Supplemental Material for: Leonardo Bursztyn, Stefano Fiorin, Daniel Gottlieb, Martin Kanz. 2019. "Moral Incentives in Credit Card Debt Repayment: Evidence from a Field Experiment." Journal of Political Economy 127(4). DOI: 10.1086/701605.

ONLINE APPENDIX

"Moral Incentives in Credit Card Debt Repayment: Evidence From a Field Experiment"

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This online appendix provides additional results, robustness checks, and background materials to the main text "Moral Incentives in Credit Card Debt Repayment: Evidence from a Field Experiment." Section A outlines a theoretical framework, which illustrates the implications of introducing a moral cost of non-repayment into a standard corporate finance model. Section B contains the messages and survey instruments used in the experiment. Section C presents tables with additional summary statistics, results, and robustness tests, and Section D provides additional figures.

A. Theoretical Results

To illustrate the implications of introducing a moral cost of non-repayment in a moral hazard model of credit, we consider the standard corporate finance model described, for example, in Tirole (2006).

A.I Contracting with Moral Hazard

A risk-neutral borrower has a project, which requires a fixed investment I and has assets $A < I$. The borrower can either invest money in the project or use it for consumption. But, since the project requires a fixed investment of $I > A$, she needs to borrow $I - A$ from a lender. There is a large number of risk-neutral lenders. If undertaken, the project either succeeds or fails. A project that succeeds generates a verifiable income of $R > 0$. A project that fails generates no income. The success of the project depends, in part, on the borrower's effort. If the borrower *exerts effort*, the project succeeds with probability p_H. If the borrower *shirks*, it succeeds with probability p_L.

To simplify notation, we assume that there is no discounting. Since there is a large number of lenders, the borrower has all bargaining power, so that each (risk-neutral) lender would accept to provide financing as long as the expected return is at least zero. The borrower is protected by limited liability, so her income cannot fall below zero. Because of limited liability, both parties will receive zero in case of failure. In case of success, they share the profit R, with R_b going to the borrower and R_l going to the seller, giving the lender a profit of

$$R_l - (I - A)$$

in case of success, and $-(I - A)$ in case of failure, and giving the borrower a profit of

$$R_b - A$$

in case of success and $-A$ in case of failure. The zero-profits constraint for lenders is then:

$$p_H R_l = I - A, \tag{A.1}$$

assuming that it is only efficient to start the project if the borrower works hard:

$$p_H R - I > 0 > p_L R - I + B.$$

The incentive compatibility constraint that ensures that the borrower works hard is

$$p_H R_b \geq p_L R_b + B \therefore R_b \geq \frac{B}{\Delta p},$$

where B is the private benefit from shirking and $\Delta p \equiv p_H - p_L$ is the effect of effort on the probability of success. Since $R_l = R - R_b$, incentive compatibility implies that the highest share of the project R_l that can be pledged to the lenders without jeopardizing the borrower's incentives is

$$R - \frac{B}{\Delta p}. \tag{A.2}$$

If the borrower had to repay a share R_l greater than this amount, she would not have an incentive to work hard, which would be unprofitable.

Since lenders must break even in order to agree to finance the project – equation (A.1) –, the project can be undertaken if and only if the maximum pledgeable income (A.2) allows the lender to break even:

$$p_H \left(R - \frac{B}{\Delta p} \right) \geq I - A.$$

In technical terms, this condition ensures that high effort is implementable. That is, the project, which has positive NPV, can only be undertaken if the borrower has at least $\bar{A}$ assets, where

$$\bar{A} \equiv I - p_H \left(R - \frac{B}{\Delta p} \right).$$

Whenever $A < \bar{A}$, the positive-NPV project cannot funded because the borrower does not have enough pledgeable income, which is inefficient.

Now, suppose the borrower has a utility cost $\kappa \geq 0$ from defaulting, meaning that her utility if the project fails is now $-A - \kappa$. The incentive compatibility constraint is now

$$p_H R_b - (1 - p_H)\, \kappa \geq p_L R_b - (1 - p_L)\, \kappa + B,$$

which can be rearranged as

$$R_b \geq \frac{B}{\Delta p} - \kappa.$$

Thus, the borrower's pledgeable income becomes

$$R - \frac{B}{\Delta p} + \kappa,$$

meaning that a higher utility cost of defaulting increases the borrower's pledgeable income, reducing the range of parameters under which efficient projects are not undertaken. Therefore, holding all other parameters constant, a higher moral cost of defaulting increases the share of projects that are funded and the efficiency of the economy.

A.II Contracting with Adverse Selection

Now, we illustrate the implications of introducing a moral cost of default in adverse selection models of debt. Consider a borrower who has no initial funds and wants to finance a project that costs $I > 0$. As before, the project yields R if it succeeds and 0 if it fails. The borrower and the lenders are risk neutral and they are both protected by limited liability. For simplicity, we normalize the interest rate to 0.

There are two types of borrowers. A good type has a probability of success p, and a bad borrower has a probability of success q, where $p > q$, meaning that a good type has a better chance of succeeding than a bad type. To ensure that the model is non-trivial, we assume that it is efficient to finance the good type but not the bad type:

$$pR > I > qR.$$

If this were not the case, adverse selection would not be "binding" in the sense that all types would always get funded (or it would be efficient not to fund anyone).

The borrower's type is her private information. Lenders accept to finance a project as long as they get a non-negative rate of return. They have prior probability α on the borrower being a good and $1 - \alpha$ on the borrower being a bad type, so that $m \equiv \alpha p + (1 - \alpha)q$ is their prior probability of success. Because lenders have limited liability, they cannot offer financing contracts that pay positive amounts in case of failure. Therefore, there is no loss of generality in considering a "pooling contract" that gives the borrower a compensation of $R_b \leq R$ in case of success and 0 in case of failure. This contract can be interpreted as a debt contract with face value R_l.[56] Because borrowers have limited liability, this compensation cannot be negative, $R_b \geq 0$, which means that both types would prefer to be funded than remaining unfunded and getting a zero payoff.

[56] Although debt contracts are not very meaningful with binary outputs, Nachman and Noe (1994) and DeMarzo and Duffie (1999) show that, under some conditions on the distribution of types, the optimal contract is still a debt contract even with a continuum of outputs.

