs, I interacted loan value with the message delivery. I categorized individuals into three separate groups: (1) *No message*: individuals who were assigned to the No message condition; (2) *Treated*: individuals who were assigned to receive any message and were treated; (3) *Not treated*: individuals who were assigned to receive any message but were not reachable. The results reveal that loan value has a statistically significant effect only among those who received a message (see Appendix F). Among these debtors, there is a strong correlation between the loan value and the repayment rate. For instance, the difference in repayment rate between a debt of €25 and a debt of €150 is around 1.5 percentage points. However, the differences between debts of €150 and €300 are not as substantive, reaching only around 0.56 percentage points. At the same time, loan value has practically no effect on payment rates among individuals who did not receive a reminder. It suggests a strong relationship between the annoyance costs (receiving a message) and repayment costs (loan value). I also interacted message treatments with gender and age. None of the interactions are statistically significant ($p>0.05$).

4. Experiment 2: NPL reminders via regular mail

The CMS firm had not reached the debtors in the sample for Experiment 2 via phone call, text message, or email since at least January 2015, i.e., almost 1.5 years from the start of the experiment. This is because the phone number and email address on file for the debtor were incorrect or no longer current/valid or because the debtor had blocked messages from the CMS firm's number or email address (or both). In all other respects, the sample is similar to Experiment 1, with the exception that the total debt size ranges from €50–€4,400.

The experimental design for Experiment 2 is an adaptive-randomized trial consisting of two phases. In Phase 1, the effect of five different messages is examined. Each debtor in the sample was randomly assigned to one of the following treatment messages: (1) a generic reminder; (2) a personalized message "signed" by the agent; (3) a social norm statement; (4) a reputation concern statement, and; (5) a combination of all previously mentioned treatments in one message. Additionally, half of all the letters were sent in red envelopes to examine the possible effect of salience on the repayment rate. As a result, Phase 1 consists of ten different experimental conditions in a factorial design. In Phase 2, the single most effective treatment from Phase 1 is examined on a different and larger sample of debtors. The sample consisted of 2,000 debtors in Phase 1 and 2,821 in Phase 2. The control group in both phases is a generic reminder sent from the CMS firm in a white envelope. In each phase, a different sample of defaulted debtors is used.

The letters were sent out on May 2, 2016. Usually, it takes 1–3 business days for the post letter to arrive in the post box. The letters were sent on Monday, meaning that individuals should receive them by the end of the week. One month after the letters were sent, the CMS firm prepared a report on the payment status of each case. It was used to create the variable of interest, i.e., payment rate.

4.1. Experiment 2 Phase 1: Results

The average payment rate in Phase 1 is 2%. The payment rate across the treatment arms ranges from 1% to 5% (see Appendix G). A message signed personally by a credit servicing agent is the most effective treatment condition in Phase 1 compared to a generic reminder (CACE = 3.2%). However, it is statistically significant only at the marginal level ($p<0.1$) when regressed with all the control variables. It becomes statistically insignificant when examined against the multiple hypothesis assumption.

At the same time, the results show that the red color of the envelope backfires, undermining successful credit servicing efforts (see Appendix H). On average, those who received the message from the CMS firm in a red envelope are 1.5 percentage points less likely to repay their debt than those who received a letter in a white envelope ($p<0.05$). Overall, all treatment messages in a red envelope have a lower payment rate than the identical treatment messages in a white envelope.

No covariate has a statistically significant effect on the payment rate. As debt size has a marginal statistical significance ($p<0.1$), I interacted it with the assigned treatments—however, no significant effects were found. I also looked at the treatment effects separately by gender and found no effects. However, it might be that the differences in the subgroups are not detectable, as Experiment 2 consists only of 2,000 observations, compared to Experiment 1, with almost 25,000 observations, where the interaction between loan size and message delivery was identified.

4.2. Experiment 2 Phase 2: Results

Based on the results from Phase 1, during Phase 2, only two experimental conditions were included: (1) a simple reminder as a control group and; (2) the agent condition as a treatment group. The treatment text of letters for each condition was the same as in Phase 1.[1] In Phase 2, both templates were sent in white envelopes. The predicted CACE of a personalized message was 1.5 percentage points. Power calculation was carried out before Phase 2 to reach 80% statistical power at a significance level of $\alpha = 0.05$.[2] As a result, each experimental condition was applied to 1,410 individuals.

[1] There were two minor changes across both conditions: (1) the footnote on data privacy was amended to comply with the EU General Data Protection Regulation, which was not in force when Phase 1 was launched and; (2) the name of the debt collection firm in Phase 2 was *Intrum*. In the intervening period, *Lindorff* had merged with *Intrum Jutstita* – a credit management services conglomerate originating in Sweden – and the combined entity was rebranded *Intrum*.

[2] Stata command: sampsi 0.0175 0.0375, power(0.8).

Table 3
Fixed Effects Meta-Analysis of Phases 1 and 2 in Experiment 2.

Study	CACE	Standard error	p-value
Phase 1	3.2%*	0.0189	0.089
Phase 2	0.45%	0.0044	0.311
Pooled results	**0.59%**	**0.0043**	**0.168**

Notes: CACE estimates from regression models with controls. *p<0.1.

The payment rate in the control group (simple reminder sent by the CMS firm) is 1.1%. For messages signed personally by a credit servicing agent, the payment rate is higher than those issued in the company's name. The CACE of a message signed by an agent is 0.5 percentage points (see Appendix I). This is substantively smaller than the treatment effect of a personalized message found in Phase 1 and not statistically significant, albeit within the 95% confidence interval of the result found in Phase 1. The exploratory analysis reveals that no control variables correlate with the payment rate, and no interaction effects are observable.

Given the similarities in experimental design and setting for both phases, it is reasonable to pool the results to obtain the most precise estimate of the effect of personalization relative to a generic reminder. In doing so, I use the fixed effects meta-analysis procedure (Gerber and Green, 2012, pp. 358–365). When pooled, the study yields a CACE estimate of 0.6% of a personalized letter from a CMS agent in a white envelope relative to a generic reminder in a white envelope (see Table 3). The result is not statistically significant (p<0.1).

Overall, Experiment 2 suggests that various nudging strategies that work on performing loans are not effective in debt collection with defaulted individuals. In contrast to the individuals with performing loans, messages with reputational concerns have no effect on payment discipline. Experiment 2 also indicates that nudging can have negative effects. Messages communicated via a red envelope decreased the payment rate. If credit servicing is considered a marketing activity, then the finding is consistent with the observational study on salience effects in the field of direct mail marketing (Feld et al., 2013). The red color of the envelope might trigger defaulted individuals to deem that the letter's content is not worth reading.

5. Experiment 3: Recovered loans via SMS & emails

The sample for Experiment 3 consists of 1,682 debtors with consumer debts. These individuals were once in a state of default but had agreed with the CMS firm on a debt-repayment plan before the experiment began. The regular monthly payment was between €20 and €50, with payment made via bank transfer to the CMS firm's bank account. At the start of the experiment, individuals in the sample were either making payments (i.e., the most recent payment had been made no later than 30 days prior) or, alternatively, they had promised to make the first payment on a previously defaulted debt in the 30 days before the start of the experiment.

The treatment conditions for Experiment 3 were the same as in Experiment 1. This experiment also examined the effects of communication, social norms, and personalization on payment behavior. Individuals received no message or one of eight assigned treatment texts via mobile messages and emails. The only difference is that I examine their effect on a sample of recently recovered consumer loans, i.e., they are on a monthly debt-repayment plan after being NPLs shortly before.

The intensity of the intervention with a treatment message replicated the daily operations of the CMS firm. The debtor received the assigned message at least two times in eight weeks. It was sent starting on February 11, 2016, during the week the monthly payment was due. Additionally, if the payment was not made before or on the due date, the debtor repeatedly received the same assigned message for another week until the end of the experiment on March 31, 2016. The final check on files was done on April 3, 2016, to identify the dependent variable (i.e., the payment rate).

5.1. Experiment 3: Results

On average, nearly half of all debtors (47%) did not make the scheduled payment during the eight weeks of the experiment (see Appendix J). Sending a simple reminder is as effective as sending no message. Moreover, all the treatment texts deliver lower payment rates than the control group. The greatest difference is with the social norm message condition. On average, receiving a social norm message decreased the payment rate by 9 percentage points. The treatment effect for the social norm message becomes statistically significant (p<0.05) when the linear probability model includes covariates. However, it is not statistically significant when examined against the multiple hypothesis assumption. Therefore, the results suggest that no communication brings a higher payment rate (see Appendix K for CACE of communication on payment rate).

As a robustness check, I used the delivery of a message as an instrument, as around one in four assigned messages (27%) were not delivered. I compared the payment rate between those who received the message (compliers) and those assigned to the treatment, but the message was not delivered (non-compliers). The results show that noncompliers have a higher payment rate than compliers (see Appendix L). In other words, if a debtor received the assigned reminder message, the likelihood of making a payment is 12 percentage points lower relative to a debtor who was assigned to receive the same reminder but the message was not delivered (p<0.01).[3] I also interacted the experimental condition with the delivery of a message (see Fig. 2) that shows the same trend regarding delivery. In all cases, the payment rate is higher among those who did not receive the assigned message. For instance, the payment rate is 46% among those who received the assigned simple reminder. However, among those who did not receive the assigned simple reminder, the payment rate is 66%. The difference between the two conditions is statistically significant (p<0.05).

