ONLINE APPENDIX:

Are Information Disclosure Mandates Effective?

Evidence from the Credit Card Market

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1 Introduction

The following Tables and Figures present supporting material to the main text in the paper. Its content follows the paper in format and sequence. The aim of the Appendix is to provide this supporting material with as little text as possible.

2 Context and Data

A. Administrative Data

Table 1 shows means and standard deviations of selected variables for the 7 treatments.[1] It also shows that randomization was successful to balance variable across treatment and control groups. To implement a formal test of balance we regress the variables in the first column of Table 1 against the seven treatment dummies while controlling for the stratification dummies. We report the p-values of an F-test of the hypothesis that all the coefficients on the treatment dummies are zero. We cannot reject the null that they are zero for any of the variables.

[1] Recall that some messages where sent to high risk or high debt clients and therefore that one cannot directly compare means across treatment.

Table 1: **Treatments and control balance: September 2010 final sample**[a]

	All	High Risk	Low Risk	High Debt + Advice	High Debt	Rate	MTP	Warning	F test[b]
Delinquent	0.135	0.245	0.015	0.152	0.154	0.126	0.127	0.126	0.96
	(0.3415)	(0.4300)	(0.1217)	(0.3586)	(0.3607)	(0.3324)	(0.3325)	(0.3314)	
Probability of default	0.255	0.405	0.114	0.247	0.246	0.259	0.259	0.259	0.96
	(0.2261)	(0.2604)	(0.0169)	(0.2095)	(0.2073)	(0.2341)	(0.2342)	(0.2329)	
Debt (MXN)	18919	15638	17118	24960	24922	16245	16196	16311	0.98
	(25800)	(23776)	(24053)	(29099)	(28636)	(23959)	(23632)	(23643)	
Tenure with Card (months)	43	46	41	42	42	44	44	43	0.16
	(26)	(27)	(25)	(24)	(25)	(26)	(26)	(26)	
Credit Limit	27287	27050	26692	28059	27932	26864	27029	26998	0.83
	(35165)	(34159)	(35280)	(34987)	(34390)	(35358)	(35152)	(35238)	
Age (years)	42	42	41	42	41	42	42	42	0.20
	(12)	(12)	(12)	(11)	(11)	(12)	(12)	(12)	
Male (percent)	0.569	0.579	0.562	0.573	0.559	0.578	0.576	0.568	0.12
	(0.4951)	(0.4937)	(0.4962)	(0.4946)	(0.4965)	(0.4939)	(0.4943)	(0.4953)	
Closed Account[c]	0.026	0.039	0.028	0.013	0.016	0.03	0.032	0.03	0.28
	(0.1602)	(0.1946)	(0.1642)	(0.1120)	(0.1239)	(0.1714)	(0.1768)	(0.1725)	
Attrition [d]	0.1499	0.2284	0.0815	0.1459	0.1496	0.1498	0.1521	0.1506	0.89
	(0.357)	(0.4198)	(0.2736)	(0.353)	(0.3567)	(0.3568)	(0.3591)	(0.3578)	
Observations	167190	6444	6456	12825	12825	12900	12825	12900	

Standard deviations are given in parentheses.

[a] Final sample refers to the sample that were actually sent messages, after the bank removed premier cards. All stats refer to September 2010 before the treatments.

[b] F-test of coefficients of all treatments being jointly equal to zero (p-values).

[c] As of February 2011.

[d] As of June 2011.

One threat to internal validity is attrition and expost sample selection. This is specially problematic in populations such as the one we study as by construction they are risky and leave the sample often (i.e. close their card accounts or the account is revoked by the bank). We have many treatment arms and observe many months. We thought that the best way to show attrition is by plotting it by arm, as in Figure 11. This Figure plots the raw data, while to do a formal test one would have to control for the strata. Table 1 estimated a regression of an attrition dummy vs treatment dummies while controlling for Strata and an F-test can not reject that attrition is non differential across arms.

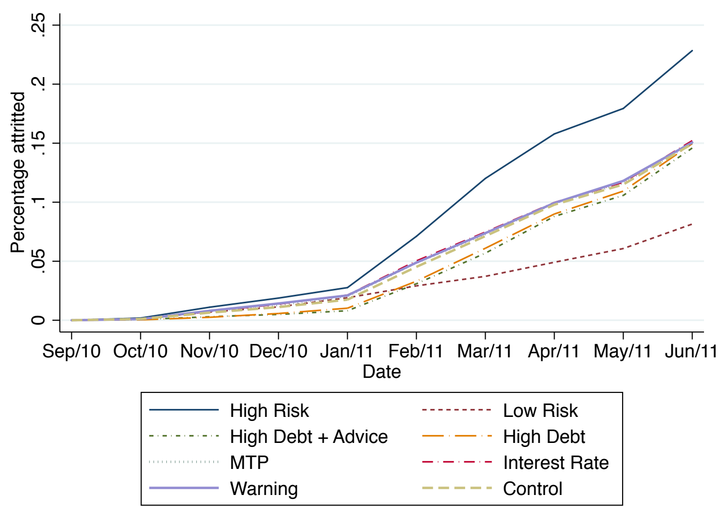


Figure 1: Attrition
This shows the percentage of the sample that attrits each month.

Not only is the amount of attrition similar across arms (when controlling for strata), but importantly the sample is still balanced after attrition. Table 2 shows the analogous table to Table 1 and shows balance in the sample after attrition. The Table uses information measured in September 2010 (before treatment) and compares means for still open accounts on June 2011 (i.e. non attriters). We used the same strategy as in Table 1 in this online appendix to calculate p-values for an F-test of all treatment coefficients being equal. We can only reject equality at conventional levels for age, but as can be seen the difference in age is at most one year.

Table 2: Balance for Non-attriter Population

	All	High Risk	Low Risk	High Debt + Advice	High Debt	Rate	MTP	Warning	F test[a]
Delinquency	0.082	0.162	0.012	0.09	0.094	0.076	0.077	0.076	0.7
	(0.2737)	(0.3682)	(0.1103)	(0.2866)	(0.2921)	(0.2659)	(0.266)	(0.2646)	
Probability of default	0.228	0.372	0.114	0.222	0.221	0.234	0.231	0.232	0.81
	(0.2016)	(0.2427)	(0.0168)	(0.1868)	(0.1855)	(0.2123)	(0.2060)	(0.2079)	
Debt (MXN)	18684	15034	17383	24320	24459	16037	16162	16187	0.9
	(25324)	(22651)	(24177)	(28486)	(28229)	(23468)	(23347)	(23269)	
Tenure with Card (months)	42	45	41	41	41	43	43	42	0.20
	(25)	(25)	(25)	(24)	(25)	(25)	(25)	(25)	
Credit Limit	26733	26000	26555	27221	27315	26387	26485	26465	0.83
	(34554)	(32567)	(34876)	(34088)	(33785)	(34898)	(34466)	(34644)	
Age (years)	41	42	41	42	41	41	41	41	0.05
	(12)	(11)	(12)	(12)	(11)	(12)	(12)	(11)	
Male (percent)	0.568	0.576	0.564	0.571	0.558	0.574	0.571	0.566	0.43
	(0.4954)	(0.4942)	(0.4959)	(0.4948)	(0.4967)	(0.4945)	(0.4949)	(0.4957)	
Observations	142122	4972	5930	10954	10906	10968	10874	10957	

Standard deviations are given in parentheses.

All stats refer to September 2010, before the treatments. We use the individuals that remained in the sample until June 2011 (approximately 85 percent of original population).

[a] Ftest of coefficients of all treatments being jointly equal to zero (p-values).

B. Survey Data

One of the niceties of this paper was that we were able to implement surveys to random samples of the population in our administrative data. Both before and after treatment. Unfortunately due to cost considerations we could not have larger samples, and this limits the use we can give to surveys. However We think the surveys are useful to give us a rich description of the context in which the experiment took place. The most important result was that clients in our sample where highly leveraged and risky, while at the same time unaware of their interest rates and MTP. The surveys were conducted over the phone for cost reasons.

Since phone response rates are not high, less than 25%, Table 3 assesses to what extent do survey respondents differ from the average cardholder in our sample.[2] One may worry that these low response rates generate substantial self-selection. Table 3 presents means and standard deviations for clients who answered and did not answer the survey and p-values of the difference in means. Indeed there is selection: those that answered are less risky and somewhat less indebted. Since this selection seems to go against our main survey finding and we still find large leverage and risk we do not think it is particularly worrisome for the purposes of this paper. Note also that we only use the survey to motivate the messages and our results are not dependent on it.