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An investor's profit from funding both types equals

$$m(R - R_b) - I = [\alpha p + (1 - \alpha)q]\,(R - R_b) - I = 0,$$

which means that the borrower's compensation in case of success is

$$R_b = R - \frac{I}{\alpha p + (1 - \alpha)q}. \tag{A.3}$$

To verify that such a contract is an equilibrium, we need to verify that it satisfies limited liability. Since $R_b < R$, it satisfies limited liabitliy for the lender. It satisfies limited liability for the borrower if and only if the borrower's compensation derived in (A.3) is positive:

$$R - \frac{I}{\alpha p + (1 - \alpha)q} \geq 0 \iff \alpha \geq \frac{qR - I}{R\,(q - p)}.$$

If this condition fails, no one gets funded (the market "breaks down"). To conclude, if there are sufficiently many good types, everyone gets funding. Otherwise, no one gets funding.

Now, suppose the borrower has a utility cost $\kappa \geq 0$ from defaulting. Then, the bad type's expected payoff is

$$qR_b - (1 - q)\,\kappa,$$

whereas the good type's expected payoff is

$$pR_b - (1 - p)\,\kappa.$$

We claim that, for intermediate values of κ, the equilibrim contract finances good types only, which is the first-best allocation that is never feasible when there are no costs from defaulting. For the contract to finance only good types, the following incentive compatibility constraints must be satisfied

$$pR_b - (1 - p)\,\kappa \geq 0 \geq qR_b - (1 - q)\,\kappa,$$

where R_b is determined by the zero-profits constraints (using the probability distribution of good types):

$$R_b = R - \frac{I}{p}.$$

Importantly, notice that a utility cost of not repaying the debt κ disproportionately hurts bad types, since they are more likely to default. These two conditions can be rewritten as:

$$\frac{p}{1 - p}\left(R - \frac{I}{p}\right) \geq \kappa \geq \frac{q}{1 - q}\left(R - \frac{I}{p}\right).$$

That is, for intermediate utility costs of debt non-repayment, the first-best allocation can be implemented. Intuitively, the moral cost of non-repayment goes in the opposite direction of the "death spiral" problem in lemons markets that causes markets to unravel. A death spiral may occur because a good borrower is more likely to succeed and, therefore, have to repay a loan. A moral cost of non-repayment, on the other hand, disproportionately hurts a bad borrower, who is more likely to be unable to repay.

In addition, when the moral cost of debt non-repayment is not observed by the lenders, the model typically has multiple equilibria. Intuitively, the interest rate charged by the lender depends on whether repayment is determined mostly by the quality of the project or by the moral cost of failing to repay the debt. We can have equilibria in which interest rates are low because default is mostly affected by morality considerations, so that many borrowers with good projects are funded, and other equilibria in which interest rates are high because default is mostly affected by the quality of the project, and mostly borrowers with bad projects are funded.

Formally, suppose that the cost of debt non-repayment is drawn from a uniform distribution in $[0, K]$, so that participation is random in the sense of Rochet and Stole (2002). As usual, this can be interpreted either as a situation with a single borrower with private information about her moral cost of debt non-repayment or as a situation in which there is a population of borrowers with heterogeneous moral costs of debt non-repayment. Now, the decision to accept financing is characterized by thresholds for the moral cost of default: individuals with moral costs below such threshold will be financed. The participation threshold for borrowers with good projects is

$$\frac{p}{1-p} R_b = \bar{\kappa}_H,$$

and the participation threshold for borrowers with bad projects is

$$\frac{q}{1-q} R_b = \bar{\kappa}_L.$$

For simplicity, we will take K to be large enough so that these cutoffs are interior in equilibrium. Notice that because a bad borrower is more likely to fail ($p > q$), her participation threshold is lower than the one of a good borrower ($\bar{\kappa}_L < \bar{\kappa}_H$). That is, as before, a disutility from not repaying the debt disproportionately affects bad borrowers.

The lender's zero-profits condition is:

$$\frac{1}{K}\left[\alpha \frac{p^2}{1-p} + (1-\alpha)\frac{q^2}{1-q}\right] R_b \left(R - R_b\right) - I = 0.$$

There are (generically) two possibilities:

- If $R < 2\sqrt{\frac{IK}{\frac{\alpha p^2}{1-p} + \frac{(1-\alpha)q^2}{1-q}}}$, there is no equilibrium with positive financing (the market breaks down);

- If $R > 2\sqrt{\frac{IK}{\frac{\alpha p^2}{1-p}+\frac{(1-\alpha)q^2}{1-q}}}$, there are two equilibria, one with a high interest rate and less projects being financed:

$$R_b^* = \frac{R + \sqrt{R^2 - \frac{4IK}{\frac{\alpha p^2}{1-p}+\frac{(1-\alpha)q^2}{1-q}}}}{2} \in \left(\frac{R}{2}, R\right),$$

and one with a low interest rate and more projects being financed:

$$R_b^* = \frac{R - \sqrt{R^2 - \frac{4IK}{\frac{\alpha p^2}{1-p}+\frac{(1-\alpha)q^2}{1-q}}}}{2} \in \left(0, \frac{R}{2}\right),$$

Therefore, the existence of heterogeneous utility costs of debt non-repayment endogenously introduces multiplicity of equilibrium. In one equilibrium, lenders fund many good projects and participation is disproportionately affected by the moral cost of debt non-repayment. In the other, lenders fund many bad projects and participation is disproportionately affected by the quality of the project.

A.III General Equilibrium with Incomplete Markets

We now discuss the implications of our results based on a literature that studies general equilibrium models with incomplete markets. For example, consider the model of Dubey, Geneakoplos, and Shubik (2005), which assumes that individuals experience an exogenous disutility when they default. While this disutility from default is often interpreted as a reduced-form of reputation considerations (which are outside the model), they may also be interpreted as a moral cost of defaulting.

Interestingly, in models with incomplete markets, increasing the moral cost of non-repayment has ambiguous effects on efficiency. When individuals have no cost of debt non-repayment, no one would be willing to lend as borrowers have no incentive to repay. On the other hand, if their cost of failing to repay their debt is high enough and their endowment is low enough in some state of the world, borrowers would choose not to borrow, since they would not want to risk being unable to repay. Typically, the most efficient outcome is therefore obtained when the moral cost of debt non-repayment is at an intermediate level.