Hence, there is strong evidence that receiving a reminder on a scheduled payment does not increase the payment rate but rather backfires collection efforts. One possible explanation is that the message, in fact, reminds the debtor that there is an option *not to pay*. Also, it is likely that reminders increase the annoyance costs related to the payment and provoke a willingness to punish the debt collector for its behavior.

The most important covariate regarding the payment rate is the type of debt (see Appendix J, Model 2). When the debt originates from a dedicated financial institution (e.g., a bank or

[3] As a robustness check, I also examined the effect of delivery on the payment rate in the other experiments reported in this paper. In contrast to Experiment 3, the delivery of a message increased the payment rate in Experiments 1 and 2. The regression results are available on request.

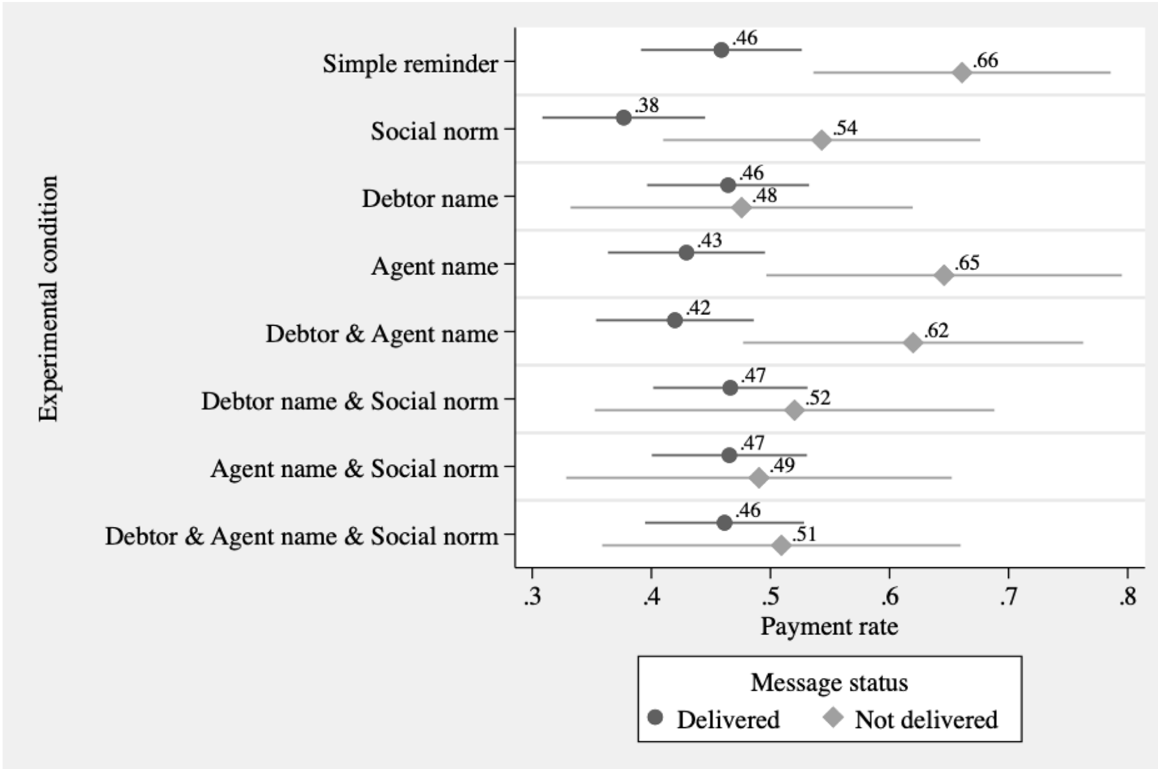

Fig. 2. Payment rates (delivered vs. non-delivered messages) in Experiment 3.
Notes: Marginal effects from the linear regression model with control variables included (see Appendix L, Model 3). Confidence intervals at 95% level.

payday loan provider), the debtor is more likely to make the payment than if the loan is taken out with catalogue merchants or service providers (e.g., a phone company). The difference in the likelihood of paying the debt ranges from 19 percentage points (payday loans) to 26 percentage points (banks) compared to catalogue merchants ($p<0.01$). The reason might be that banks and payday loan providers undertake substantial screening of the potential loan-taker. In contrast, catalogue merchants and service providers do little evaluation of the person's creditworthiness before extending credit. As a result, banks and payday loan service providers attract less-risky borrowers, who are less likely to default on their debts (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981).

The size of the debt has no statistically significant effect on debt repayment. Nevertheless, the share of collection fees in the total value of debt correlates with the likelihood of making a payment. Notably, every 10-percentage-point increase in collection fees as a share of total debt value decreases the payment rate by 2 percentage points.

There are significant differences in the payment rate regarding the communication channel through which the message is delivered. The most effective way to increase the payment rate is to remind the debtor of the scheduled payment via both mobile text message and email. In that case, the probability of making a payment increases by 5.2 percentage points relative to sending only a text message ($p<0.05$). There are no significant differences if a message is sent only through one communication channel (a mobile text message or an email). However, it must be remembered that the communication channel was not randomized among the individuals in the experiment, and generally, receiving a message backfires on collection efforts.

Concerning gender, women debtors are 9.7 percentage points more likely to repay their debt than men. Also, the debtor's age influences whether the scheduled payment is fulfilled. For example, a debtor who is 20 years old is 20 percentage points less likely to make a payment than a 50-year-old. In addition, as the size of the loan increases, the likelihood of payment decreases. Finally, loan gestation matters; the further back in time the loan was taken, the lower the probability that payment will be made. None of the subgroup analyses (gender, age, loan value) of the experimental results show any statistically significant differences under various experimental conditions.

6. Conclusions

This paper reports the results from three field experiments examining debtors' behavior vis-à-vis their NPLs. The experiments show that improving payment behavior for individuals with NPLs is not an effective strategy and may even backfire on collection efforts (see Table 4 for the overview of the experimental results). This finding contrasts with many successful nudging attempts that have been applied to debtors with performing loans. Surprisingly, the positive effect in this study is achieved only through communication, i.e., sending repeated reminders, which is the least promising nudging strategy for performing loans. However, such a nudging strategy only marginally improves debt-recovery efforts, as the improvement in payment rate was no larger than 1.5 percentage points (Experiment 1). Neither social norms, personalization, nor long-term economic consequences delivered behavioral change among defaulted individuals. Rather, the potential exists for nudging to backfire on the collection efforts of NPLs if an inappropriate messaging strategy is applied, such as sending a collection letter that stands out (Experiment 2) or reminding of a due payment when the promise to pay has already been made (Experiment 3).

Table 4
Overview of the experimental results of the study.

Treatment	Factor	Experiment 1 (consumer debts; SMS and email)	Experiment 2 (consumer debts; regular mail)	Experiment 3 (Consumer debts on a repayment plan)
Communication effect		**Positive effect**	N/A	**Negative effect**
Personalization	Debtor name	No effect	N/A	No effect
	Agent name	No effect	No effect	No effect
Social norm		No effect	No effect	No effect
Reputational concerns		N/A	No effect	N/A
Salience	Red color	N/A	**Negative effect**	N/A

The findings suggest a particular trade-off in applying a nudging strategy in debt collection on NPLs. After receiving a message, some will start to pay, while others will counteract by backfiring on collection efforts. That might be the reason why nudging delivers mixed results also on performing loans, as with the increase of annoyance costs, the probability of counteraction by the debtor also increases. It highlights that overindebtedness is not related only to high anxiety levels, depression, and other psychological ill effects (Braucher, 2006; Lea, 2021; Ranyard et al., 2017) but can trigger anger and guide strategic behavior (Saulitis, 2022; Tufail and Polletta, 2015). Particularly, with a promise to repay the debt, individuals might expect that no further communication from the CMS firm will be carried out, i.e., there will be no more added annoyance costs after the behavioral change. When this does not happen, it provokes a feeling of injustice for the debtor and thus increases the willingness to default repeatedly – this time strategically – on a debt.

An alternative interpretation of the negative effect of a reminder among individuals on a debt-repayment plan is that a reminder effectively pushes an individual to reconsider a previous decision to repay the debt. This is related to the phenomenon of limited attention (DellaVigna, 2009). Reminders do help to improve financial well-being, such as increasing the level of savings (Karlan et al., 2016). However, the opposite can be true for debt repayment. The decision to comply with the payment schedule leaves the mind when a defaulted debtor has agreed on a repayment plan. When a debtor is reminded by a message about the payment that must be made, the question of defaulting comes to mind. Similarly, when loan contracts explicitly state the possibility of walking away from the debt, it effectively increases the number of defaults (Wilkinson-Ryan, 2011). Although the goal of additional information – a reminder not to miss a payment – is to improve the payment rate, this study suggests that it can trigger the opposite effect by effectively getting the idea of defaulting to the top of mind.