[2] We could not have access to the account level responses from survey 2 (the bank conducted them).

Table 3: **Survey Self Selection**

	Baseline Survey			Endline Survey		
	Population Complement	Answered	P-value	Refused to Answer	Answered	P-value
Debt (MXN)	17858	14320	0	17007	15494	0
	(24277)	(18773)		(21279)	(21254)	
Delinquent (percent)	10.89	4.30	0	7.11	3.24	0
	(16.38)	(9.65)		(11.38)	(7.75)	
Closed Card by June (percent)	4.38	4.47	0.9	0.67	0.09	0
	(20.47)	(20.68)		(8.18)	(2.93)	
Purchases (MXN)	1038	952	0.19	757	934	0
	(2382)	(1816)		(1565)	(1827)	
Payments (MXN)	1911	1658	0	1724	1766	0.43
	(2915)	(2077)		(2171)	(2313)	
Probability of Default (percent)	22.41	17.83	0	22.08	16.68	0
	(15.48)	(12.93)		(14.12)	(11.64)	
Credit Limit (MXN)	27332	22995	0	23481	25695	0
	(34486)	(29109)		(27991)	(33109)	
Tenure (Months)	43	38	0	41	42	0.46
	(26)	(23)		(21)	(25)	
Age (Years)	42	44	0	41	45	0
	(12)	(12)		(11)	(12)	
Male (percent)	57.01	44.83	0	58.22	51.80	0
	(49.51)	(49.76)		(49.32)	(49.98)	
Observations	166407	783		7271	2328	

For the endline survey we have information on every contacted individual whether the subject answered or not.
For the baseline we can only identify the ones that answered and thus we compared them with the whole population.

Table 4 shows summary statistics from the surveys for selected questions, and also presents translations of the questions.

Questions in the ex-ante survey: (not all questions are tabulated in the above Table)

1. In the registered address, do you receive your bank statement every month? (Yes/No)
2. Do you read attentively your bank statement? (Yes/No)
3. Would you like that your bank statement were clearer? (Yes/No)
4. Do you think that a clearer bank statement would help to reduce delinquency? (Yes/No)
5. Do you know, even if its only very approximately (within 5 percentage points), the annual interest rate of your credit card? (Yes/No)
6. Do you know your exact interest rate? (Yes/No)
7. If you have more than one credit card, do you know which one is cheaper this month? (Yes/No)
8. Do you know, even if its only very approximately (within 5 days), the statement date of your card? (Yes/No)
9. Do you know, even if its only very approximately, the amount of money you owe? (Yes/No) How much?
10. Did you incur in overdraft fees for the last statement date? (Yes/No)
11. Did you have to pay interest for the last statement date? (Yes/No)
12. Did you pay the minimum on time for the last statement date? (Yes/No)
13. In the last 6 months, have you over-estimated the amount you can pay and end up paying less of what you had planned? (Yes/No)
14. Why do you think people incur in delinquencies? (They are unaware of the fact that they are accumulating debt very quickly/ They are aware of the situation but have no alternatives/ They just don't care to incur in delinquencies)
15. Even if you are not completely sure, how much interest do you think you will pay for January, February and March? (zero/ more than zero but less of what you are paying today/ more than zero and more than what you are paying today)

Questions used from the ex-post survey: (not all questions are tabulated in the above Table)

1. Do you know the monthly interest rate of our credit card? (Yes/No)
2. How much do you think you have paid of interest during this year?
3. Relative to people of the same age, sex and credit limit, do you think you are more, less or, equally likely to default your credit card? (more likely/ less likely/ equally likely)
4. How likely do you think it is that you could find in the market a cheaper credit card than the one you currently have? (Very likely/Impossible)
5. With which of the following phrases would you be more likely to agree: "Reducing my debt, and what it implies in sacrifice, would improve my welfare"; "Reducing my debt, and what it implies in sacrifice, would not affect my welfare" or "Reducing my debt, and what it implies in sacrifice, would worsen my welfare"?
6. How much do you think the welfare of people is affected by defaulting on their credit card (taking all the benefits and costs into account? (A lot/Not much/Nothing)

Table 4: **Baseline and Follow Surveys**

	Yes (%)	No (%)	N/A (%)
Panel A. Monthly Statement			
Receives bank statement monthly (B-Q1)	78.3	21.3	0.4
Reads the statement (B-Q2)	92	7.9	0.1
Would prefer a clearer statement (B-Q3)	48	50.9	1.1
Believes a clearer statement would help reduce delinquencies (B-Q4)	55.2	42.3	2.45
Panel B. Knowledge			
Claims to know interest rate of her CC (B-Q5)	34.2	62.2	3.6
Claims to know exactly the interest rate of her CC* (F-Q1)	3	97	
Claims to know which CC is cheaper[a] (B-Q7)	36.3	36.7	27
Claims to know the statement date (B-Q8)	34.2	62.2	3.6
Claims to know debt at statement date (B-Q9)	68.7	20.1	11.2
Gives an accurate estimation of her previous debt[b]	54.3	29.5	
Knows how much interest she has paid during that year* (F-Q2)	60.3	39.7	
Panel C. Awareness			
Incurred in overdraft fee at previous statement date (claimed) (B-Q10)	18.4	78.9	2.7
Had to paid interest at previous statement date (claimed) (B-Q11)	50	43.9	6.1
Correctly answered previous question†	56	37.9[c]	
Paid the minimum on time at previous statement date (claimed) (B-Q12)	76.7	22.1	1.2
Correctly answered previous question†	70.8	28	
Believes to be at most as risky (in terms of default) as her peers[d] * (F-Q3)	81.1	8.9	10
Believes that unawareness of debt acummulation is leading to delinquency (B-Q14)	38.3	61.7	
Could very likely find a cheaper credit card[e] in the market* (F-Q4) (claimed)	75.5	21.3	3.2
Panel D. Prediction Accuracy	Wrong (%)	Overconfident[f] (%)	
Has over-estimated payment capability in previous 6 months (claimed) (B-Q13)	35.7	62.2	2.1
Expectation of interest to be paid in January (B-Q15)	47.4	44.7	
Expectation of interest to be paid in February (B-Q15)	61.5	77.9	
Expectation of interest to be paid in March (B-Q15)	52.6	75.4	
Panel E. "Welfare" auto-evaluation and other claims	A lot (%)	Not much (%)	Nothing (%)
Believes that debt reduction improves welfare* (F-Q5)	83.7	14.4	1.9
Defaulting credit card decreases people's welfare* (F-Q6)	92.9	4.8	2.3
Panel F. Other	Mean	St. Deviation	
Total monthly expenditures* (MXN) (F-Q7)	8563	(7444)	
Education* (Years)	15.5	(3.8)	

* These results correspond to a different survey realized ex-post to 2,304 individuals. We are grouping questions by topic.
The number of the question is reported between parentheses and a B or and F indicate if the question belongs to the Baseline or the Follow-ip survey respectively.
† Obtained by comparing responses against administrative data.
[a] If the individual has more than one credit card.
[b] Percentage of people that correctly recalled the amount of debt at previous statement date. We obtained this after comparing responses against administrative data and allowed for a 10 percent error.
[c] Of those answering incorrectly, 83.5 percent say they did not incur in interests when they actually did.
[d] People of the same age, sex and credit limit.
[e] Compared to the one she has.
[f] Of those answering incorrectly, these individuals expected to pay less interest than what they actually end up paying.

7. How much do you spend in an average month (include all expenses: housing, interest payments, food, clothing, etc.?
8. How many months do you think it would take you to pay your current debt if you make no further purchases and only pay the minimum each month?

We tried to use the ex-post survey in two different ways but since we had too small samples we could not go too far. First we tried to measure effects of the messages in survey responses (see Table 5) but we found no effect was statistically different from zero. Second, we tried using our administrative data to predict who is 'MTP overconfident' or 'interest rate unaware' in our survey. We ran into some problems however. The number of observations is not that high, as the survey has about 2000+ observations and about 500 for the control group (which is uncontaminated by treatment messages). Second, there is no obvious model (x's) to use to predict overconfidence, or what threshold to use to classify somebody as overconfident, so we tried several models and different overconfidence cutoffs.[3] In all specifications we get small variance explained, the maximum variance explained is an R^2=0.13 which arises even when we maximize the adjusted R^2 using 30 covariates.[4]

[3]We used using three different definitions for overconfidence or lack of it. The first one is the most strict definition of overconfidence involves classifying as overconfident all cardholders that had at least one month of overconfidence; the second separates the sample in those who underestimated MTP by more than three months and the third one for those that underestimated it by more than 10 months. We used many models, three of them were as follows: Model 1: X's include: age, gender, income; second degree polynomials on probability of default, debt, payment, purchases; Model 2:The same as 1 but adding 3 lags of the polynomials; Model 3:The same as 1 but using quintile dummies for each variable instead of the polynomial.