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B. Text Messages and Survey Instruments

B.I Text Messages

Treatment	Bahasa indonesia	English
Control group	Bpk/Ibu Yth. Tag [name of the card] Anda tlh jth tempo. Utk kenyamanan & keleluasaan bertransaksi, segera lakukan pemby. Jk tlh membayar, abaikan SMS ini.[customer service number]	Dear Mr/Mrs. Your [name of the card] has reached the due date. Please make a payment at your earliest convenience. If you have already paid, ignore this text. Call [customer service number].
Moral incentive [religious]	Bpk/Ibu Yth.Nabi SAW bersabda:"Menunda pembayaran yang dilakukan oleh orang mampu adalah suatu kezaliman"HR.Bukhari.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. The Prophet (Peace and blessings be upon Him) says: "non-repayment of debts by someone who is able to repay is an injustice" (Imam al-Bukhari). Please repay your credit card balance at your earliest convenience. Call [customer service number].
Moral incentive [implicit]	Bpk/Ibu Yth.Menunda pembayaran yang dilakukan oleh orang mampu adalah suatu kezaliman.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. Non-repayment of debts by someone who is able to repay is an injustice. Please repay your credit card balance at your earliest convenience. Call [customer service number].
Moral incentive [non-religious]	Bpk/Ibu Yth.Menunda pembayaran yang dilakukan oleh orang mampu adalah suatu ketidakadilan.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. Non-repayment of debts by someone who is able to repay is an injustice [non-arabic]. Please repay your credit card balance at your earliest convenience. Call [customer service number].
Cash rebate	Bpk/Ibu Yth.Bulan ini:slsaikan tag Anda utk mendapatkan hadiah uang tunai sebesar 50% dr pembayaran minimum pada tag berikutnya.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. This month, make your credit card payment to get a cash rebate equal to 50of your minimum payment on your next statement. Please repay your credit card balance at your earliest convenience. Call [customer service number].
Credit reputation (a)	Bpk/Ibu Yth.Ketrlmbtn pembyr dilaporkan k SistemInformasiDebitur BI,yg semua bank berkonsltasi&mengurangi kemampuan mendptkan krdt.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. Late payments are reported monthly to Bank Indonesia Sistem Informasi Debitur (SID), which all banks consult. This will diminish your ability to get credit in the future. Please repay your credit card balance at your earliest convenience. Call [customer service number].
Credit reputation (b)	Bpk/Ibu Yth.Ketrlmbtn pembyr dilaporkan k SistemInformasiDebitur BI,yg semua bank dapat berkonsultasi.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. Late payments are reported monthly to Bank Indonesia Sistem Informasi Debitur (SID), which all banks can consult. Please repay your credit card balance at your earliest convenience. Call [customer service number].
Placebo: simple reminder	Bpk/Ibu Yth.Tagihan [name of the card] Anda jatuh tempo pada tanggal [due date] dan pmbayarn belum diterima.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. The due date of your [name of the card] bill was on [due date] and your payment has not been received yet. Please repay your credit credit card balance at your earliest convenience. Call [customer service number].
Placebo: religious message	Bpk/Ibu Yth.Nabi SAW bersabda:"Jika Allah menginginkan yg terbaik buat umatnya,IA melimpahkan padanya pengetahuan Kitab"HR.Bukhari.Sgra slsaikan tag Anda.[customer service number]	Dear Mr/Mrs. The Prophet (Peace and blessings be upon Him) says: When Allah wishes good for someone, He bestows upon him the understanding of the Book (Imam al-Bukhari). Please repay your credit card balance at your earliest convenience. Call [customer service number].

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B.II Religion and Religiosity

Assalamu'alaikum Sir/Madam,

May I please speak to Mr./Mrs. [cardholder name]. I am calling from [bank name] and would like to ask a few questions to improve the services we offer with [name of the credit card]. This will take less than 5 minutes. Are you willing to participate?

1. Please rank the following in terms of importance in your life, from 1 (most important) to 4 (least important)
   - Family
   - Work
   - Friends
   - Religion
2. How important is religion in your life?
   Not important at all [1] [2] [3] [4] [5] *Extremely important*
3. To you personally, how important is it to behave morally?
   Not important at all [1] [2] [3] [4] [5] *Extremely important*
4. To you personally, how important are the rules of Islam and Islamic law (Sharia)?
   Not important at all [1] [2] [3] [4] [5] *Extremely important*
5. Who do you think might have said the following phrase:
   "Non repayment of debt by someone who can afford is an injustice"?
   - Islamic Council
   - Prophet Mohammad (peace and blessings be upon Him)
   - Director of [bank name]
   - Director of Bank Indonesia
   - Don't Know

Thank you so much for your participation in this survey designed to improve our service. Have a nice day. Wassalamu'alaikum warahmatullahi wabarakatuh!

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B.III Enforcement and Disutility from the Message [Control]

Assalamu'alaikum Sir/Madam,

May I please speak to Mr./Mrs. [cardholder name]. I am calling from [bank name] and would like to ask a few questions to improve the services we offer with [name of the credit card]. This will take less than 5 minutes. Are you willing to participate?

1. How committed do you think [name of bank] is to collect debts from delinquent customers on a scale from 1 (not very committed) to 5 (very committed)?

2. [Name of bank] is sending reminder messages to its customers to help them make their payments on time. You received one of these messages last week. Would you like to receive the same message in the future? Yes [ ] No [ ]

3. What do you think would be the consequences of being reported to the *Bank Indonesia Sistem Informasi Debitur* credit registry for non-repayment of debts?
    - Will not be able to open new deposit accounts
      Yes [ ] No [ ]
    - Will not be able to get new credit from [bank name]
      Yes [ ] No [ ]
    - Will not be able to get new credit from any other bank
      Yes [ ] No [ ]
    - Will have to go on trial/appear in front of a judge
      Yes [ ] No [ ]

Thank you so much for your participation in this survey designed to improve our service. Have a nice day. Wassalamu'alaikum warahmatullahi wabarakatuh!

B.IV Enforcement and Disutility from the Message [Treatment]

Assalamu'alaikum Sir/Madam,

May I please speak to Mr./Mrs. [cardholder name]. I am calling from [bank name] and would like to ask a few questions to improve the services we offer with [name of the credit card]. This will take less than 5 minutes. Are you willing to participate?

1. How committed do you think [name of bank] is to collect debts from delinquent customers on a scale from 1 (not very committed) to 5 (very committed)?

2. [Name of bank] is sending reminder messages to its customers to help them make their payments on time. You received one of these messages last week. Would you like to receive the same message in the future? Yes [ ] No [ ]

3. We sent this SMS to some of our customers being late on their credit card repayment: "Dear Mr/Mrs. Late payments are reported monthly to Bank Indonesia Sistem Informasi Debitur, which all banks consult. This will diminish your ability to get credit in the future. Please repay your card balance at your earliest convenience. Call [customer service number]." What do you think would be the consequences if you get reported to the *Bank Indonesia Sistem Informasi Debitur* credit registry for missed payments?