Therefore, the nudging strategy in debt collection – on both performing and non-performing loans – must be accurately considered before being enacted. Other policy measures must be introduced to address the issue of NPL in credit markets, such as effective debt relief programs and out-of-court debt restructuring procedures. This is not to say that nudging should be dropped as an option in debt collection. Optimally, hybrid policy actions that combine traditional and behavioral interventions should be implemented, as Loewenstein and Chater (2017) have suggested. Reminders have the greatest potential to increase payment discipline when debtors have expressed willingness to receive these (Cadena and Schoar, 2011; Roll and Moulton, 2019) or are sent early enough to address both cognitive biases (i.e., forgetfulness) and liquidity constraints by giving reasonable time to solve possible financial distress and make a payment. If the precise moment to send a reminder is missed, or consent to receiving a message is not given, the nudging can backfire rather than improve collection efforts.

It must be noted that the current research on nudging in debt collection is based on text reminders that paternalistically ask for a payment to be made. Thaler and Sunstein (2008) emphasize that nudges not only organize the social context within which the decision is being made, but a good nudge will help people make better choices. Nudges with various choice offers for making a payment could be more effective than reminders with no choice options. Recent technological innovations have enabled interactive communication with borrowers and the ability to engage in a reflective communication process. These innovations offer the possibility in the future to examine alternative nudges that could trigger a deliberate choice and develop reciprocal relationships between lenders and borrowers that might be more effective than a top-down communication mode.

Acknowledgments

I would like to thank Intrum Baltics (formerly Lindorff Latvija), Ilva Valeika, Diāna Sprindža, Iveta Rieksta, Airita Šulce, Jeļena Lozovska, Kristaps Tomsons and Aija Kārkliņa for assistance during the data collection. I would also like to thank Krzysztof Krakowski, Lea Kroeger and Ieva Grumbinaite, for comments on this draft, Diego Gambetta, Christina Gravert, Peter John and Philipp Genschel, the editor and the reviewers for comments that have greatly improved this study. Current research has been supported by the European Regional Development Fund under the activity "Post-doctoral Research Aid", project Nr. 1.1.1.2/VIAA/4/20/612.

Ethics statement

The experimental design was reviewed and approved by the European University Institute Ethics Committee on February 4th, 2016.

Appendix A

See Table A.1.

Appendix B. Descriptive statistics of the experiments and balance tests

See Tables B.1–B.4.

Appendix C. Treatments in the experiments

See Tables C.1 and C.2.

Appendix D

See Table D.1.

Table A.1
Field experiments on nudging borrowers for loan repayment.

Author & source	Experimental setting (country; sample size & debt type; sending strategy)	Control group	Treatments examined			Effect on delinquencies
			Sending strategy	Economic conse-quences	Prosocial motives	
Bhanot (2017) *Journal Of Economic Behavior & Organization*	USA 4883 first-time microloan borrowers Single email by the lender three days before the due date	Generic reminder			Personaliza-tion	No effect of a personalized reminder on a previously written pledge to repay the debt.
Bracha and Meier (2014) Working paper	USA 247 individuals opted for a credit counseling service A monthly text message by the credit counseling agency	No message		Long-term: credit score		Text messages have a positive effect on low credit score individuals, no effect on mid-score individuals, and a negative effect on high credit score individuals relative to no message.
Bursztyn et al. (2019) *Journal of Political Economy*	Indonesia 12,104 credit card holders have missed the monthly payment due date A single text message by the bank 8 days after the due day and 7 days after an initial generic reminder sent to all in the sample	Generic reminder	Repeated reminder	Long-term: credit score	Moral appeals	Credit reputation message is the most effective message; Prosocial motives are as effective as economic rewards; sending a generic reminder has no effect.
Cadena and Schoar (2011) Working paper	Uganda 1121 business microloan holders A monthly text message by the bank 3 days before the due date	No message	Reminder effect			Sending a generic reminder is as effective as the loan contract with financial rewards.
Du et al. (2019) *Management Science*	China 2,012 peer-to-peer consumer loans to college students 2-3 text messages by the lender: (1) on the approval date; (2) 1 day before the due date; (3) 30 days after the due date in case of no payment.	Generic reminder		Short-term: legal enforcement	Moral appeals and personaliza-tion	Moral appeals significantly increase payment discipline relative to any other message (generic reminder, enforcement, and personalization).
Holzmeister et al. (2022) *Journal of Economic Behavior & Organization*	Undisclosed European country 76,000 debtors with non-performing loans Single regular mail letter by the credit management firm	No message	Reminder effect; varied envelope design	Long- & short-term: penalty fee; interest rate change, legal enforcement	Social norm	All reminders modestly increase payment rate relative to not sending a message. No effect for the design of the envelope. Messages containing economic consequences and social norms have no effect or modestly backfires on collection efforts relative to generic reminder.
Homonoff et al. (2019) *The Review of Economics and Statistics*	USA 406,994 student loan holders Quarterly email by the lender	No message	Repeated reminder effect	Long-term: credit score	Social norm	Significant effect of credit reputation; no effect of economic consequences or prosocial motives; no effect of a repeated reminder.

(*continued on next page*)

Table A.1 (*continued*).

Huang and Bao (2020) Working paper	China 58,345 peer-to-peer consumer loan holders with no overdue record A single text message by the lender on the due date	No message	Reminder effect	Long-term: interest rate change	Social norm; Peer effect	Messages with economic consequences are the most effective reminders. Prosocial messages are more effective than a simple reminder. Generic reminder significantly increases payment behavior.
Karlan et al. (2015) *Behavioral Science & Policy*	Philippines 943 individuals with microloans Weekly text messages by the bank or officer two days before, one day before, or on the due date	No message	Timing	Long-term: credit score; Short-term: penalty fee	Personaliza-tion	No effect of credit reputation or penalties; no framing or timing effect; personalized messages by the bank manager to repeated borrowers significantly improve the payment behavior.
Medina (2020) *The Review of Financial Studies*	Brazil 26,069 credit cardholders with a late payment history 1-5 monthly push notifications on the bank's app 27 to 3 days before the due date	No message	Repeated reminder effect	Short-term: penalty fee		Significant positive effect of a repeated reminder and for a message with information on penalties.
Moulton (2015) *Journal of Policy Analysis and Management*	USA 425 individuals with mortgage loans Quarterly email and a phone call by credit counseling officer	No message	Reminder effect			Significant positive effect of regular reminders about financial goals by credit counseling agent.
Roll and Moulton (2019) *Journal of Consumer Affairs*	USA 1676 individuals in credit distress that participate in credit counseling program Email by credit counseling officer in a frequency set by the receiver.	No message	Reminder effect			Significant positive effect of various reminders (financial goals and due payments) on decreasing delinquency rates.
Seira et al. (2017) *American Economic Journal: Economic Policy*	Mexico 167,190 of indebted credit cardholders Single regular mail letter by the lender	No message	Reminder effect		Personaliza-tion; Social norm	No effect of the generic reminder. Negative effect (more delinquencies) of personalized information disclosure among holders of large debts/regular interest ratepayers. Positive effect of social norm messages.

Table B.1
Experiment 1: NPL reminder via SMS and email messages.

Covariate	Simple reminder	No message	Social norm	Debtor name	Agent name	Debtor & Agent name	Debtor name & Social norm	Agent name & Social norm	Agent & Debtor name & Social norm	p-value from joint orthogonality test of treatment arms
Gender	0.430	0.441	0.455	0.447	0.434	0.446	0.430	0.467	0.443	0.168
	(0.010)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	
Loan size (log)	5.615	5.685	5.651	5.682	5.660	5.691	5.687	5.656	5.710	0.341
	(0.027)	(0.019)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)	(0.028)	
Fee ratio	0.231	0.220	0.218	0.221	0.221	0.215	0.219	0.222	0.219	0.398
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	
Ethnicity	0.263	0.276	0.266	0.253	0.268	0.273	0.257	0.258	0.271	0.502
	(0.009)	(0.006)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	
Debtor age	41.624	41.168	41.557	41.480	41.619	41.483	41.503	41.193	41.247	0.688
	(0.240)	(0.169)	(0.246)	(0.236)	(0.240)	(0.237)	(0.239)	(0.231)	(0.235)	
Debt due age	7.730	7.727	7.761	7.766	7.833	7.795	7.776	7.835	7.978	0.255
	(0.071)	(0.050)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.073)	
Region	3.064	2.958	2.966	2.960	3.013	2.994	3.004	2.954	3.050	0.114
	(0.034)	(0.024)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.033)	(0.034)	
Channel	2.314	2.291	2.311	2.325	2.305	2.324	2.314	2.289	2.298	0.074
	(0.011)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	
Debt type	2.042	2.080	2.120	2.081	2.053	2.105	2.060	2.051	2.028	0.165
	(0.025)	(0.017)	(0.026)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)	
N	2,495	4,990	2,495	2,495	2,495	2,495	2,495	2,495	2,495	

Note: Standard errors in parenthesis.

Table B.2
Experiment 2: NPL reminder via regular mail; Phase 1.