[4]We used a forward selection algorithm to find the model with the largest adjusted R^2. One challenge is to avoid overfitting. We tried using machine learning methods to verify fit out of sample but the small sample size does bite us.

Table 5: Effect on Ex-post-survey Responses

	Dependent Variables					
	Claims to know	Correctly estimates	Compares Own Risk vs. Peers			Believes can
	Interest Rate	MTP	Less	Equally	More	get another card
			Panel A			
High Debt + Advice	0.00863	-0.0448**	0.0543	-0.0555	0.000919	-0.000609
	(0.0114)	(0.0227)	(0.0341)	(0.0338)	(0.0203)	(0.0298)
Warning	0.00823	0.00506	0.0358	-0.0150	-0.0276	-0.0201
	(0.0106)	(0.0211)	(0.0316)	(0.0313)	(0.0188)	(0.0275)
Rate	0.00210	-0.00736	0.0304	0.00956	-0.00845	-0.0318
	(0.00964)	(0.0192)	(0.0289)	(0.0286)	(0.0172)	(0.0252)
MTP	0.00104	-0.0269	0.0420	-0.0282	-0.0199	-0.0268
	(0.0110)	(0.0219)	(0.0329)	(0.0325)	(0.0195)	(0.0286)
F-test TILA	0.977	0.463	0.382	0.496	0.595	0.413
F-test Non-TILA	0.647	0.0865	0.236	0.257	0.281	0.741
			Panel B			
TILA	0.00187	-0.0149	0.0354	-0.00648	-0.0118	-0.0288
	(0.00868)	(0.0173)	(0.0260)	(0.0257)	(0.0155)	(0.0227)
Non-TILA	0.00881	-0.0129	0.0447*	-0.0341	-0.0144	-0.0106
	(0.00903)	(0.0180)	(0.0270)	(0.0268)	(0.0161)	(0.0236)
F-test	0.389	0.897	0.700	0.248	0.858	0.389
N	2326	2326	2326	2326	2326	2326

Significance level: * 10 percent ** 5 percent *** 1 percent. Standard errors in parenthesis.

This table shows the effect of treatment on the expost-survey responses of selected questions. The survey was conducted on individuals in the High Debt + Advice, Warning, Rate and MTP treatments and on the controls.

On each panel, each column represents a regression. On panel A each of the variables on the first row is regressed on dummies for all treatments and stratification indicators (just as equation (1):$Y_{ijt} = \alpha_t + \sum_{j=1}^{7} \beta_{tj} T_{ij} + S_{ik} + \epsilon_{ijt}$; but now Y_{int} corresponds to the survey response. At the bottom of the panel we report the p-values of testing whether the coefficients of Rate and MTP (TILA) are jointly different from zero and whether the other 5 treatments have jointly different from zero results. Panel B reports the coefficients of regressing the same outcome variables on two dummies, the first one takes the value of one when the cardholder is in the interest rate or months-to-pay treatment groups and the other one when the individual was on any other treatment group with the exception of the Low Risk message (because the effect intended of this message goes in the opposite direction).

The questions in the same order as the columns of the table are:

[1] Do you know the monthly interest rate of our credit card?

[2] Relative to people of the same age, sex and credit limit, do you think you are more, less or, equally likely to default your credit card? (more likely/ less likely/ equally likely)

[3] How many months do you think it would take you to pay your current debt if you make no further purchases and only pay the minimum each month? (the dependent variable is 1 if the real number of months to pay was in the category of the survey response and zero otherwise)

[4] How likely do you think it is that you could find in the market a cheaper credit card than the one you currently have? (Very likely/Impossible)

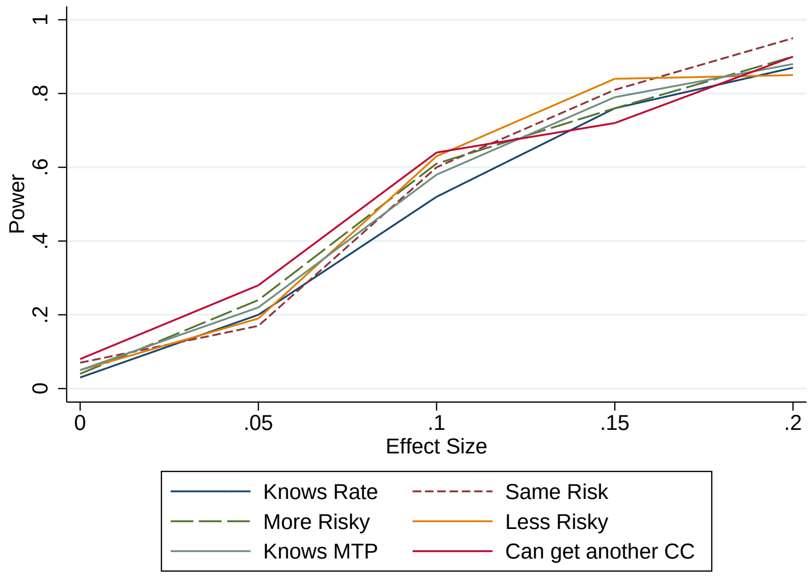


Figure 2: Power estimation for the regressions in table 5

Effect sizes are standardized as percentage of standard deviation.

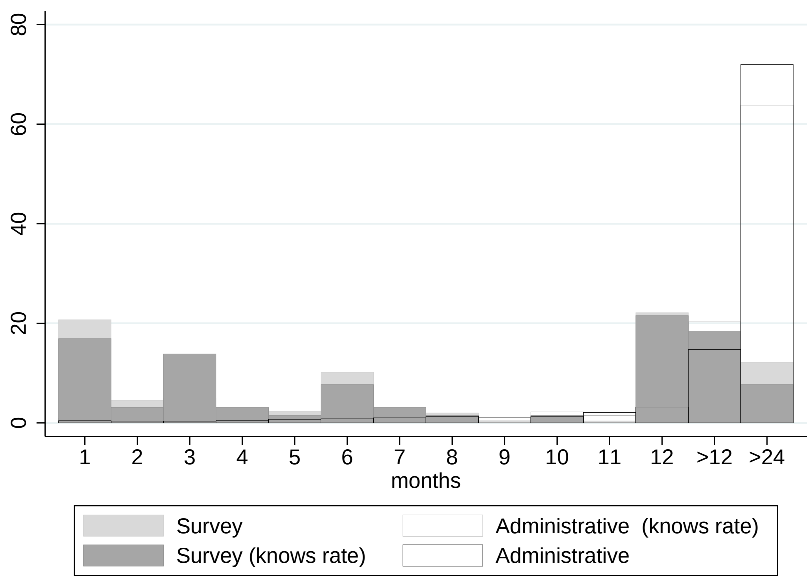


Figure 3: Survey Data vs Administrative Data

This figure shows the months-to-pay as reported in the survey and actual number form the administrative data. We condition on claiming to know the interest rate in another question of the survey.

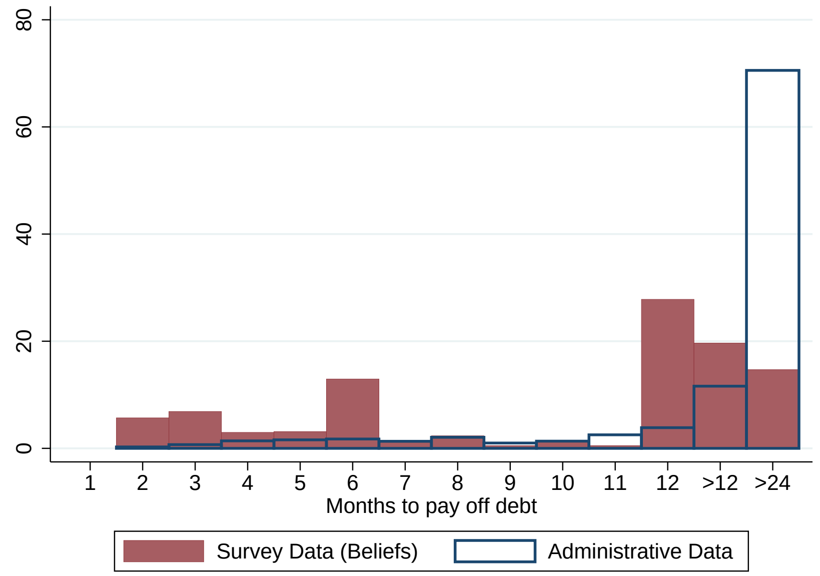


Figure 4: Survey Data vs Administrative Data conditional on not answering 1 month

This figure shows the months-to-pay as reported in the survey and actual number form the administrative data. We intentionally leave out the one month answers to see with more detail the rest of the distribution.