    - Will not be able to open new deposit accounts
      Yes [ ] No [ ]
    - Will not be able to get new credit from [bank name]
      Yes [ ] No [ ]
    - Will not be able to get new credit from any other bank
      Yes [ ] No [ ]
    - Will have to go on trial/appear in front of a judge
      Yes [ ] No [ ]

Thank you so much for your participation in this survey designed to improve our service. Have a nice day. Wassalamu'alaikum warahmatullahi wabarakatuh!

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B.V Preferences for Delayed Cash Rebate

Assalamu'alaikum Sir/Madam,

May I please speak to Mr./Mrs. [cardholder name]. I am calling from [bank name] and would like to ask a few questions regarding cash rebates on your [name of the credit card]. Do you have a couple of minutes to answer?

1. We want to understand how much value customers give to cash rebates on their [name of the credit card], and whether they prefer cash rebates or deposits on their checking account. Among these two, what would you prefer? *[if (b) then stop]*
   (a) Rp 100,000 as a deposit on your checking account today, or
   (b) Rp 100,000 as a cash rebate on your next credit card statement?
2. How about: *[if (b) then stop]*
   (a) Rp 95,000 as a deposit on your checking account today, or
   (b) Rp 100,000 as a cash rebate on your next credit card statement?
3. How about: *[if (b) then stop]*
   (a) Rp 90,000 as a deposit on your checking account today, or
   (b) Rp 100,000 as a cash rebate on your next credit card statement?
4. How about: *[if (b) then stop]*
   (a) Rp 85,000 as a deposit on your checking account today, or
   (b) Rp 100,000 as a cash rebate on your next credit card statement?

[Continue asking until respondent says (b): ask about Rp 80,000, 75,000, 70,000, etc.]

Thank you so much for your participation in this survey.
Have a nice day. Wassalamu'alaikum warahmatullahi wabarakatuh!

C. Appendix Tables

TABLE A.1
Sample Sizes by Wave

Sample	Treated (1)	Control (2)	Repeated (3)	Excluded (4)	Other study (5)	Total (6)
Wave I	2,000	871	0	83	800	3,754
Wave II	2,000	985	0	1,018	800	4,803
Wave III	1,000	965	0	1,823	600	4,388
Wave IV	1,344	343	0	1,652	0	3,339
Wave V	1,516	590	306	1,075	0	3,487
Wave VI	1,448	366	592	1,343	0	3,749
Total	9,308	4,120	898	6,994	2,200	23,520

Note.—Columns (1) and (2) show the number of customers randomized into treatment and control for the main experiment. Column (3) reports the number of customers randomized into treatment and control for the follow-up experiment examining the effect of repeated messages. Customers assigned to the control group in a previous month remained in the sample and could either be part of the control group or be assigned to one of the treatments. Column (5) reports the number of customers randomized into treatment for a separate project that was run concurrently, and to the restructuring offer treatment that the bank was ultimately unable to operationalize. Column (6) reports the total number of late paying customers.

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TABLE A.2
REPEATED MESSAGE EXPERIMENT: BALANCE AND TREATMENT CELL SIZE

	Full sample (1)	TREATMENT: Repeated moral incentive (2)	TREATMENT: Control group (3)	p-value (4)
	A. Balance of covariates			
Age	42.29	42.43	42.15	0.653
	[9.375]	[9.375]	[9.384]	
Female	0.41	0.44	0.38	0.080
	[0.492]	[0.497]	[0.486]	
Muslim	0.90	0.91	0.89	0.321
	[0.296]	[0.282]	[0.309]	
Annual income (Rp million)	126.72	124.07	129.35	0.702
	[206.906]	[171.322]	[237.255]	
Credit limit (Rp million)	13.10	13.38	12.82	0.368
	[9.386]	[9.445]	[9.329]	
	B. Treatment cell size			
Wave V	306	153	153	
Wave VI	592	295	297	
Total	898	448	450	

NOTE.—Panel A reports summary statistics for the follow-up experiment and presents a test of random assignment. Column (1) reports the mean level of each variable, with standard deviations in brackets, for the full sample. Columns (2) and (3) report the mean level of each variable, with standard deviations in brackets, for the two experimental conditions. Column (4) reports the p-value of a test for equality of means in the two experimental conditions. Panel B reports treatment cell sizes by month.

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TABLE A.3
Heterogeneous Treatment Effects

	Dummy for delinqency					
	Male	Age	Muslim	Local religiosity	Debt-to-income ratio	Poor credit history
	(1)	(2)	(3)	(4)	(5)	(6)
Trait*moral incentive	0.015	0.012	-0.038	-0.011	0.043**	-0.027
	[0.021]	[0.020]	[0.035]	[0.021]	[0.020]	[0.021]
Moral incentive	-0.059***	-0.056***	-0.015	-0.046***	-0.072***	-0.057***
	[0.017]	[0.015]	[0.034]	[0.014]	[0.015]	[0.013]
Trait	-0.013	-0.007	-0.007	-0.119	-0.023	0.175***
	[0.015]	[0.020]	[0.026]	[0.076]	[0.015]	[0.015]
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample
Observations	8,730	8,730	8,730	8,730	8,730	8,730
R^2	0.048	0.048	0.048	0.048	0.048	0.048

Note.—This table reports heterogeneous treatment effects for the moral message (all versions). Each column shows results from a separate regression. The dependent variable in all regressions is an indicator for delinquency, which is regressed on a dummy equal to one if a customer received any version of the moral incentive treatment, the trait indicated at the top of the table and their interaction. “Age” is a dummy for age that is equal to one for customers above the median age in the sample, “local religiosity” is a dummy for local religiosity that is equal to one for customers living in provinces where the measure of local religiosity is higher than the province-level median, “debt-to-income ratio” is a dummy equal to one for customers with a debt-to-income ratio above the sample median, and “poor credit history” is a dummy equal to one for customers that have been delinquent at least once in the previous 12 months.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Supplemental Material for: Leonardo Bursztyn, Stefano Fiorin, Daniel Gottlieb, Martin Kanz. 2019. "Moral Incentives in Credit Card Debt Repayment: Evidence from a Field Experiment." Journal of Political Economy 127(4). DOI: 10.1086/701605.