Covariate	Simple reminder	Social norm	Agent	Reputation	All treatments	RED Simple reminder	RED Social norm	RED Agent	RED Reputation	RED All treatments	p-value from joint orthogonality test of treatment arms
Gender	0.635	0.645	0.670	0.575	0.625	0.660	0.695	0.585	0.585	0.650	0.192
	(0.034)	(0.034)	(0.033)	(0.035)	(0.034)	(0.034)	(0.033)	(0.035)	(0.035)	(0.034)	
Loan size (log)	6.078	6.143	6.138	6.222	6.180	6.260	6.197	6.125	6.077	6.139	0.689
	(0.070)	(0.074)	(0.070)	(0.068)	(0.071)	(0.068)	(0.069)	(0.069)	(0.068)	(0.070)	
ratio	0.125	0.114	0.101	0.098	0.097	0.103	0.098	0.105	0.110	0.109	0.258
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	
Ethnicity	0.380	0.440	0.410	0.410	0.445	0.410	0.410	0.435	0.420	0.415	0.977
	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	
Debtor age	41.410	40.115	41.315	39.810	41.500	40.525	40.985	41.055	41.105	42.140	0.866
	(0.936)	(0.932)	(0.978)	(0.884)	(1.015)	(0.935)	(0.957)	(0.939)	(0.998)	(1.012)	
Debt due age	5.231	4.928	4.942	4.997	4.891	5.117	5.101	4.986	4.911	5.108	0.930
	(0.177)	(0.169)	(0.174)	(0.167)	(0.165)	(0.186)	(0.186)	(0.166)	(0.180)	(0.180)	
Region	2.870	3.120	2.875	3.010	3.000	2.990	2.995	2.870	2.995	3.120	0.772
	(0.113)	(0.125)	(0.113)	(0.113)	(0.121)	(0.117)	(0.109)	(0.117)	(0.116)	(0.113)	
Type	2.400	2.475	2.380	2.435	2.395	2.425	2.375	2.345	2.435	2.400	0.912
	(0.059)	(0.054)	(0.057)	(0.054)	(0.057)	(0.055)	(0.054)	(0.058)	(0.053)	(0.056)	
N	200	200	200	200	200	200	200	200	200	200	

Note: Standard errors in parenthesis.

Table B.3
Experiment 2: NPL reminder via regular mail; Phase 2.

Covariate	Simple reminder	Personalization (Female agent)	Personalization (Male agent)	p-value from joint orthogonality test of treatment arms
Gender	0.608	0.576	0.619	0.218
	(0.013)	(0.019)	(0.018)	
Loan size (log)	5.295	5.325	5.335	0.448
	(0.020)	(0.028)	(0.028)	
Fee ratio	0.111	0.107	0.106	0.482
	(0.003)	(0.004)	(0.004)	
Ethnicity	0.418	0.404	0.422	0.763
	(0.013)	(0.018)	(0.019)	
Debtor age	42.979	43.067	43.689	0.393
	(0.307)	(0.431)	(0.440)	
Debt due age	8.570	8.416	8.512	0.705
	(0.107)	(0.149)	(0.149)	
Region	2.422	2.336	2.456	0.383
	(0.046)	(0.062)	(0.065)	
Debt type	3.283	3.312	3.275	0.818
	(0.032)	(0.044)	(0.045)	
N	1,410	705	706	

Note: Standard errors in parenthesis.

Table B.4
Experiment 3: recovered loans via SMS & emails.

Covariates	Simple reminder	No message	Social norm	Debtor name	Agent name	Debtor & Agent name	Debtor name & Social norm	Agent name & Social norm	Debtor & Agent name & Social norm	p-value from joint orthogonality test of treatment arms
Gender	0.347	0.326	0.322	0.322	0.339	0.343	0.298	0.331	0.355	0.958
	(0.031)	(0.021)	(0.030)	(0.030)	(0.030)	(0.031)	(0.029)	(0.030)	(0.031)	
Debt amount (log)	5.870	5.978	5.938	5.802	5.803	5.841	5.874	5.982	5.678	0.311
	(0.094)	(0.071)	(0.098)	(0.098)	(0.092)	(0.098)	(0.096)	(0.097)	(0.090)	
Fee ratio	0.193	0.189	0.196	0.199	0.187	0.193	0.200	0.172	0.203	0.883
	(0.014)	(0.010)	(0.014)	(0.015)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	
Ethnicity	0.285	0.225	0.223	0.260	0.252	0.310	0.244	0.215	0.289	0.138
	(0.029)	(0.019)	(0.027)	(0.028)	(0.028)	(0.030)	(0.028)	(0.026)	(0.029)	
Debtor age	43.120	42.740	42.236	42.880	41.554	42.636	41.674	42.822	43.050	0.817
	(0.774)	(0.560)	(0.744)	(0.760)	(0.793)	(0.833)	(0.717)	(0.762)	(0.836)	
Debt due age	7.385	7.409	7.324	7.194	7.420	7.788	7.226	7.061	7.048	0.418
	(0.218)	(0.159)	(0.213)	(0.223)	(0.226)	(0.235)	(0.231)	(0.228)	(0.229)	
Region	3.033	3.050	3.091	3.112	2.913	2.860	2.777	2.839	3.058	0.188
	(0.110)	(0.075)	(0.110)	(0.110)	(0.103)	(0.111)	(0.104)	(0.104)	(0.104)	
Channel	2.566	2.568	2.570	2.607	2.620	2.537	2.574	2.645	2.566	0.424
	(0.033)	(0.024)	(0.033)	(0.032)	(0.033)	(0.035)	(0.032)	(0.033)	(0.033)	
Debt type	2.161	2.202	2.248	2.219	2.240	2.161	2.140	2.355	2.256	0.703
	(0.082)	(0.056)	(0.085)	(0.079)	(0.080)	(0.078)	(0.073)	(0.077)	(0.081)	
N	242	484	242	242	242	242	242	242	242	

Note: Standard errors in parenthesis.

Table C.1

	Experiment 1: Treatment line in email	Experiment 1: Mobile text message	Experiment 3: Treatment line in email	Experiment 3 Mobile text message
[Control group]	Reminder about the debt!	This is a reminder that you have a debt, case nr. 1234567. Contact us to find a solution: 76543210	Reminder about the payment!	This is a reminder that you have a payment due, case nr. 1234567. Thank you if the payment has already been made. Tel. 76543210
No message				
Social norm	Around 80% pay their liabilities on time. You are in a minority that has not done so.	This is a reminder that you have a debt, case nr. 1234567. Around 80% pay their liabilities on time. You are in a minority that has not done so. Contact us to find a solution: 76543210	Around 80% pay their liabilities on time. Don't be in the minority that does not do so.	This is a reminder that you have a payment due, case nr. 1234567. Around 80% pay their liabilities on time. Don't be in the minority that does not do so. Thank you if the payment has already been made. Tel. 76543210.
Personalization: Debtor name	[Name], reminder about the debt!	{name], this is a reminder that you have a debt, case nr. 1234567. Contact us to find a solution: 76543210	[Name], reminder about the payment!	[Name], this is a reminder that you have a payment due, case nr. 1234567. Thank you if the payment has already been made. Tel. 76543210
Personalization: Agent name	Contact me, [company] consultant [name] to find an individual solution!	This is a reminder that you have a debt, case nr. 1234567. Contact me, [company] specialist [name] to find a solution: 76543210	I remind you of a payment due!	I remind you of a payment due, case nr. 1234567. Thank you if the payment has already been made. Tel. 76543210. Best, [name].
Personalization: Debtor & Agent name	[Name], contact me, [company] consultant [name] to find an individual solution!	[Name], This is a reminder that you have a debt, case nr. 1234567. Contact me, [company] specialist [name] to find a solution: 76543210	[Name], I remind you of a payment due!	[Name], I remind you of a payment due, case nr. 1234567. Thank you if the payment has already been made. Tel. 76543210. Best, [name].
Personalization (Debtor name) & Social norm	[Name], around 80% pay their liabilities on time. You are in a minority that has not done so.	[Name], This is a reminder that you have a debt, case nr. 1234567. Around 80% pay their liabilities on time. You are in a minority that has not done so. Contact us to find a solution: 76543210	[Name], around 80% pay their liabilities on time. Don't be in the minority that does not do so.	[Name], this is a reminder that you have a payment due, case nr. 1234567. Around 80% pay their liabilities on time. Don't be in the minority that does not do so. Thank you if the payment has already been made. Tel. 76543210.
Personalization (Agent name) & Social norm	Around 80% pay their liabilities on time. You are in a minority that has not done so. Contact me: consultant [name]!	This is a reminder that you have a debt, case nr. 1234567. Around 80% pay their liabilities on time. You are in a minority that has not done so. Contact me, [company] specialist [name] to find a solution: 76543210	Around 80% pay their liabilities on time. Don't be in the minority that does not do so.	I remind you of a payment due, case nr. 1234567. Around 80% pay their liabilities on time. Don't be in the minority that does not do so. Thank you if the payment has already been made. Tel. 76543210. Best, [name].
Personalization (Debtor & Agent name) & Social norm	[Name], around 80% pay their liabilities on time. You are in a minority that has not done so. Contact me: consultant [name]!	[Name], this is a reminder that you have a debt, case nr. 1234567. Around 80% pay their liabilities on time. You are in a minority that has not done so. Contact me, [company] specialist [name] to find a solution: 76543210	[Name], around 80% pay their liabilities on time. Don't be in the minority that does not do so.	[Name], I remind you of a payment due, case nr. 1234567. Around 80% pay their liabilities on time. Don't be in the minority that does not do so. Thank you if the payment has already been made. Tel. 76543210. Best, [name].