C. More explanation of the LTM treatment and compliance with human subjects

There has been some confusion regarding the peer-comparison messages. Here we want to highlight that they are perfectly accurate, since the information was based on clients *comparable to him/her in terms of income, age and gender.* These variables are defined according to the cells where the client belongs to. The message *does not* compare across cells. This was transparent in the message itself.[5]

We should say also that when signing the card contract the client authorizes the bank to send messages *in accordance with the bank's policies and classifications.* Banks in Mexico routinely send information messages and offers to their clients, often with a randomized control group to measure impact. The LTM was designed and sent by the bank with little input from researchers.

We looked closer at the LTM as it is the one that a priori could be concerning and far

[5]Note also that for the thermometer messages one cannot strictly talk abut deception as we providing a thermometer with a body temperature scale. We view the thermometer message as appealing to emotions rather than providing precise numerical information. Indeed the information provided is not falsifiable. Bertrand et al (2010) have also a similar view, they say: "The evidence also suggests that advertising content persuades by appealing peripherally to intuition rather than reason."

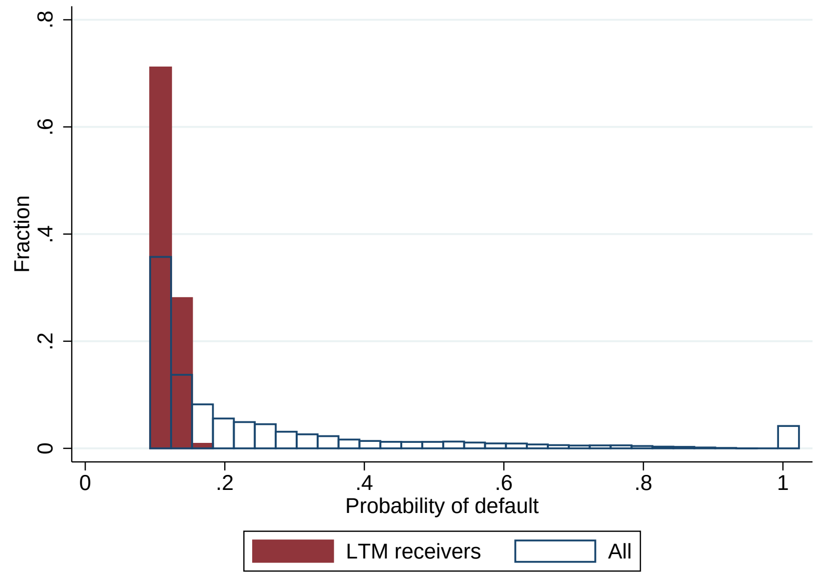


Figure 5: Probability of Default distribution as of September 2010

This histogram shows the distribution of the Probability of Default in September 2010 for the LTM receivers and compares it with the distribution of the sample. Everyone that received the LTM had a PD below 0.2, notice how these individuals are located only on the left tail of the distribution.

from the truth, but the data suggest that it is not. The reasons are as follows. The bank personnel defines good credit behavior as not having more than 90 days past due.[6] It turns out that only 1.4 percent of clients that received the low thermometer message had 90 days or more of payment due at any time during the last semester of 2010; whereas in the paper's entire sample the analogous number is 8.6 percent (see Figure 5 below for a comparison of distributions). Clients that received the low thermometer message are profitable for the bank. Unprofitable clients are sent into special loan collection programs; the clients in the sample were *not* in any of those programs.

LTM recipients compare favorably vs the market in Mexico. It is not easy to compare the LTM group with the entire population of Mexico's cardholders as we don't have the predicted PD's outside our sample; however, the following comparison may be illustrative: The riskiest person (i.e. that with the maximum PD) that received the message has a predicted probability of default in the next 12 months of 15.9 percent. While the average realized default rate in all credit cards in Mexico is about 16 percent ("Tasa de Deterioro Ajustada").[7]

[6]The law qualifies a loan as a loan in default if it is more than 90 days past due. Furthermore the bank has the obligation to "reserve the loan" fully only after 120 days past due.

[7]To have greater comparability, ideally we would like to have the fraction of credit card loans in default. The banking commission does not report this statistic unfortunately, it reports proxies of de-

Table 6: Transition matrix by deciles of predicted Probability of Default

		PD deciles Sep10		
		8	9	10
	1	9.15	9.29	10.99
	2	9.78	9.13	10.51
	3	10.88	9.92	10.19
PD	4	14.04	12.76	6.69
deciles	5	3.94	6.46	8.28
Jan11	6	4.1	3.46	5.1
	7	11.51	4.57	6.69
	8	14.04	13.07	13.69
	9	12.46	16.22	13.69
	10	10.09	15.12	14.17

This presents a transition matrix by deciles of predicted PD for the LTM receivers. It shows how the share of the individuals that transitioned from one of the highest three deciles in September 2010 to each decile in January 2011.

This suggests that cardholders in our cooperating bank that received the LTM have risk that is not too far from the average risk in the market (i.e. it seems that our bank is situated in the left tail of market risk).

Another interesting fact we found is that the risk classification using PD is volatile: risky individuals –as predicted with the PD model– *do not* stay risky for long. Table 6 shows a transition matrix by deciles of predicted PD. It shows, for instance, that 86 percent of the low-risk-message-receiving clients that were in the 10th risk decile in September 2010 transitioned into a lower decile. In this environment a given individual may be high risk some months and low risk in others.

We do not think the LTM is misleading the clients to default. If that were the case one would expect that the message is more misleading the riskier the client and that it would therefore lead to more default for these clients. Results do not support this conjecture. Table 7 estimates five regressions of the effect on default of the low thermometer message, where each regression represents a quintile of the ex-ante PD risk in September 2010. Not only are most coefficients not statistically different from zero, but the magnitudes are *not* increasing with ex-ante risk. Finally we should say that the messages passed ITAM's IRB examination.

Finally, it is important to note that the bank has no incentives to mislead in order to

fault using peso amounts. The "Tasa de Deterioro Ajustada" is the ratio of peso amount of credit card debt in default in the last 12 months over the peso amount of total credit card debt. See http://portafoliodeinformacion.cnbv.gob.mx/bm1/Paginas/infosituacion.aspx. To the extent that bigger card debts default more, the TDA would overstate the PD as the PD does not include the severity of default.

Table 7: Regressions of LTM by quintiles of PD

	Delinquent
1st quintile	0.007
	(0.008)
2nd quintile	-0.009
	(0.011)
3rd quintile	0.002
	(0.012)
4th quintile	0.017
	(0.014)
5th quintile	-0.023
	(0.017)

This table reports the coefficients of five regressions of the effect on default of the low thermometer message, where each regression represents a quintile of the ex-ante PD as measured in September 2010.

induce more default, as this would *reduce* its profits. If it induced a minor increase in default it certainly had no intention to do so, and had no way to know what would happen. The fact that (a) there was no intentionality to cause any particular outcome, and that (b) the consequence was unknown and could be reasonably be expected to cause no harm means that it was not unethical. The message actually *is* explicit in encouraging them to keep their finances healthy.

Figure 6 uses the subsample of clients with two cards in this bank and plots the share of interest-paying debt in the cheaper of these two cards (white bars) and the counterfactual share had debt been allocated to minimize interest cost (red bars), taking potentially binding credit limits into account. It shows that distributions are substantially different, and therefore that it appears that money is being left on the table from not allocating debt to the cheaper card. The aim of this Figure is just to motivate that not knowing interest rates may be plausible and that information messages could potentially help. The aim is not to show that consumers are not minimizing some more complex cost function.