TABLE A.4
First Three Waves Including Crowding-Out Experiment

	Dummy for delinquency		
	(1)	(2)	(3)
	A. Main experiment		
Moral incentive	-0.060***	-0.065***	-0.063***
	[0.018]	[0.018]	[0.017]
Simple reminder	-0.006	-0.011	-0.010
	[0.018]	[0.018]	[0.017]
Religious placebo	-0.002	-0.007	-0.008
	[0.018]	[0.018]	[0.017]
Credit reputation	-0.098***	-0.103***	-0.103***
	[0.014]	[0.014]	[0.014]
	B. Crowding-out experiment (multiple messages in one day)		
Moral incentive	-0.094***	-0.099***	-0.091***
+ Credit reputation	[0.018]	[0.018]	[0.018]
Simple reminder	-0.072***	-0.077***	-0.075***
+ Due date message	[0.018]	[0.018]	[0.017]
Delinquency rate control group		0.66	
Month fixed effects	No	Yes	Yes
Controls	No	No	Yes
Sample	Waves I, II, and III	Waves I, II, and III	Waves I, II, and III
Observations	9,821	9,821	9,821
R^2	0.008	0.018	0.076

Note.— Columns (1)-(3) restrict the sample to customers late in February, March, and May 2015 and include two treatment groups in which customers received multiple text messages on the same day ("moral incentive+credit reputation" and "simple reminder+due date message"), in addition to the control group and all other treatments run in the same months. Column (1) presents OLS regression of a delinquency dummy on treatment group indicators. The omitted category in all regressions is the control group, for which we report the mean delinquency rate. Column (2) adds month fixed effects. Column (3) adds individual covariates (age, gender, Muslim dummy, province dummy, income, a dummy for having been in the sample in a previous month, and a dummy for having been delinquent at least once in the previous 12 months). * significant at 10%; ** significant at 5%; *** significant at 1%.

Note on crowding-out experiment.—We implemented a set of treatmets, intended to be part of a separate "crowding-out" experiment, in which respondents were sent multiple messages on the same day. Because of problems with the implementation, we had to abandon this intervention. The main treatment involved sending the moral *and* credit reputation messages to clients on the 16th day of the month. We find that the effect of receiving the two messages is similar to the effect of receiving the reputational message only. This is consistent with strong crowding-out, but also with a ceiling effect. We are therefore not able to disentangle these two potential explanations. Before taking the intervention to the field, we decided to include an additional placebo group for this separate exercise: in case the two messages had an effect over and above the effect of the reputational incentive alone, in principle, this could be due to the effect of receiving any additional message on the same day (in addition to the reputational message). However, since the moral message did not have an effect over and above that of the reputational message, there was ex-post no need for this placebo. Moreover, the placebo approach used in this design was not ideal. The correct placebo would have been to send a neutral message in addition to the reputational message. Instead, two neutral messages were sent on the same day, which complicates the interpretation. There were also problems with the implementation of this intervention. Because the bank was reluctant to send two identical messages in one day, one of the messages in the "same day double reminder" group was a neutral reminder, while the other one was the same message customers were used to receiving at the end of the billing cycle. This created confusion among customers who received both messages. Some customers erroneously believed that the bank had changed the billing cycle dates, or that they were at a later point in the billing cycle than was actually the case, as they had also received the standard end-of-billing-cycle message. Since these treatments were part of a separate experiment and have a number of design and implementation issues, the results are not part of the main paper and the crowding-out experiment was eventually abandoned altogether.

TABLE A.5
SIMPLE REMINDER AS COMPARISON GROUP

	DUMMY FOR DELINQUENCY			DUMMY FOR DEFAULT		
	Full sample			High credit risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Moral incentive	-0.054**	-0.054**	-0.053**	-0.094**	-0.093**	-0.089**
	[0.022]	[0.022]	[0.021]	[0.037]	[0.037]	[0.037]
Credit reputation	-0.092***	-0.092***	-0.093***	-0.067*	-0.066*	-0.070*
	[0.019]	[0.019]	[0.018]	[0.037]	[0.037]	[0.038]
Religious placebo	0.004	0.004	0.002	0.015	0.015	0.014
	[0.021]	[0.021]	[0.021]	[0.047]	[0.047]	[0.048]
Control group	0.006	0.011	0.010	0.011	0.013	0.017
	[0.018]	[0.018]	[0.017]	[0.040]	[0.040]	[0.041]
Delinquency rate Simple reminder group		0.65				
Default rate Simple reminder group					0.12	
Month fixed effects	No	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Sample	Waves I, II, and III					
Observations		7,821			717	
R^2	0.008	0.017	0.077	0.021	0.022	0.057

NOTE.—Columns (1)-(6) restrict the sample to customers late in February, March, or May 2015. This is the sample in which moral incentive, credit reputation, religious placebo, simple reminder, and control were run simultaneously, and for which information on credit card default is available. Using customers in the control group, we estimate default probabilities by running an OLS regression of a default dummy on month fixed effects and individual covariates (age, gender dummy, Muslim dummy, province dummy, income, a dummy for having been in the sample in a previous month, and a dummy for having been delinquent at least once in the previous 12 months). We use the model to predict the probability of default for each customer and focus on the 10% of customers with the highest predicted probability of default ("high credit risk"). Columns (1)-(3) show treatment effects on delinquency using the full sample. Columns (4)-(6) show treatment effects on default, and restrict the sample to "high credit risk" customers. Columns (1), (3), and (5) present OLS regressions of a delinquency dummy on treatment group indicators. Columns (2), (4), and (6) add month fixed effects and individual covariates. Column (1) reports results from an OLS regression of a delinquency dummy on treatment group indicators. Column (2) adds month fixed effects, and column (3) adds individual covariates. Column (4) reports results from an OLS regression of a default dummy on treatment group indicators. Column (5) adds month fixed effects, and column (6) adds individual covariates. The omitted group in all regressions is the simple reminder, for which we report average delinquency and default rates. Robust standard errors in brackets.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

TABLE A.6
FIRST TIME AND REPEATED SAMPLE

	First message sample (1)	Repeated message sample (2)	p-value (3)
	A. Balance of covariates		
Age	41.93	42.29	0.267
	[9.320]	[9.375]	
Female	0.39	0.41	0.382
	[0.489]	[0.492]	
Muslim	0.91	0.90	0.376
	[0.283]	[0.296]	
Income (Rp million)	151.52	126.72	0.013
	[827.617]	[206.906]	
Credit Limit (Rp million)	13.64	13.10	0.092
	[9.678]	[9.386]	
Poor credit history	0.29	0.39	0.000
	[0.452]	[0.488]	
In sample previously	0.10	1.00	0.000
	[0.298]	[0.000]	
	B. Treatment cell size		
Wave I	2,871	0	
Wave II	2,985	0	
Wave III	1,965	0	
Wave IV	1,687	0	
Wave V	2,106	306	
Wave VI	1,814	592	
Total	13,428	898	

NOTE.—Panel A reports summary statistics for the follow-up experiment and presents a test of random assignment. Columns (1) and (2) report the mean level of each variable, with standard deviations in brackets, for the two samples. Column (3) reports the p-value of a test for equality of means in the two samples. Panel B reports sample sizes by month.