Table C.2

	Experiment 2: Treatment line in header	Experiment2: Treatment text in the body	Experiment 2: Signature
[Control group]	THIS IS A REMINDER & OFFER	So far, we have not reached agreement on repayment of the debt.	Lindorff
Social norm	YOU'RE ONE OF THE FEW WHO DOES NOT PAY; WE HAVE AN OFFER	Around 80% of Latvians pay their liabilities on time.* You are one of the few who does not do so.	Lindorff
Personalization (Agent)	MY OFFER FOR YOU	This is [name] writing, a consultant from Lindorff. After investigating your case, I can see that so far you have not reached agreement on repayment of the debt.	[Name], Lindorff consultant
Reputation	YOUR REPUTATION IS IMPORTANT	This envelope was delivered by the postal worker to you because so far, we have not reached agreement on repayment of the debt.	Lindorff
All in one (Reputation & Social norm & Agent)	YOUR REPUTATION IS IMPORTANT; YOU'RE ONE OF THE FEW WHO DOES NOT PAY; I HAVE AN OFFER FOR YOU	This is [name] writing, a consultant from Lindorff. After investigating your case, I can see that so far you have not reached agreement on repayment of the debt. This red envelope was delivered by the postal worker to only a few people, as around 80% pay their liabilities on time.* You are one of the few who does not do so.	[Name], Lindorff consultant

Table D.1
Effect of the treatment message on the payment rate in Experiment 1 (Linear probability regression).

	Model (1)	Model (2)	Model (3)	Model (4)
Treatment (baseline: Simple reminder)				
No message	−0.00741**	−0.00680**		
	(0.00303)	(0.00303)		
Social norm	−0.00120	−0.000808	−0.000710	−0.000521
	(0.00371)	(0.00369)	(0.00668)	(0.00666)
Debtor name	−0.00200	−0.00170	−0.00425	−0.00414
	(0.00366)	(0.00366)	(0.00646)	(0.00646)
Agent name	−0.00321	−0.00283	−0.00418	−0.00380
	(0.00360)	(0.00360)	(0.00651)	(0.00653)
Debtor & Agent name	−0.000401	6.11e−05	0.000610	0.00100
	(0.00375)	(0.00375)	(0.00674)	(0.00673)
Debtor name & Social norm	0.00240	0.00271	0.00596	0.00620
	(0.00389)	(0.00389)	(0.00701)	(0.00701)
Agent name & Social norm	−0.00361	−0.00268	−0.00526	−0.00429
	(0.00358)	(0.00357)	(0.00643)	(0.00643)
Agent & Debtor name & Social norm	0	0.000998	0.000489	0.00172
	(0.00377)	(0.00377)	(0.00672)	(0.00675)
Gender		−0.00646***		−0.0113***
		(0.00170)		(0.00361)
Loan size (log)		−0.00277**		−0.00421*
		(0.00108)		(0.00236)
Fee ratio		0.0280***		0.0547***
		(0.00862)		(0.0169)
Ethnicity		−0.00366**		−0.00648*
		(0.00171)		(0.00379)
Debtor age		0.000129*		0.000186
		(7.14e−05)		(0.000171)
Debt due age		−0.000367		−0.000859
		(0.000294)		(0.000643)
Region (baseline: Riga)				
Pierīga		6.66e−06		0.00103
		(0.00256)		(0.00530)
Kurzeme		−0.000641		0.000319
		(0.00245)		(0.00518)
Zemgale		−0.00213		−0.00237
		(0.00241)		(0.00518)
Vidzeme		−0.000580		−0.00243
		(0.00274)		(0.00560)
Latgale		−0.00184		−0.00465
		(0.00280)		(0.00617)

(*continued on next page*)

Table D.1 (*continued*).

	Model (1)	Model (2)	Model (3)	Model (4)
Delivery channel (baseline: SMS)				
Only email		−0.000412		−0.0145**
		(0.00329)		(0.00581)
Both		0.0128***		0.000490
		(0.00196)		(0.00390)
Debt type (baseline: Catalogue merchants)				
Banks & Leasing		0.0140***		0.0286***
		(0.00312)		(0.00762)
Fast credits		0.0140***		0.0239***
		(0.00288)		(0.00601)
Services		0.00464		0.0145
		(0.00667)		(0.0136)
CMS firms		0.0109**		0.0240***
		(0.00442)		(0.00825)
Constant	0.0180***	0.0181**	0.0320***	0.0371**
	(0.00266)	(0.00797)	(0.00469)	(0.0166)
Observations	24,950	24,950	10,847	10,847
R-squared	0.001	0.008	0.000	0.008

Notes: Robust standard errors in parentheses. Models (1) and (2) present estimates on full sample, i.e., intention-to-treat effect; Models (3) and (4) present estimates on reached only sample, i.e., compliance average causal effect.
*** p<0.01, ** p<0.05, * p<0.1.

Table E.1
Compliant average causal effect of communication on the payment rate (two-stage least squares regression).

	Model (1)	Model (2)
CACE of Simple reminder	0.0131**	0.0126**
	(0.00536)	(0.00537)
Gender		−0.00498*
		(0.00291)
Loan size (log)		−0.00157
		(0.00183)
Fee ratio		0.0135
		(0.0130)
Ethnicity		−0.00553**
		(0.00274)
Debtor age		0.000112
		(0.000118)
Debt due age		−0.000469
		(0.000454)
Region (baseline: Riga)		
Pierīga		−0.00304
		(0.00425)
Kurzeme		−0.00741*
		(0.00383)
Zemgale		−0.00692*
		(0.00386)
Vidzeme		0.00299
		(0.00530)
Latgale		−0.00238
		(0.00493)
Delivery channel (baseline: SMS)		
Only email		−0.0108***
		(0.00354)
Both		0.00304
		(0.00321)
Debt type (baseline: Catalogue merchants)		
Banks & Leasing		0.0138**
		(0.00586)
Fast credits		0.0116**
		(0.00474)
Services		0.00231
		(0.0120)
CMS firms		0.00555
		(0.00704)
Constant	0.0106***	0.0161
	(0.00145)	(0.0137)
Observations	7,485	7,485
R-squared	0.005	0.010

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table F.1
Treatment effect of the message delivery with interaction of loan size on the payment rate (Linear probability regression) in Experiment 1.

	Model (1)	Model (2)	Model (3)
Treatment (baseline: Treated)			
No message	−0.0204***	−0.0199***	−0.0440***
	(0.00221)	(0.00225)	(0.0100)
Not treated	−0.0307***	−0.0297***	−0.0644***
	(0.00168)	(0.00191)	(0.00804)
Loan size (log)		−0.00230**	−0.00572***
		(0.00108)	(0.00161)
Interaction effects			
No message*Loan size (log)			0.00430***
			(0.00164)
Not treated*Loan size (log)			0.00615***
			(0.00135)
Fee ratio		0.0263***	0.0246***
		(0.00856)	(0.00850)
Gender		−0.00532***	−0.00537***
		(0.00168)	(0.00168)
Ethnicity		−0.00342**	−0.00352**
		(0.00170)	(0.00170)
Debtor age		7.87e−05	8.35e−05
		(7.07e−05)	(7.07e−05)
Debt due age		−0.000475	−0.000431
		(0.000293)	(0.000292)
Region (baseline: Riga)			
Pierīga		0.000150	0.000119
		(0.00255)	(0.00255)
Kurzeme		−0.000763	−0.000708
		(0.00244)	(0.00244)
Zemgale		−0.00246	−0.00241
		(0.00240)	(0.00240)
Vidzeme		−0.000929	−0.000855
		(0.00273)	(0.00273)
Latgale		−0.00152	−0.00149
		(0.00279)	(0.00278)
Delivery channel (baseline: SMS)			
Only email		−0.0114***	−0.0107***
		(0.00343)	(0.00344)
Both		6.83e−05	0.000379
		(0.00224)	(0.00224)
Debt type (baseline: Catalogue merchants)			
Banks & Leasing		0.0134***	0.0128***
		(0.00309)	(0.00309)
Fast credits		0.0132***	0.0135***
		(0.00286)	(0.00287)
Services		0.00363	0.00432
		(0.00659)	(0.00658)
CMS firms		0.0118***	0.0118***
		(0.00441)	(0.00441)
Constant		0.0364***	0.0551***
		(0.00784)	(0.0103)
Observations		24,950	24,950
R-squared		0.017	0.018

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix E

See Table E.1.

Appendix F

See Table F.1.

Appendix G

See Table G.1.

Appendix H

See Table H.1.

Appendix I

See Table I.1.

Appendix J

See Table J.1.

Appendix K

See Table K.1.

Appendix L

See Table L.1.