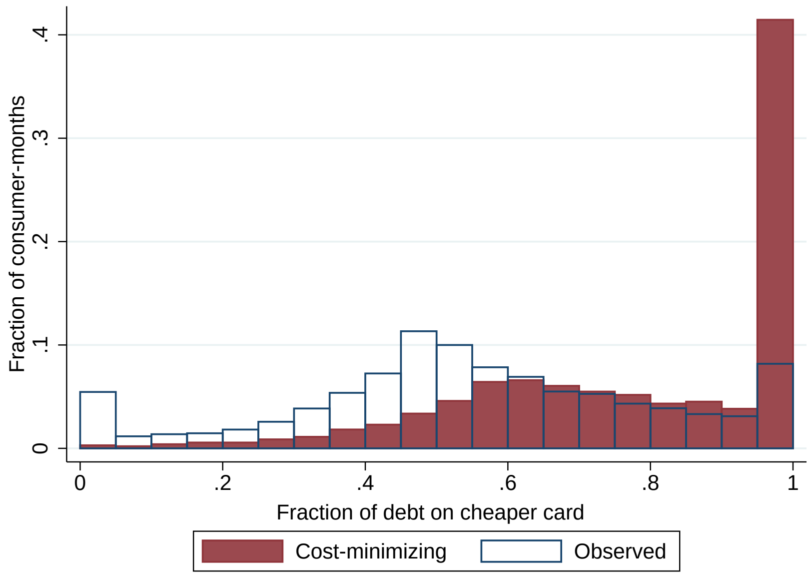


Figure 6: Debt Allocation

D. Multiple Testing Concerns

We emphasize in the paper that *all* treatments are very ineffective, and even the treatments that seem to work have very modest effects. *The main message of the paper is thus a null effect of messages.* We are mostly *not* rejecting the null of no effect. But if we do not reject the null then there multiple testing turns out not to be such a serious problem. Having said this, there are some results that although small are statistically significant. The paper lists five exercises we have done to asses if multiple testing issues are driving the result non-TILA messages are slightly more effective than non-TILA and concludes that this in unlikely to be the case.

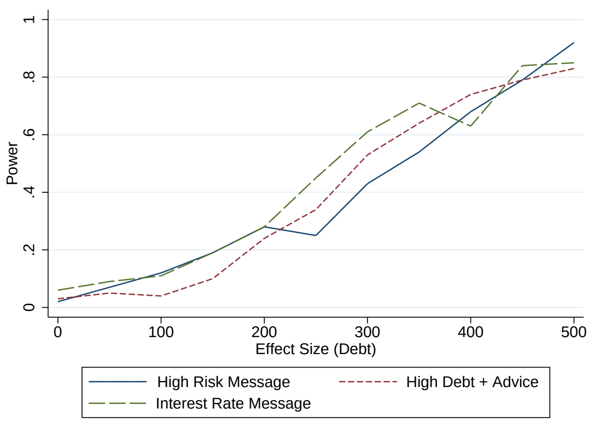
Table 8 below computes Bonferroni p-values that control for the Family Wise Error Rate (FWER) –the probability of rejecting *at least one* true null hypothesis. We mentioned in the text that Bonferroni p-values are overly conservative and a large cost in terms of power. Figure 7 shows the power simulation with and without the Bonferroni adjustment. Power decreases by 20%-53% even in our large sample, and is lower than the standard 90% power recommended in the literature for reasonably sized effects.[8].

[8]Due to simulation/sampling error some slopes are slightly negative.

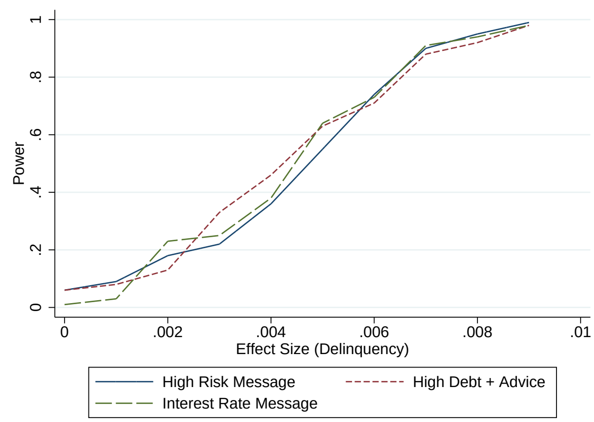
Table 8: Baseline Results (Adjusted p-values)

	Dependent Variables				
	Debt		Delinquent		Closed
	March	April	March	April	June
	Panel A				
Mean Dep.	17391	16541	0.183	0.198	0.043
S.D. Dep.	(24425)	(23964)	(0.387)	(0.398)	(0.204)
Rate	-35	14	0	0	0.001
	(63)	(81)	(0.004)	(0.004)	(0.002)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.86^BH]	[0.97^BH]	[0.97^BH]	[0.97^BH]	[0.62^BH]
MTP	43	90	0	0.006	-0.002
	(64)	(83)	(0.004)	(0.004)	(0.002
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.82^BH]	[0.62^BH]	[0.37^BH]	[0.97^BH]	[0.77^BH]
High Risk	-233***	-172	-0.015***	-0.006	0.007***
	(90)	(118)	(0.005)	(0.005)	(0.003)
	[0.35^B]	[1^B]	[0.105^B]	[1^B]	[0.21^B]
	[0.07^{BH}]†	[0.422^{BH}]	[0.07^{BH}]†	[0.616^{BH}]	[0.07^{BH}]†
Low Risk	4.4	82	0.014***	0.013***	0.001
	(84)	(108)	(0.005)	(0.005)	(0.003)
	[1^B]	[1^B]	[0.21^B]	[0.35^B]	[1^B]
	[0.967^{BH}]	[0.82^{BH}]	[0.07^{BH}]†	[0.07^{BH}]†	[0.858^{BH}]
High Debt + Advice	-29	-127	0.002	0.005	-0.003*
	(64)	(83)	(0.004)	(0.004)	(0.00195)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.86^BH]	[0.42^BH]	[0.83^BH]	[0.58^BH]	[0.32^BH]
High Debt	-104	32.77	-0.002	0	0
	(62)	(81)	(0.004)	(0.004)	(0.002)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.37^BH]	[0.86^BH]	[0.82^BH]	[0.97^BH]	[0.97^BH]
Warning	-126**	-147*	-0.002	-0.002	-0.002
	(62)	(81)	(0.004)	(0.004)	(0.002)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.25^BH]	[0.32^BH]	[0.82^BH]	[0.86^BH]	[0.77^BH]
F-test TILA	0.64	0.54	0.99	0.27	0.54
F-test Non-TILA	0.04	0.14	0	0.07	0.03
	Panel B				
TILA	6	48	-0.001	0.002	-0.001
	(46)	(60)	(0.003)	(0.003)	(0.002)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.89^BH]	[0.8^BH]	[0.8^BH]	[0.8^BH]	[0.8^BH]
Non-TILA	-107***	-99**	-0.004*	-0.001	0
	(38)	(50)	(0.003)	(0.002)	(0.001)
	[0.05^B]††	[0.48^B]	[0.93^B]	[1^B]	[1^B]
	[0.05^{BH}]††	[0.24^{BH}]	[0.31^{BH}]	[0.8^{BH}]	[0.8^{BH}]
F-test	0.03	0.03	0.38	0.31	0.95
N	147634	143484	167190	167190	167190

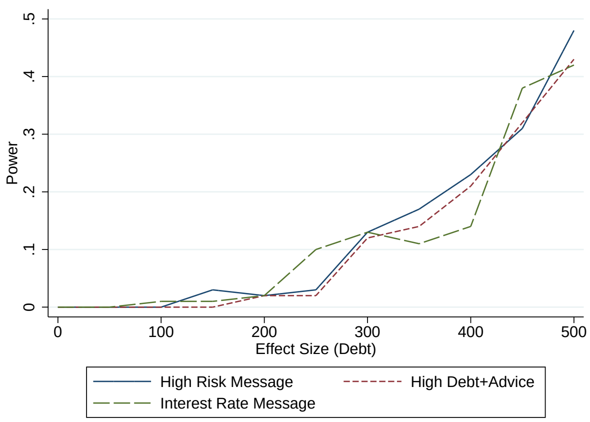
Significance level: * 10 percent ** 5 percent *** 1 percent. Standard errors in parentheses.
† Adjusted p-values significant at 10%.
†† Adjusted p-values significant at 5%.