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TABLE A.7

Effect on Default: Robustness – Credit Risk Cutoffs

	Dummy for delinquency				Dummy for default			
	Top 5 (1)	Top 10 (2)	Top 25 (3)	Top 50 (4)	Top 5 (5)	Top 10 (6)	Top 25 (7)	Top 50 (8)
Moral incentives	-0.237***	-0.167***	-0.067*	-0.061**	-0.109**	-0.106***	-0.043**	-0.022*
	[0.088]	[0.061]	[0.038]	[0.027]	[0.048]	[0.029]	[0.020]	[0.013]
Credit reputation	-0.131*	-0.192***	-0.115***	-0.072***	-0.088**	-0.087***	-0.045***	-0.014
	[0.070]	[0.052]	[0.032]	[0.024]	[0.042]	[0.029]	[0.017]	[0.011]
Simple reminder	-0.035	-0.082	-0.064*	0.006	-0.024	-0.017	-0.028	-0.005
	[0.088]	[0.060]	[0.038]	[0.027]	[0.064]	[0.041]	[0.021]	[0.014]
Religious placebo	0.066	-0.019	0.032	0.012	0.021	-0.003	0.009	0.008
	[0.070]	[0.055]	[0.036]	[0.027]	[0.065]	[0.042]	[0.025]	[0.015]
Delinquency rate control group	0.76	0.74	0.72	0.68				
Default rate control group					0.15	0.13	0.11	0.08
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Waves I, II, and III							
Observations	348	717	1,771	3,537	348	717	1,771	3,537
R^2	0.137	0.121	0.104	0.087	0.056	0.057	0.021	0.015

Note.—Columns (1)-(8) restrict the sample to customers late in February, March, and May 2015. This is the sample of customers for which information on default is available. Using customers in the control group, we estimate the probability of default by running an OLS regression of a dummy for credit card default on month fixed effects and individual covariates (age, gender dummy, Muslim dummy, province dummy, income, a dummy for having been in the sample in a previous month, and a dummy for having been delinquent at least once in the previous 12 months). We use the model to predict the probability of default for each customer, and split the sample in two groups according to the predicted probability of default. Columns (1) and (5) restrict the sample to the 5% of customers with the highest credit risk (Top 5), columns (2) and (6) to the 10% of customers with the highest credit risk (Top 10), columns (3) and (7) to the 25% of customers with the highest credit risk (Top 25), and columns (4) and (8) to the 50% of customers with the highest credit risk (Top 50). Columns (1)-(4) present OLS regression of a delinquency dummy on treatment group indicators, month fixed effects, and individual covariates. Columns (5)-(8) present OLS regressions of a dummy for credit card default on treatment group indicators, month fixed effects, and individual covariates. The omitted category in all regressions is the control group, for which we report the mean delinquency and default rates. Robust standard errors in brackets.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

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TABLE A.8

EFFECT ON DEFAULT: ROBUSTNESS – MACHINE LEARNING I

	DUMMY FOR DELINQUENCY				DUMMY FOR DEFAULT			
	Top 5	Top 10	Top 25	Top 50	Top 5	Top 10	Top 25	Top 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Moral incentives	-0.157*	-0.093	-0.086**	-0.089***	-0.022	-0.088**	-0.042**	-0.023*
	[0.090]	[0.061]	[0.038]	[0.027]	[0.059]	[0.034]	[0.021]	[0.013]
Credit reputation	-0.161**	-0.158***	-0.138***	-0.113***	-0.010	-0.064**	-0.035*	-0.011
	[0.074]	[0.050]	[0.033]	[0.024]	[0.047]	[0.032]	[0.018]	[0.011]
Simple reminder	-0.110	-0.045	-0.091**	-0.050*	0.040	-0.006	-0.015	0.010
	[0.086]	[0.059]	[0.038]	[0.027]	[0.065]	[0.043]	[0.023]	[0.015]
Religious placebo	0.034	-0.030	-0.034	-0.033	0.057	-0.021	-0.017	0.012
	[0.078]	[0.057]	[0.037]	[0.027]	[0.069]	[0.041]	[0.023]	[0.015]
Delinquency rate control group	0.78	0.72	0.74	0.73				
Default rate control group					0.12	0.14	0.11	0.08
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Waves I, II, and III							
Observations	356	728	1,747	3,500	356	728	1,747	3,500
R^2	0.175	0.128	0.114	0.093	0.062	0.056	0.030	0.016

NOTE.—Columns (1)-(8) restrict the sample to customers late in February, March, and May 2015. This is the sample of customers for which information on default is available. We estimate a model of default probabilities using a machine learning approach. In particular, we train a gradient boosting (GB) classifier model on customers in the control group. The model predicts default probability based on month fixed effects and individual covariates (age, gender dummy, Muslim dummy, province dummy, income, a dummy for having been in the sample in a previous month, and a dummy for having been delinquent at least once in the previous 12 months), along with square and cubic terms of the continuous variables (age and income) and up to three-way interactions between all covariates. The algorithm uses 10-fold cross-validation (CV), re-sampled ten times. We use the model to predict the probability of default for each customer, and split the sample in two groups according to the predicted probability of default. Columns (1) and (5) restrict the sample to the 5% of customers with the highest credit risk (Top 5), columns (2) and (6) to the 10% of customers with the highest credit risk (Top 10), columns (3) and (7) to the 25% of customers with the highest credit risk (Top 25), and columns (4) and (8) to the 50% of customers with the highest credit risk (Top 50). Columns (1)-(4) present OLS regressions of a delinquency dummy on treatment group indicators, month fixed effects, and individual covariates. Columns (5)-(8) present OLS regressions of a dummy for default on treatment indicators, month fixed effects, and individual covariates. The omitted category in all regressions is the control group, for which we report the mean delinquency and default rates. Robust standard errors in brackets.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