Table G.1
Treatment effect on the payment rate in Experiment 2 Phase 1 (Linear probability regression).

	Model (1)	Model (2)	Model (3)	Model (4)
Treatment (baseline: Simple reminder)				
Social norm	0.0150	0.0147	0.0159	0.0152
	(0.0164)	(0.0165)	(0.0169)	(0.0170)
Agent	0.0300	0.0314*	0.0309	0.0321*
	(0.0184)	(0.0185)	(0.0188)	(0.0189)
Reputation	0.0250	0.0260	0.0265	0.0273
	(0.0177)	(0.0179)	(0.0183)	(0.0185)
All in one	−0.00500	−0.00494	−0.00419	−0.00431
	(0.0131)	(0.0132)	(0.0138)	(0.0138)
RED Simple reminder	−0.00500	−0.00340	−0.00437	−0.00308
	(0.0131)	(0.0132)	(0.0137)	(0.0138)
RED Social norm	−0	0.00240	0.000210	0.00263
	(0.0140)	(0.0141)	(0.0144)	(0.0144)
RED Agent	0.00500	0.00600	0.00619	0.00698
	(0.0149)	(0.0147)	(0.0155)	(0.0153)
RED Reputation	−0.0100	−0.0111	−0.0100	−0.0112
	(0.0122)	(0.0121)	(0.0125)	(0.0124)
RED All in one	−0	−0.000307	0.000317	4.29e−05
	(0.0140)	(0.0141)	(0.0144)	(0.0145)
Loan size (log)		−0.00844		−0.00890
		(0.00610)		(0.00636)
Fee ratio		0.0226		0.0195
		(0.0544)		(0.0564)
Ethnicity		0.00293		0.00262
		(0.00743)		(0.00772)
Gender		−0.00808		−0.00839
		(0.00753)		(0.00781)
Debtor age		0.000157		0.000185
		(0.000287)		(0.000304)
Debt due age		0.000641		0.000787
		(0.00268)		(0.00280)
Region (baseline: Riga)				
Pierīga		0.00944		0.00916
		(0.0128)		(0.0133)
Kurzeme		−0.00240		−0.00328
		(0.00940)		(0.00977)
Zemgale		0.00151		0.000952
		(0.00987)		(0.0103)
Vidzeme		0.0114		0.0113
		(0.0134)		(0.0141)
Latgale		0.00745		0.00727
		(0.0157)		(0.0163)
Debt type (baseline: Catalogue merchants)				
Banks & Leasing		−0.00356		−0.00334
		(0.0202)		(0.0211)
Fast credits		0.0119		0.0127
		(0.0203)		(0.0210)
Services		−0.0263		−0.0271
		(0.0178)		(0.0185)
CMS firms		−0.0424*		−0.0427*
		(0.0247)		(0.0255)
Constant	0.0200**	0.0545	0.0204**	0.0564
	(0.00992)	(0.0451)	(0.0101)	(0.0471)
Observations	2,000	2,000	1,916	1,916
R-squared	0.007	0.013	0.007	0.013

Notes: Robust standard errors in parentheses. Models (1) and (2) present estimates on full sample, i.e., intention-to-treat effect; Models (3) and (4) present estimates on reached only sample, i.e., compliance average causal effect.
*** p<0.01, ** p<0.05, * p<0.1.

Table H.1
Treatment effect of the red envelope on the payment rate in Experiment 2 Phase 1 (Linear probability regression).

	Model (1)	Model (2)	Model (3)	Model (4)
Red envelope	−0.0150**	−0.0148**	−0.0155**	−0.0152**
	(0.00705)	(0.00700)	(0.00734)	(0.00727)
Loan size (log)		−0.00830		−0.00874
		(0.00614)		(0.00640)
Fee ratio		0.0208		0.0177
		(0.0544)		(0.0565)
Ethnicity		0.00295		0.00274
		(0.00743)		(0.00771)
Gender		−0.00798		−0.00840
		(0.00740)		(0.00769)

(*continued on next page*)

Table H.1 (*continued*).

	Model (1)	Model (2)	Model (3)	Model (4)
Debtor age		0.000143		0.000174
		(0.000287)		(0.000304)
Debt due age		0.000632		0.000729
		(0.00269)		(0.00280)
Region (baseline: Riga)				
Pieriga		0.00873		0.00886
		(0.0126)		(0.0131)
Kurzeme		−0.00133		−0.00211
		(0.00949)		(0.00986)
Zemgale		0.00169		0.00119
		(0.00984)		(0.0102)
Vidzeme		0.0108		0.0110
		(0.0132)		(0.0140)
Latgale		0.00706		0.00700
		(0.0156)		(0.0162)
Debt type (baseline: Catalogue merchants)				
Banks & Leasing		−0.00353		−0.00335
		(0.0203)		(0.0211)
Fast credits		0.0113		0.0120
		(0.0203)		(0.0210)
Services		−0.0349**		−0.0363**
		(0.0160)		(0.0166)
CMS firms		−0.0337		−0.0341
		(0.0227)		(0.0236)
Constant	0.0330***	0.0681	0.0343***	0.0708
	(0.00565)	(0.0430)	(0.00588)	(0.0451)
Observations	2,000	2,000	1,916	1,916
R-squared	0.002	0.008	0.002	0.008

Notes: Robust standard errors in parentheses. Models (1) and (2) present estimates on full sample, i.e., intention-to-treat effect; Models (3) and (4) present estimates on reached only sample, i.e., compliance average causal effect.
*** p<0.01, ** p<0.05, * p<0.1.

Table I.1
Personalization effect on the payment rate in Experiment 2 Phase 2 (Linear probability regression).

	Model (1)	Model (2)	Model (3)	Model (4)
Personalization (Agent)	0.00495	0.00484	0.00456	0.00451
	(0.00428)	(0.00425)	(0.00443)	(0.00441)
Loan size (log)		−0.00720		−0.00710
		(0.00878)		(0.00924)
Fee ratio		−0.0435		−0.0422
		(0.0688)		(0.0722)
Ethnicity		−0.00265		−0.00421
		(0.00455)		(0.00455)
Gender		−0.00725		−0.00653
		(0.00467)		(0.00479)
Debtor age		−5.72e−05		−4.59e−06
		(0.000168)		(0.000169)
Debt due age		−0.000475		−0.000533
		(0.00116)		(0.00120)
Region (baseline: Riga)				
Pieriga		0.00607		0.00596
		(0.00777)		(0.00812)
Kurzeme		0.00814		0.00848
		(0.00912)		(0.00964)
Zemgale		0.00206		0.00170
		(0.00736)		(0.00770)
Vidzeme		0.0164		0.0124
		(0.0116)		(0.0114)
Latgale		0.000485		0.000270
		(0.00814)		(0.00840)
Debt type (baseline: Banks)				
Fast credits		−0.0216*		−0.0229*
		(0.0120)		(0.0125)
Services		−0.00691		−0.00723
		(0.00916)		(0.00953)
CMS firms		−0.0191*		−0.0195
		(0.0115)		(0.0119)

(*continued on next page*)

Table I.1 (*continued*).

	Model (1)	Model (2)	Model (3)	Model (4)
Constant	0.0106***	0.0684	0.0111***	0.0672
	(0.00273)	(0.0607)	(0.00285)	(0.0639)
Observations	2,821	2,821	2,692	2,692
R-squared	0.000	0.006	0.000	0.005

Notes: Robust standard errors in parentheses. Models (1) and (2) present estimates on full sample, i.e., intention-to-treat effect; Models (3) and (4) present estimates on reached only sample, i.e., compliance average causal effect.
*** p<0.01, ** p<0.05, * p<0.1.

Table J.1
Treatment effects on the payment rate in Experiment 3 (Linear probability regression).