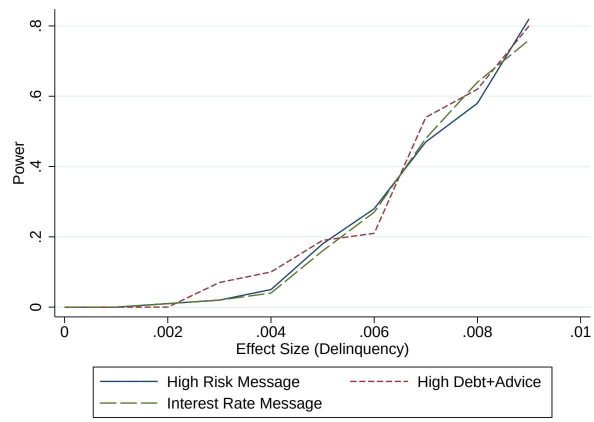
(a) Debt



(b) Delinquency



(c) Debt Bonferroni



(d) Delinquency Bonferroni

Figure 7: Statistical Power

These graphs report the statistical power to identify effects for selected treatments. We simulated placebo treatments of different sizes for January 2011 (i.e., just before treatment). (a) and (b) show the original figures while (c) and (d) show the power when using bonferroni adjusted p-values.

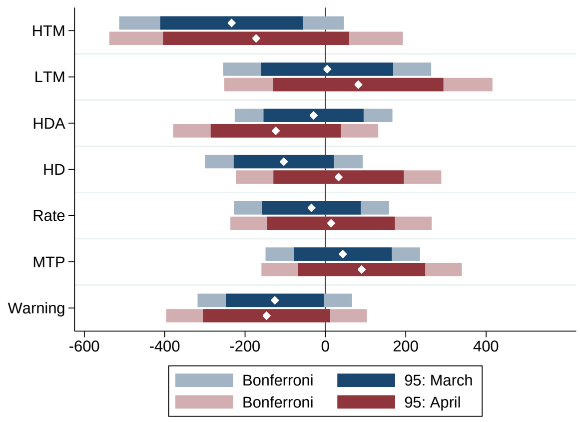
Table 8 also reports the False-Discovery-Rate (FDR) Benjamini and Hochber (1995) procedure –a multiple testing procedure which controls for the *expected proportion of falsely rejected hypothesis*. The FDR is equivalent to the family wise error rate (i.e. the one Bonferroni controls for) when all null hypothesis are true, but smaller otherwise and therefore has more power. When we use the FDR, the results are that the coefficients that were individually significant before at a 1 percent level in the test-by-test p-values are still significant at a 10 percent level when corrected for multiple testing. In contrast, none is in the placebo Table (see Table 9). That is implementing the widely used FDR we get that 4 out of the 8 significant individual coefficient survive at standard levels of significance.

Table 9: Placebo tests (Adjusted p-values)

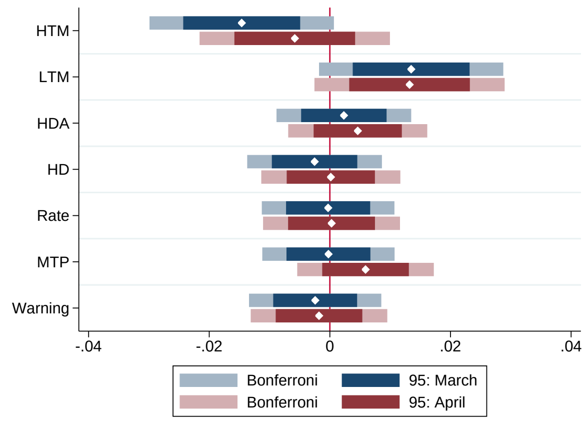
	Dependent Variables				*Dependent Variables (subsample)*		
	Debt		Delinquent		Credit Score	Open Cards	#CC in Default
	September 2010	October 2010	September 2010	October 2010	June 2010	March-June 2010	June 2010
			Panel A				
Mean Dep.	18919	18937	0.135	0.145	642	0.07	0.293
S.D. Dep.	(25800)	(25727)	(0.341)	(0.352)	(50)	(0.254)	(0.969)
Rate	54	47	0	-0.003	1.291	0.001	-0.016
	(117)	(120)	(0.003)	(0.003)	(1.44)	(0.007)	(0.029)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.982$^B H$]	[0.982$^B H$]	[.863$^B H$]
MTP	59	11	0	-0.003	-0.151	-0.001	-0.03
	(116)	(120)	(0.003)	(0.003)	(1.45)	(0.007)	(0.028)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.972$^B H$]	[0.972$^B H$]	[0.949$^B H$]	[0.863$^B H$]	[0.982$^B H$]	[0.982$^B H$]
High Risk	-48	11	0.004	0.002	-0.351	-0.003	-0.025
	(163)	(168)	(0.004)	(0.004)	(2.1)	(0.012)	(0.042)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.972$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.982$^B H$]	[0.863$^B H$]	[0.982$^B H$]
Low Risk	139	129	0.001	-0.001	0.238	-0.008	0.009
	(162)	(166)	(0.004)	(0.004)	(1.89)	(0.001)	(0.037)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.982$^B H$]	[0.863$^B H$]	[0.982$^B H$]
High Debt + Advice	22	48	0	0.003	-0.161	-0.003	0.005
	(119)	(122)	(0.003)	(0.003)	(1.38)	(0.007)	(0.028)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.982$^B H$]	[0.863$^B H$]	[0.982$^B H$]
High Debt	-40	-74	0.002	0.002	3.44**	-0.007	-0.051*
	(119)	(122)	(0.003)	(0.003)	(1.42)	(0.007)	(0.028)
	[1^B]	[1^B]	[1^B]	[1^B]	[0.315^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.315$^B H$]	[0.982$^B H$]	[0.745$^B H$]
Warning	70	98	-0.001	-0.001	-0.671	0.006	-0.035
	(116)	(120)	(0.003)	(0.003)	(1.43)	(0.007)	(0.028)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.949$^B H$]	[0.982$^B H$]	[0.863$^B H$]	[0.863$^B H$]
F-test TILA	0.81	0.93	0.99	0.41	0.65	0.99	0.52
F-test Non-TILA	0.93	0.87	0.87	0.9	0.24	0.76	0.41
			Panel B				
TILA	47	19	0	-0.002	0.588	0	-0.024
	(87)	(89)	(0.002)	(0.002)	(1.07)	(0.005)	(0.021)
	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]	[1^B]
	[0.981$^B H$]	[0.981$^B H$]	[0.65$^B H$]	[0.981$^B H$]	[0.792$^B H$]	[0.876$^B H$]	[0.985$^B H$]
Non-TILA	2	17	0.001	0.001	0.674	-0.001	-0.027
	(71)	(73)	(0.002)	(0.002)	(0.86)	(0.004)	(0.017)
	[1^B]	[1^B]	[1^B]	[1^B]	[0.714^B]	[1^B]	[1^B]
	[0.981$^B H$]	[0.981$^B H$]	[0.981$^B H$]	[0.981$^B H$]	[0.714$^B H$]	[0.868$^B H$]	[0.985$^B H$]
F-test	0.65	0.98	0.74	0.09	0.94	0.8	0.9
N	165042	163113	167190	167190	17077	17815	17815

Significance level: * 10 percent ** 5 percent *** 1 percent. Standard errors in parentheses.
† Adjusted p-values significant at 10%.
†† Adjusted p-values significant at 5%.

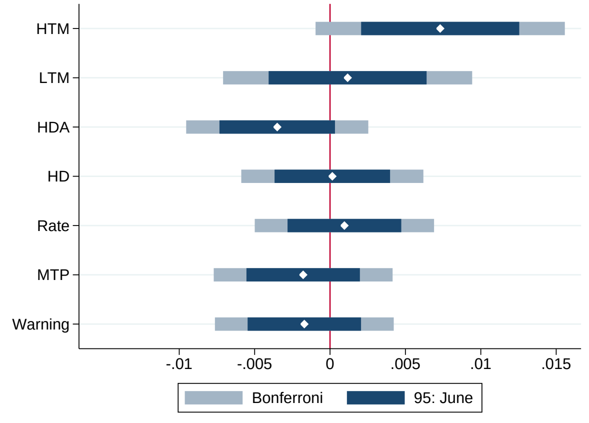
In conclusion: multiple testing by construction does decrease significance, but some Non-TILA messages survive while no TILA message is statistically significant. We believe these 5 exercises are strong evidence of a differential effect of TILA vs non-TILA messages, and that results are not due to sampling noise. However, we don't want to overemphasize this point, as our main finding is *precisely* that the effects are zero or close to zero for all messages. This is a result that is *not* affected by multiple testing issues as we are not rejecting the null hypothesis. We view the small differences across TILA and non-TILA messages as an interesting but ancillary result.



(a) Debt



(b) Delinquency



(c) Closed Accounts

Figure 8: Confidence Intervals for Table 2 Panel A

These graphs report confidence intervals for the equations estimated in Panel A of Table 2. The Bonferroni intervals control for the fact that we are testing 35 five hypotheses.