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TABLE A.9
EFFECT ON DEFAULT: ROBUSTNESS – MACHINE LEARNING II

	DUMMY FOR DELINQUENCY				DUMMY FOR DEFAULT			
	Top 5	Top 10	Top 25	Top 50	Top 5	Top 10	Top 25	Top 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Moral incentives	-0.199**	-0.089	-0.097***	-0.078***	-0.135***	-0.106***	-0.060***	-0.029**
	[0.091]	[0.064]	[0.037]	[0.028]	[0.050]	[0.033]	[0.020]	[0.013]
Credit reputation	-0.169**	-0.162***	-0.128***	-0.095***	-0.097**	-0.093***	-0.047***	-0.013
	[0.072]	[0.052]	[0.032]	[0.024]	[0.046]	[0.031]	[0.018]	[0.011]
Simple reminder	-0.053	-0.099	-0.092**	-0.008	0.001	-0.049	-0.034	-0.001
	[0.095]	[0.065]	[0.037]	[0.028]	[0.072]	[0.043]	[0.022]	[0.015]
Religious placebo	0.087	0.024	-0.006	-0.005	0.055	0.005	-0.021	0.017
	[0.073]	[0.059]	[0.037]	[0.027]	[0.071]	[0.044]	[0.023]	[0.015]
Delinquency rate control group	0.76	0.72	0.73	0.69				
Default rate control group					0.17	0.14	0.11	0.08
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Waves I, II, and III							
Observations	352	710	1,780	3,496	352	710	1,780	3,496
R^2	0.127	0.100	0.107	0.082	0.074	0.058	0.021	0.016

NOTE.—Columns (1)-(8) restrict the sample to customers late in February, March, and May 2015. This is the sample of customers for which information on default is available. We estimate a model of default probabilities using a machine learning approach. In particular, we train a gradient boosting (GB) classifier model on customers in the control group. The model predicts default probability based on month fixed effects and individual covariates (age, gender dummy, Muslim dummy, province dummy, income, a dummy for being in the sample in a previous month, and a dummy for having been delinquent at least once in the previous 12 months), along with square and cubic terms of the continuous variables (age and income) and up to three-way interactions between all covariates. The algorithm uses decision trees iterated 1500 times, with a learning rate of .01, a fixed Bernoulli distribution, and a minimum number of observations in each terminal node of 30. We use the model to predict the probability of default for each customer, and split the sample in two groups according to the predicted probability of default. Columns (1) and (5) restrict the sample to the 5% of customers with the highest credit risk (Top 5), columns (2) and (6) to the 10% of customers with the highest credit risk (Top 10), columns (3) and (7) to the 25% of customers with the highest credit risk (Top 25), and columns (4) and (8) to the 50% of customers with the highest credit risk (Top 50). Columns (1)-(4) report OLS regressions of a default dummy on treatment group indicators, month fixed effects, and individual covariates. Columns (5)-(8) report OLS regressions of a default dummy on treatment group indicators, month fixed effects, and individual covariates. The omitted category in all regressions is the control group, for which we report the mean delinquency and default rates. Robust standard errors in brackets.

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

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TABLE A.10

Benchmarking against other studies – persuasion rates

Paper	Treatment description	Control description	Outcome description	Sample size	Treatment outcome	Control outcome	Persuasion rate	Persuasion rate per message
This paper	1) Single text message with moral appeal.	No reminder.	Percentage of customers having made at least the minimum payment on their credit card debt within the repayment deadline.	6,364	38.19%	33.76%	6.69%	6.69%
Cadena and Schoar (2011)	1) Monthly text messages with a thank note and a reminder about importance of paying on time.	No reminders.	Percentage of clients repaying every installment of the loan in time.	1,121	42.81%	33.81%	14.24%	2.04%
Fellner, Sausgruber, and Traxler (2013)	1) Baseline letter explaining that the enforcement authority is legally obliged to clarify why the recipient is not paying the fee.	No mail.	Percentage of households starting to pay the annual fee for public broadcasting withing 50 days from the experiment.	50,498	7.40%	0.81%	6.64%	6.64%
	2) Threat letter also stressing the high detection risk and increasing the salience of legal and financial sanctions.				8.27%		7.52%	7.52%
	3) Social information letter also highlighting the high level of compliance of other households.				7.03%		6.27%	6.27%
	4) Moral appeal letter also emphasizing that compliance is a matter of fairness.				7.01%		6.25%	6.25%
	5) Threat and social information letter.				8.33%		7.58%	7.58%
	6) Threat and moral appeal letter.				7.94%		7.19%	7.19%
Hallsworth et al. (2015)	1) Letter also pointed out that the tax authority was attempting to resolve the issue.	Original letter with information about the size of debt and how to pay asking to call the tax authority.	Percentage of receivers repaying their tax debt obligation with the UK government within 30 days after letters have been sent.	38,290	13.10%	12.00%	1.25%	1.25%
	2) Letter also suggested making a plan to call the tax authority.				12.80%		0.91%	0.91%
	3) Letter also provided a summary box of the main points of the letter.				12.50%		0.57%	0.57%
	4) Letter also provided more information about call center opening times.				14.20%		2.50%	2.50%
	5) Letter also stating that lack of response will be treated as an active choice, and not as an oversight (with an individual framing).				22.90%		12.39%	12.49%
	6) Letter also stating that lack of response will be treated as an active choice, and not as an oversight (with a collective framing).				23.20%		12.73%	12.74%
Hallsworth et al. (2017)	1) Letter also stating that nine out of ten people pay takes on time.	Original letter with information about the size of debt and how to pay asking to call the tax authority.	Percentage of receivers starting to pay their tax debt obligation with the UK government within 8 days after letters have been sent.	98,748	37.10%	35.80%	2.02%	2.02%
	2) Letter also stating that nine out of ten people in the UK pay takes on time.				37.90%		3.27%	3.27%
	3) Letter also stating that nine out of ten people in the UK pay takes on time, and that the taxpayer is in a small minority of people not having paid yet.				39.60%		5.92%	5.92%
	4) Letter also stating that taxes are used for public services (gain-framed).				37.40%		2.49%	2.49%
	5) Letter also stating that taxes are used for public services (loss-framed).				37.40%		2.49%	2.49%
Karlan, Morten, and Zinman (2016)	1) Weekly text messages with reminder to repay loan, mentioning the account officers name and using a positive framing.	No reminders.	Percentage of clients having repaid the loan in full 30 days past maturity.	943	96.50%	86.50%	74.07%	7.41%
	2) Weekly text messages with reminder to repay loan, mentioning the account officers name and using a negative framing.				91.60%		37.78%	3.79%
	3) Weekly text messages with reminder to repay loan, mentioning the clients name and using a positive framing.				87.90%		10.37%	1.04%
	4) Weekly text messages with reminder to repay loan, mentioning the clients name and using a negative framing.				86.60%		0.74%	0.07%
Karlan et al. (2016)	1) Monthly reminders delivered either by text message (Philippines and Bolivia) or letter (Peru).	No reminders.	Percentage of clients attaining their commitment on a commitment savings account.	13,560	58.50%	55.30%	7.16%	2.39%
Kast, Meier, and Pomeranz (2016)	1) Weekly text messages with information about saving behavior of peers.	No reminders.	Average number of monthly deposits in a saving account over a three month period.	871	0.424	0.126	N/A	N/A
	2) Weekly text messages with reminder that the customer saving behavior is observable by a peer.				0.363			
Pruckner and Sausgruber (2013)	1) Message also stating that stealing a paper is illegal.	Sign stating the cost of a paper.	Percentage of customers paying for the paper in a honor system with unmonitored payments	120	36.58%	32.50%	6.04%	6.04%
	2) Message also thanking the customer for being honest.				33.33%		1.23%	1.23%