	Model (1)	Model (2)	Model (3)	Model (4)
Treatment (baseline: Simple reminder)				
No message	0.0124	−0.00653		
	(0.0394)	(0.0377)		
Social norm	−0.0826*	−0.0872**	−0.0743	−0.0843*
	(0.0451)	(0.0437)	(0.0496)	(0.0489)
Debtor name	−0.00826	−0.0290	0.0305	0.00715
	(0.0455)	(0.0438)	(0.0503)	(0.0489)
Agent name	−0.0248	−0.0327	−0.0202	−0.0282
	(0.0454)	(0.0438)	(0.0497)	(0.0483)
Debtor & Agent name	−0.0413	−0.0462	−0.0378	−0.0375
	(0.0454)	(0.0435)	(0.0496)	(0.0483)
Debtor name & Social norm	−0.00826	−0.0239	0.0178	0.00804
	(0.0455)	(0.0434)	(0.0495)	(0.0479)
Agent name & Social norm	0.00826	−0.0289	0.0364	0.0103
	(0.0455)	(0.0434)	(0.0497)	(0.0479)
Agent & Debtor name & Social norm	−0.0124	−0.0255	0.0164	0.00486
	(0.0455)	(0.0436)	(0.0499)	(0.0484)
Gender		−0.0995***		−0.0938***
		(0.0222)		(0.0276)
Loan size (log)		0.00291		0.0159
		(0.00972)		(0.0124)
Fee ratio		−0.200***		−0.113
		(0.0639)		(0.0801)
Ethnicity		−0.000963		0.0140
		(0.0233)		(0.0285)
Debtor age		0.00398***		0.00369***
		(0.000875)		(0.00109)
Debt due age		−0.00558		−0.00796*
		(0.00395)		(0.00475)
Region (baseline: Riga)				
Pieriga		−0.0361		−0.0180
		(0.0304)		(0.0370)
Kurzeme		0.0621**		0.0687*
		(0.0314)		(0.0383)
Zemgale		0.0271		0.0551
		(0.0306)		(0.0370)
Vidzeme		−0.00633		0.0357
		(0.0337)		(0.0408)
Latgale		0.0639*		0.0941*
		(0.0382)		(0.0485)
Delivery channel (baseline: SMS)				
Only email		0.104		0.0833
		(0.0849)		(0.111)
Both		0.0544**		0.0509*
		(0.0218)		(0.0268)
Debt type (baseline: Catalogue merchants)				
Banks & Leasing		0.258***		0.213***
		(0.0379)		(0.0484)
Fast credits		0.194***		0.186***
		(0.0304)		(0.0373)
Services		0.00258		−0.127
		(0.0941)		(0.0937)
CMS firms		−0.0234		−0.00333
		(0.0445)		(0.0540)
Constant	0.483***	0.280***	0.447***	0.165
	(0.0322)	(0.0811)	(0.0355)	(0.103)
Observations	2,420	2,420	1,618	1,618
R-squared	0.003	0.086	0.005	0.083

Notes: Robust standard errors in parentheses. Models (1) and (2) present estimates on full sample, i.e., intention-to-treat effect; Models (3) and (4) present estimates on reached only sample, i.e., compliance average causal effect.
*** p<0.01, ** p<0.05, * p<0.1.

Table K.1
Compliant average causal effect of communication on the payment rate in Experiment 3 (two-stage least squares regression).

	Model (1)	Model (2)
CACE of Simple reminder	−0.0152	0.00939
	(0.0483)	(0.0461)
Gender		−0.135***
		(0.0396)
Loan size (log)		−0.0106
		(0.0173)
Fee ratio		−0.303***
		(0.106)
Ethnicity		−0.0440
		(0.0427)
Debtor age		0.00408***
		(0.00156)
Debt due age		−0.00318
		(0.00714)
Region (baseline: Riga)		
Pierīga		−0.0938*
		(0.0560)
Kurzeme		−0.0321
		(0.0564)
Zemgale		−0.0908
		(0.0587)
Vidzeme		−0.104*
		(0.0593)
Latgale		−0.0655
		(0.0662)
Delivery channel (baseline: SMS)		
Only email		0.105
		(0.160)
Both		0.0812**
		(0.0392)
Debt type (baseline: Catalogue merchants)		
Banks & Leasing		0.344***
		(0.0647)
Fast credits		0.198***
		(0.0553)
Services		0.105
		(0.180)
CMS firms		−0.0108
		(0.0816)
Constant	0.496***	0.418***
	(0.0227)	(0.136)
Observations	726	726
R-squared	0.001	0.109

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table L.1
Message delivery effect on payment rate in Experiment 3 (linear probability regression).

	Model (1)	Model (2)	Model (3)
Message received	−0.117***	−0.120***	−0.204***
	(0.0305)	(0.0293)	(0.0737)
Treatment (baseline: Simple reminder)			
Social norm		−0.0898**	−0.121
		(0.0434)	(0.0939)
Debtor name		−0.0299	−0.180*
		(0.0437)	(0.0990)
Agent name		−0.0271	−0.0154
		(0.0433)	(0.0999)
Debtor & Agent name		−0.0394	−0.0368
		(0.0432)	(0.0975)
Debtor name & Social norm		−0.0164	−0.139
		(0.0435)	(0.108)
Agent name & Social norm		−0.0208	−0.174*
		(0.0435)	(0.105)
Debtor & Agent name & Social norm		−0.0241	−0.152
		(0.0436)	(0.100)

(*continued on next page*)

Table L.1 (*continued*).

	Model (1)	Model (2)	Model (3)
Interactions			
Delivery*Social norm			0.0386
			(0.106)
Delivery*Debtor name			0.184*
			(0.111)
Delivery*Agent name			−0.0109
			(0.111)
Delivery*Debtor & Agent name			−0.000538
			(0.109)
Delivery*Debtor name & Social norm			0.147
			(0.118)
Delivery*Agent name & Social norm			0.183
			(0.116)
Delivery*Debtor & Agent name & Social norm			0.155
			(0.112)
Gender		−0.0970***	−0.0987***
		(0.0248)	(0.0250)
Loan size (log)		0.0189**	0.0192**
		(0.00851)	(0.00851)
Ethnicity		0.0131	0.00982
		(0.0258)	(0.0259)
Debtor age		0.00411***	0.00418***
		(0.000984)	(0.000987)
Debt due age		−0.00965**	−0.0100**
		(0.00406)	(0.00406)
Region (baseline: Riga)			
Pierīga		−0.0178	−0.0163
		(0.0335)	(0.0336)
Kurzeme		0.0916***	0.0876**
		(0.0351)	(0.0352)
Zemgale		0.0557*	0.0560*
		(0.0337)	(0.0338)
Vidzeme		0.0481	0.0448
		(0.0378)	(0.0379)
Latgale		0.0846**	0.0847**
		(0.0429)	(0.0427)
Delivery channel (baseline: SMS)			
SMS & Email		0.0554**	0.0551**
		(0.0244)	(0.0243)
Only email		0.134	0.132
		(0.0957)	(0.0943)
Debt type (baseline: Catalogue merchants)			
Banks & Leasing		0.233***	0.237***
		(0.0429)	(0.0432)
Fast credits		0.202***	0.200***
		(0.0337)	(0.0337)
Services		−0.0140	−0.0168
		(0.0925)	(0.0908)
CMS firms		−0.000566	−0.00163
		(0.0493)	(0.0494)
Constant	0.560***	0.240***	0.309***
	(0.0279)	(0.0814)	(0.0964)
Observations	1,936	1,936	1,936
R-squared	0.008	0.091	0.095

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

References

Alm, J., 2012. Measuring, explaining, and controlling tax evasion: lessons from theory, experiments, and field studies. Int. Tax Public Finance 19, 54–77. http://dx.doi.org/10.1007/s10797-011-9171-2.

Athey, S., Imbens, G.W., 2017. Chapter 3 - The econometrics of randomized experiments. In: Banerjee, A.V., Duflo, E. (Eds.), Handbook of Economic Field Experiments. In: Handbook of Field Experiments, North-Holland, pp. 73–140. http://dx.doi.org/10.1016/bs.hefe.2016.10.003.

Balgova, M., Nies, M., Plekhanov, A., 2016. The economic impact of reducing non-performing loans. SSRN Electron. J. http://dx.doi.org/10.2139/ssrn.3119677.

Behavioural Insights Team, 2018. Testing behaviourally-informed messaging to increase rates of contact between mortgage lenders and customers facing arrears.

Bracha, A., Meier, S., 2014. Nudging Credit Scores in the Field: the Effect of Text Reminders on Creditworthiness in the United States (No. 15–2). Working Papers, Federal Reserve Bank of Boston.

Braucher, J., 2006. Theories of overindebtedness: Interaction of structure and culture. Theor. Inq. Law 7, 323–346. http://dx.doi.org/10.2202/1565-3404.1128.

Brehm, J.W., 1966. A Theory of Psychological Reactance. Academic Press, Oxford, England.

Bursztyn, L., Fiorin, S., Gottlieb, D., Kanz, M., 2019. Moral incentives in credit card debt repayment: Evidence from a field experiment. J. Polit. Econ. 1641–1683. http://dx.doi.org/10.1086/701605.

Cadena, X., Schoar, A., 2011. Remembering to Pay? Reminders vs. Financial Incentives for Loan Payments. Working Paper No. 17020, National Bureau of Economic Research, http://dx.doi.org/10.3386/w17020.

Carpio, L.D., 2014. Are the neighbors cheating? Evidence from a social norm experiment on property taxes in Peru. Princeton University, Princeton (unpublished manuscript).

Cialdini, R.B., Kallgren, C.A., Reno, R.R., 1991. A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In: Zanna, M.P. (Ed.), Advances in Experimental Social Psychology. Academic Press, pp. 201–234.

Damgaard, M.T., Gravert, C., 2018. The hidden costs of nudging: Experimental evidence from reminders in fundraising. J. Public Econ. 157, 15–26. http://dx.doi.org/10.1016/j.jpubeco.2017.11.005.

DellaVigna, S., 2009. Psychology and economics: Evidence from the field. J. Econ. Lit. 47, 315–372. http://dx.doi.org/10.1257/jel.47.2.315.

Deville, J., 2015. Lived Economies of Default: Consumer Credit, Debt Collection and the Capture of Affect. Routledge, London New York.

Du, N., Li, L., Lu, T., Lu, X., 2019. Prosocial compliance in P2P lending: A natural field experiment. Manag. Sci. 66, 315–333. http://dx.doi.org/10.1287/mnsc.2018.3216.