D. Treatment Effect Heterogeneity

Table 10: **Conditional on Amount of Products with the Bank**

	Dependent Variables				
	Debt		Delinquent		Closed
	March	April	March	April	June
	Panel A: One product with the bank				
Mean Dep.	16845	15868	0.236	0.254	0.0530
S.D. Dep.	(23693)	(23217)	(0.425)	(0.436)	(0.224)
Rate	5	16	-0.003	-0.004	0
	(86)	(118)	(0.00581)	(0.00597)	(0.00314)
MTP	69	189	0.001	0.009	-0.002
	(86)	(118)	(0.00580)	(0.00597)	(0.00314)
High Risk	-438***	-336**	-0.017**	-0.006	0.013***
	(122)	(168)	(0.00785)	(0.00807)	(0.00424)
Low Risk	-160	-62	0.009	0.007	0.002
	(117)	(158)	(0.00820)	(0.00843)	(0.00443)
High Debt + Advice	-73	-233*	0.001	0.004	-0.003
	(87)	(120)	(0.00588)	(0.00604)	(0.00318)
High Debt	-19	93	0.005	0.007	0
	(87)	(120)	(0.00587)	(0.00603)	(0.00317)
Warning	-119	-214*	0.002	0.003	-0.004
	(86)	(118)	(0.00582)	(0.00598)	(0.00314)
F-test TILA	0.73	0.28	0.8	0.22	0.77
F-test Non-TILA	0.008	0.048	0.22	0.686	0.022
N	64499	62009	75267	75267	75267
	Panel B: At least three products with the bank				
Mean Dep.	18731	17942	0.124	0.134	0.0322
S.D. Dep.	(25738)	(25239)	(0.330)	(0.341)	(0.177)
Rate	32	67	-0.00337	0.000288	0.00476*
	(120)	(146)	(0.00518)	(0.00536)	(0.00283)
MTP	-17	10	-0.00220	0.00221	0.000772
	(119)	(145)	(0.00515)	(0.00533)	(0.00281)
High Risk	-36	-9	-0.0118	-0.00811	0.0000884
	(180)	(221)	(0.00757)	(0.00783)	(0.00413)
Low Risk	160	151	0.0177**	0.00860	0.000908
	(158)	(192)	(0.00699)	(0.00723)	(0.00382)
High Debt + Advice	78.21	48.14	0.00556	0.00585	-0.000929
	(121)	(147)	(0.00519)	(0.00537)	(0.00283)
High Debt	-119	47	-0.0144***	-0.00564	0.00183
	(121)	(148)	(0.00521)	(0.00539)	(0.00285)
Warning	-98	-76	-0.00797	-0.00653	0.000172
	(119)	(145)	(0.00513)	(0.00531)	(0.00280)
F-test TILA	0.95	0.9	0.76	0.92	0.24
F-test Non-TILA	0.62	0.95	0	0.23	0.99
N	53266	52367	58192	58192	58192

This table estimates the treatment effect for all 7 treatments splitting the sample across clients with only this card with the bank, and those with at least three products with the bank. The idea is to explore if those more tied with the bank close the account less as a result of treatment, and have different responses in general. We do find some evidence for the this, however responses are still small.

Significance level: * 10 percent ** 5 percent *** 1 percent. Standard errors in parentheses.

Table 11: **Conditional on Income Level**

	Dependent Variables				
	Debt		Delinquent		Closed
	March	April	March	April	June
	Panel A: Low Income				
Mean Dep.	13077	12438	0.148	0.160	0.0480
S.D. Dep.	(18338)	(18044)	(0.355)	(0.366)	(0.214)
Rate	112	269**	0.003	0.01	-0.003
	(94)	(130)	(0.00706)	(0.00729)	(0.00433)
MTP	146	179	0.003	0.007	0
	(92)	(127)	(0.00694)	(0.00717)	(0.00425)
High Risk	-13	41	-0.027***	-0.034***	0.01
	(138)	(192)	(0.0100)	(0.0104)	(0.00615)
Low Risk	-118	-106	0.004	-0.001	0.003
	(126)	(172)	(0.00973)	(0.0101)	(0.00596)
High Debt + Advice	89	-22	-0.001	0.004	0
	(95)	(131)	(0.00714)	(0.00738)	(0.00438)
High Debt	-122	-151	-0.002	0.004	-0.0003
	(95)	(130)	(0.00710)	(0.00733)	(0.00435)
Warning	-124	-7	-0.013*	-0.008	0.005
	(93)	(128)	(0.00701)	(0.00723)	(0.00429)
F-test TILA	0.18	0.06	0.89	0.29	0.83
F-test Non-TILA	0.38	0.87	0.06	0.03	0.6
N	32708	31957	36636	36636	36636
	Panel B: High Income				
Mean Dep.	39058	37833	0.219	0.233	0.0305
S.D. Dep.	(43969)	(43544)	(0.414)	(0.423)	(0.172)
Rate	-581	299	-0.001	0.02	-0.002
	(671)	(835)	(0.0215)	(0.0221)	(0.00922)
MTP	7	373	0.022	0.004	-0.003
	(656)	(819)	(0.0209)	(0.0214)	(0.00896)
High Risk	-633	-1022	-0.004	0.021	0.01
	(931)	(1167)	(0.0283)	(0.0290)	(0.0121)
Low Risk	534	2288**	0.007	0.022	0.001
	(892)	(1110)	(0.0299)	(0.0306)	(0.0128)
High Debt + Advice	-344	-636	0.006	-0.009	-0.003
	(666)	(836)	(0.0213)	(0.0218)	(0.00910)
High Debt	-1176*	-632	-0.009	0.008	-0.008
	(662)	(827)	(0.0211)	(0.0217)	(0.00905)
Warning	-1257*	-2119***	-0.027	-0.011	-0.0014
	(649)	(809)	(0.0209)	(0.0214)	(0.00895)
F-test TILA	0.68	0.86	0.56	0.56	0.92
F-test Non-TILA	0.2	0.02	0.85	0.88	0.87
N	4623	4518	5378	5378	5378

This table estimates the treatment effect for all 7 treatments splitting the sample across clients with low and high Income. Income information was obtained through the application form and given to us aggregated and splitted in 5 categories: A,B,C,D,E. Panel A estimates the regressions for category D and Panel B for category A. There is some heterogeneity across income groups: in particular high income groups have much greater debt responses to messages (even in percentage terms), while low income individuals respond mainly trough less delinquency. The interest rate message does have a positive and significant (at 10 percent confidence) coefficient.

Significance level: * 10 percent ** 5 percent *** 1 percent. Standard errors in parenthesis.

3 Quasi-experimental Evaluation of First Time Price Comparisons

This section evaluates with quasi-experimental matching methods the effects of sending price comparisons. Although the main text of the paper presented results of an experiment, here we have the advantage of evaluating the effect when this information was sent *for the first time*. This may be important if the reader believes that failure to have an effect is due to the fact that clients already have the information.

The Central Bank of Mexico mandated disclosing the interest rates and APRs of *competitor banks* for similar cards –defined as classic, gold or platinum – in monthly statements starting April 2011. The comparison table was standardized and designed at the Central Bank, Figure 7 in the paper shows the one for classic cards. This is clearly a strong disclosure. Banks resisted this direct comparison in their own monthly statements since it surely reduces comparison frictions and has the potential to create competition, switching and reallocation of debt to cheaper cards. We expected a large response since our bank was in the top 5 most expensive banks and since this was *new* information.

Because we do not have a randomized control group to measure causal impacts, we rely on propensity score matching methods. Fortunately for us, our bank did not send the comparison price table to their top notch (TN) clients –3,581 cards in our sample–, so we use them as a control group.[9] TN clients are more wealthy and may have different spending and payment patterns. Figure 4 shows they have about twice as much debt but have similar time trends, which suggest the use of a differences in differences (DID) strategy.