Note.—This table reports persuasion rates for a number of studies that have used reminder or moral suasion interventions, and compares them to the persuasion rates found in this paper. The persuasion rate of an intervention is defined as the change in behavior, scaled by exposure to the treatment and the population share left to be persuaded. This can be expressed as $f = 100 * \frac{y_T - y_C}{e_T - e_C}\frac{1}{1-y_0}$, where e_i is the share of group i receiving the message, y_i is the share of group i changing behavior, and y_0 is the counterfactual share that would change behavior if there were no message.

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D. Appendix Figures

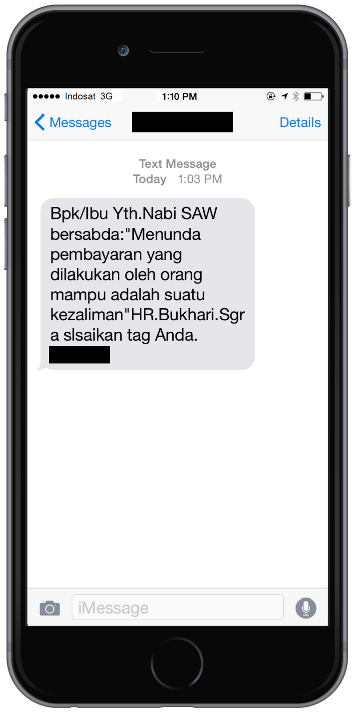

FIG. A.1.— The figure shows the text message sent to participants assigned to the moral incentive treatment condition.

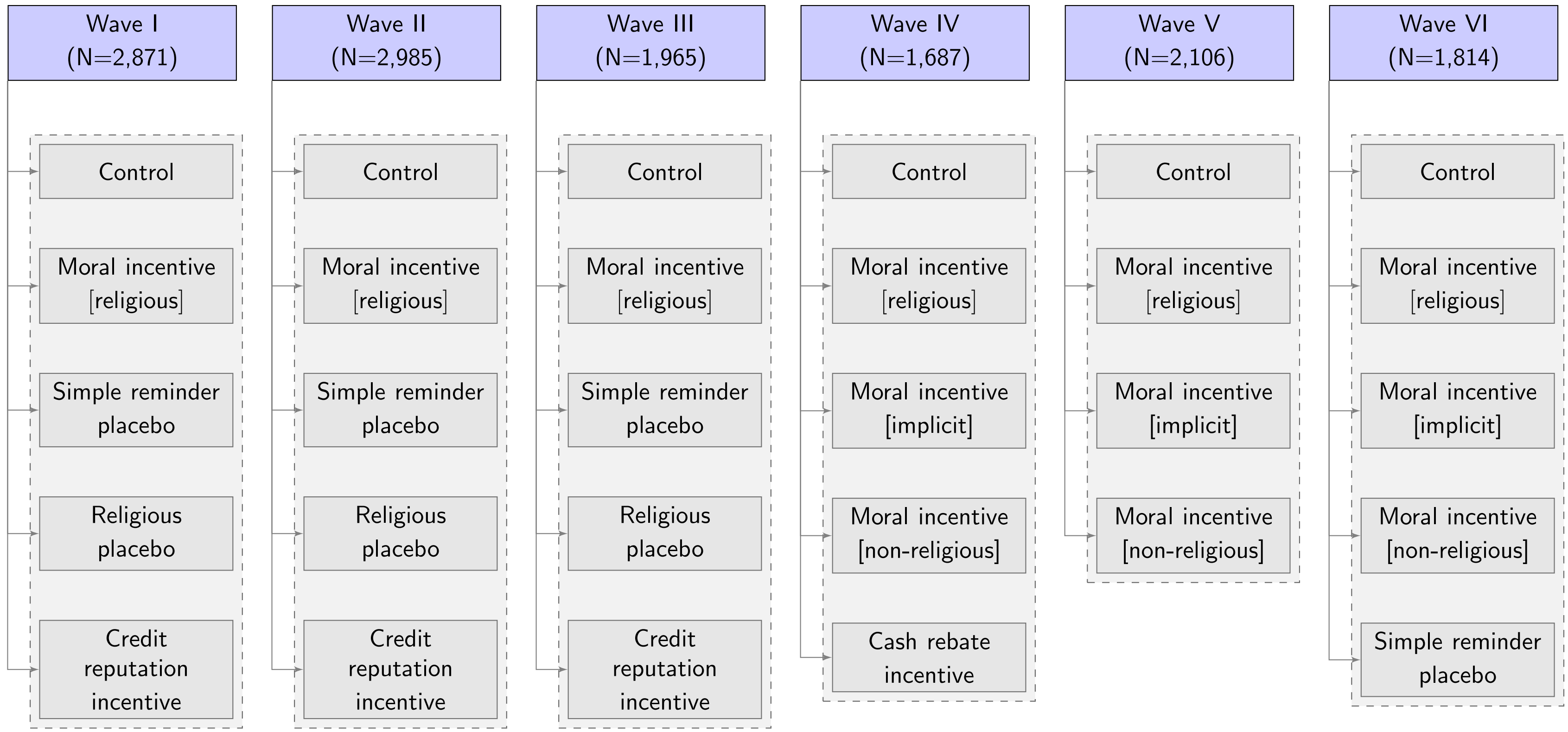

FIG. A.2.—The figure summarizes the experimental design. The main experiment was conducted in four waves, coinciding with the monthly credit card repayment cycle, between February 2015 and April 2016. Waves I and II were conducted February and March 2015. Waves III and IV were conducted in May and June 2015. A follow-up experiment, consisting of waves V and VI, was conducted in February and April 2016. Within each wave of the experiment, credit card customers that had not made their minimum required payment by the due and were still past-due two days before the end of a ten-day grace period were randomly and individually assigned to the treatment conditions shown in the figure.

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