Dwenger, N., Kleven, H., Rasul, I., Rincke, J., 2016. Extrinsic and intrinsic motivations for tax compliance: Evidence from a field experiment in Germany. Am. Econ. J. Econ. Policy 8, 203–232. http://dx.doi.org/10.1257/pol.20150083.

European Commission, 2020. Tackling non-performing loans in the aftermath of the COVID-19 pandemic.

Feld, S., Frenzen, H., Krafft, M., Peters, K., Verhoef, P.C., 2013. The effects of mailing design characteristics on direct mail campaign performance. Int. J. Res. Mark. 30, 143–159. http://dx.doi.org/10.1016/j.ijresmar.2012.07.003.

Freedman, D.A., 2008. Randomization does not justify logistic regression. Statist. Sci. 23, 237–249. http://dx.doi.org/10.1214/08-STS262.

Gerardi, K., Herkenhoff, K.F., Ohanian, L.E., Willen, P.S., 2018. Can't pay or won't pay? Unemployment, negative equity, and strategic default. Rev. Financ. Stud. 31, 1098–1131. http://dx.doi.org/10.1093/rfs/hhx115.

Gerber, A.S., Green, D.P., 2012. Field Experiments: Design, Analysis, and Interpretation. W. W. Norton & Company, New York.

Guiso, L., Sapienza, P., Zingales, L., 2013. The determinants of attitudes toward strategic default on mortgages. J. Finance 68, 1473–1515. http://dx.doi.org/10.1111/jofi.12044.

Hallsworth, M., 2014. The use of field experiments to increase tax compliance. Oxf. Rev. Econ. Policy 30, 658–679. http://dx.doi.org/10.1093/oxrep/gru034.

Haynes, L.C., Green, D.P., Gallagher, R., John, P., Torgerson, D.J., 2013. Collection of delinquent fines: An adaptive randomized trial to assess the effectiveness of alternative text messages. J. Policy Anal. Manage. 32, 718–730. http://dx.doi.org/10.1002/pam.21717.

Holzmeister, F., Huber, J., Kirchler, M., Schwaiger, R., 2022. Nudging debtors to pay their debt: Two randomized controlled trials. J. Econ. Behav. Organ. 198, 535–551. http://dx.doi.org/10.1016/j.jebo.2022.04.006.

Homonoff, T., O'Brien, R., Sussman, A.B., 2019. Does knowing your FICO score change financial behavior? Evidence from a field experiment with student loan borrowers. Rev. Econ. Stat. 1–45. http://dx.doi.org/10.1162/rest_a_00888.

Huang, D., Bao, Z., 2020. Gender Differences in Reaction to Enforcement Mechanisms: A Large-Scale Natural Field Experiment (SSRN Scholarly Paper No. ID 3641282). Social Science Research Network, Rochester, NY, http://dx.doi.org/10.2139/ssrn.3641282.

Jaffee, D.M., Russell, T., 1976. Imperfect information, uncertainty, and credit rationing. Q. J. Econ. 90, 651–666. http://dx.doi.org/10.2307/1885327.

James, E.L., Li, H., 1993. Why do consumers open direct mail? Contrasting perspectives. J. Direct Mark. 7, 34–40. http://dx.doi.org/10.1002/dir.4000070206.

John, P., 2017. Field Experiments in Political Science and Public Policy : Practical Lessons in Design and Delivery. Routledge.

Karlan, D., McConnell, M., Mullainathan, S., Zinman, J., 2016. Getting to the top of mind: How reminders increase saving. Manag. Sci. 62, 3393–3411. http://dx.doi.org/10.1287/mnsc.2015.2296.

Karlan, D., Morten, M., Zinman, J., 2015. A personal touch in text messaging can improve microloan repayment. Behav. Sci. Policy 1, 25–31. http://dx.doi.org/10.1353/bsp.2015.0016.

Krumer-Nevo, M., Gorodzeisky, A., Saar-Heiman, Y., 2017. Debt, poverty, and financial exclusion. J. Soc. Work 17, 511–530. http://dx.doi.org/10.1177/1468017316649330.

Lea, S.E.G., 2021. Debt and overindebtedness: Psychological evidence and its policy implications. Soc. Issues Policy Rev. 15, 146–179. http://dx.doi.org/10.1111/sipr.12074.

List, J.A., Shaikh, A.M., Xu, Y., 2019. Multiple hypothesis testing in experimental economics. Exp. Econ. http://dx.doi.org/10.1007/s10683-018-09597-5.

Loewenstein, G., Chater, N., 2017. Putting nudges in perspective. Behav. Public Policy 1, 26–53. http://dx.doi.org/10.1017/bpp.2016.7.

Mann, R.J., Porter, K., 2009. Saving up for bankruptcy. Georget. Law J. 98, 289.

Medina, P.C., 2020. Side effects of nudging: Evidence from a randomized intervention in the credit card market. Rev. Financ. Stud. http://dx.doi.org/10.1093/rfs/hhaa108.

Mind, 2008. In the Red: Debt and Mental Health. Mind, London.

Nettleton, S., Burrows, R., 2001. Families coping with the experience of mortgage repossession in the new landscape of precariousness. Community Work Fam. 4, 253–272. http://dx.doi.org/10.1080/01405110120089332.

Pal, A., 2017. Debt Collectors Make Europe's Bad Loans Pay Again. Reuters.

Papamichai, A., Mizamidis, P., 2015. The experiences of individuals in debt during an era of extreme austerity in Greece. In: Değirmencioğlu, S.M., Walker, C. (Eds.), Social and Psychological Dimensions of Personal Debt and the Debt Industry. Palgrave Macmillan, pp. 101–119.

Polletta, F., Tufail, Z., 2014. The moral obligations of some debts. Sociol. Forum 29, 1–28. http://dx.doi.org/10.1111/socf.12067.

Ranyard, R., Mchugh, S., Mcnair, S., 2017. The psychology of borrowing and over-indebtedness. In: Ranyard, R. (Ed.), Economic Psychology. John Wiley & Sons, Ltd, Chichester, UK, pp. 222–238. http://dx.doi.org/10.1002/9781118926352.ch14.

Rock, P., 2013. Making People Pay. Routledge, New York.

Roll, S.P., Moulton, S., 2019. The impact of automated reminders on credit outcomes: Results from an experimental pilot program. J. Consum. Aff. 53, 1693–1724. http://dx.doi.org/10.1111/joca.12252.

Saulitis, A., 2022. Debt relief or exit: The long-term effects of Forex loans on Latvian households. Crit. Hous. Anal. 9, 48–56. http://dx.doi.org/10.13060/23362839.2022.9.1.540.

Seira, E., Elizondo, A., Laguna-Müggenburg, E., 2017. Are information disclosures effective? Evidence from the credit card market. Am. Econ. J. Econ. Policy 9, 277–307. http://dx.doi.org/10.1257/pol.20140404.

Steindl, C., Jonas, E., Sittenthaler, S., Traut-Mattausch, E., Greenberg, J., 2015. Understanding psychological reactance. Z. Psychol. 223, 205–214. http://dx.doi.org/10.1027/2151-2604/a000222.

Stiglitz, J.E., Weiss, A., 1981. Credit rationing in markets with imperfect information. Am. Econ. Rev. 71, 393–410.

Thaler, R.H., Sunstein, C.R., 2008. Nudge: Improving Decisions About Health, Wealth, and Happiness. Yale University Press, New Haven.

Thorne, D., Anderson, L., 2006. Managing the stigma of personal bankruptcy. Sociol. Focus 39, 77–97. http://dx.doi.org/10.1080/00380237.2006.10571278.

Tölö, E., Virén, M., 2021. How much do non-performing loans hinder loan growth in Europe? Eur. Econ. Rev. 136, 103773. http://dx.doi.org/10.1016/j.euroecorev.2021.103773.

Trautmann, S.T., Vlahu, R., 2013. Strategic loan defaults and coordination: An experimental analysis. J. Bank. Financ. 37, 747–760. http://dx.doi.org/10.1016/j.jbankfin.2012.10.019.

Tufail, Z., Polletta, F., 2015. The gendering of emotional flexibility: Why angry women are both admired and devalued in debt settlement firms. Gend. Soc. 29, 484–508. http://dx.doi.org/10.1177/0891243215569050.

Walker, R., Kyomuhendo, G.B., Chase, E., Choudhry, S., Gubrium, E.K., Nicola, J.Y., Lødemel, I., Mathew, L., Mwiine, A., Pellissery, S., Ming, Y., 2013. Poverty in global perspective: Is Shame a common denominator? J. Soc. Policy 42, 215–233. http://dx.doi.org/10.1017/S0047279412000979.

Webley, P., Nyhus, E.K., 2001. Life-cycle and dispositional routes into problem debt. Br. J. Psychol. 92, 423–446. http://dx.doi.org/10.1348/000712601162275.

Wilkinson-Ryan, T., 2011. Breaching the mortgage contract: The behavioral economics of strategic default. Vanderbilt Law Rev. 1545.

Wilkinson-Ryan, T., 2015. Incentives to breach. Am. Law Econ. Rev. 17, 290–311. http://dx.doi.org/10.1093/aler/ahu019.