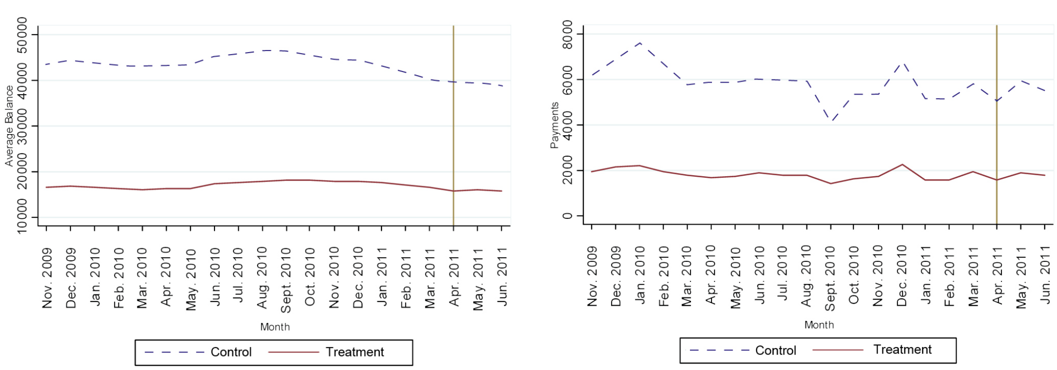


Figure 9: Debt and payment trends TN (control) vs not TN (treatment) clients.

[9]The TN client could have compared interest rates herself if she wanted. Kling et al. (2012) have shown however that making information slightly easier to access may have significant effects.

To measure impacts non-experimentally we use two empirical strategies: a propensity score matching and a DID kernel matching strategy. As it is well known the latter controls for time invariant unobservable differences across treatment and control groups. For ease of computation, we matched 10,000 randomly selected treatment accounts with the 3,581 control accounts who did not receive the comparison table.[10]

Table 12 presents our results. Column 1 and 3 present falsification tests where we measure "impacts" in the pretreatment period; both show zero effects giving us confidence that we have a correct specification. Column 2 shows the propensity score matching impact estimates, where we compare the average debt on May and June 2011 of non-premier vs their matches in the premier control group for the same period. The effects are economically small –around 90 pesos for debt– and statistically not different from zero for both payments and debt[11]. Column 4 reports results for the matching diff-in-diff strategy. Again effects are negligible.

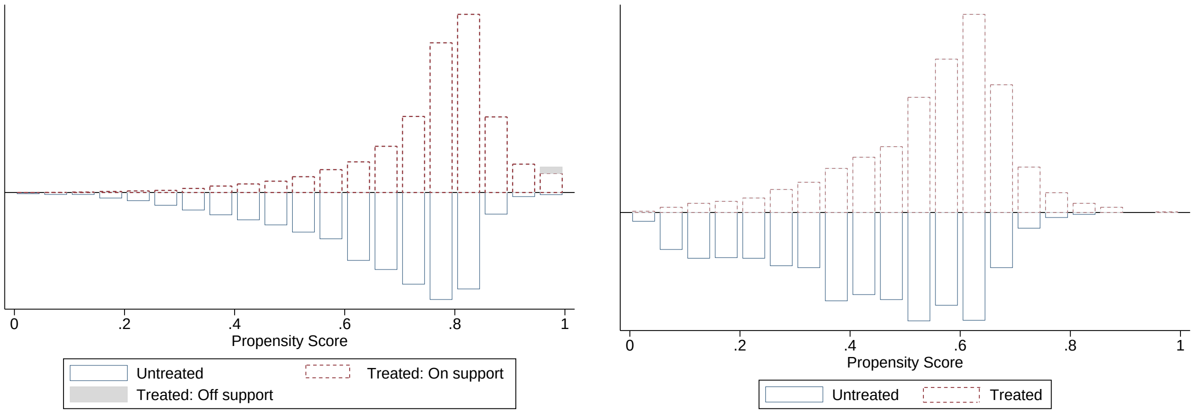
Table 12: **Propensity Score**

	Levels		Differences	
	Falsification	Real	Falsification[b]	Real[a]
	[1]	[2]	[3]	[4]
Average Balance	-37	91	990	-35
	(-0.03)	(0.07)	(0.48)	(-0.01)
Average Payments	-159	-179	257	-98
	(-0.42)	(-0.61)	(0.56)	(-0.15)

t-stats in parenthesis
[a] Before: Jan-Feb-Mar 2011; After: May-Jun 2011
[b] Falsification: Before: Sep-Oct-Nov 2010; After: Jan-Feb-Mar 2011
The propensity score was estimated using the following variables: Debt Growth Rate, Debt in Feb2011, Num. Of Purchases Feb2011, Payment Due Feb2011, Payments Dec2010, Credit Limit Feb2011, Purchases Jan2011, Squared Debt, Average Debt Dec2010, Average Debt Feb2011, Risk Score Dec2010, Non Interest Debt Dec2010, Amount to Pay Dec2010, Payment Due Dec2010, Risk Score Feb2011, Cash Dispositions Feb2011, Payments Jan2011, Non Interest Debt Feb2011, Purchases Dec2010, Payments Feb2011 , Sex * Average Payments , Distrito Federal State * Average Debt, Distrito Federal State * Average Purchases, Distrito Federal State * Average Payments, Mexico State *Average Debt, Mexico State * Average Purchases, Mexico State * Average Payments, Dummy Default Dec2010, Dummy Default Jan2011, Squared Risk Score, Squared Purchases, Squared Debt to Pay, Squared Debt Growth Rate, Cubic Debt, Cubic Purchase, Cubic Debt Growth Rate, Cubic Risk Score and Cubic Payments.

[10] We estimated a logit propensity score which includes debt, payments, purchases, credit limit, behavior score, late payments, number of purchases, number of cash withdrawals, and some quadratic and cubic terms of this variables as covariates. The specification successfully balances observed covariates (unreported). We use one neighbor with replacement and trimming on common support at 95 percent.

[11] We also estimated the model for purchases as dependent variables, however we could not find an specification of the propensity score that balanced the observable pretreatment variables, and therefore we are not confident to present results as causal.



(a) Propensity Score match (b) Difference in Differences

Figure 10: Propensity Score Graphs

4 Messages and Examples of Monthly Statments

Estado de Cuenta Tarjeta de Crédito

[redacted]

NUMERO DE CUENTA
[redacted]
RFC
[redacted]
PERIODO
22 Abr - 21 May 13

RESUMEN DE MOVIMIENTOS	
Fecha Límite de pago	**10 Jun 13**
Pago Mínimo	**$ 825.00**
Pago para no generar intereses	**$ 33,644.95**
Saldo Anterior	$ 46,436.65
Compras	+41,830.67
Disposiciones en efectivo	+1,000.00
Pagos y Créditos	- 55,639.77
Intereses	+0.00
Comisiones	+ 15.00
IVA	+2.40
Saldo Actual	$ 33,644.95
Tasa Anual Personalizada	0.00%
Tasa Anual	**22.99%**
Costo Anual Total sin IVA	0.0%
Tasa Moratoria Anual	**0.00%**

El tiempo necesario para liquidar su saldo deudor realizando sólo el pago mínimo es de: 41 meses. El monto para pagar su saldo deudor si se encuentra al día en sus pagos en 12 meses es de: $ 2,803.75. No considera compras, intereses, disposiciones ni comisiones posteriores a la presente fecha de corte.

INFORMACIÓNAL CORTE			
Límite de Crédito	$ 66,000.00	Días del Periodo	30
Saldo Promedio Diario*	$ 39,391.69	Tasa Anual de Inversión	0.00%
Fecha de Corte	21 MAY 2013		

Emitido por: [redacted]

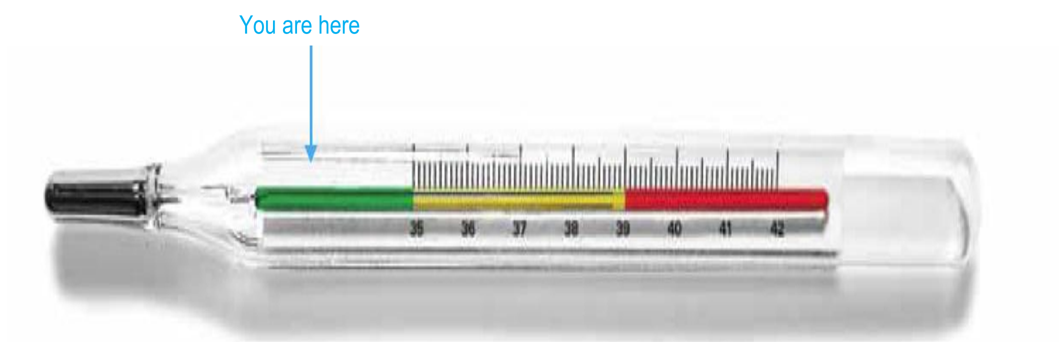
Hard information is located in the bottom. Annual interest rate is called TASA ANUAL.

Figure 11: Bank Statement

Figure 11 above is a real credit card monthly statement from our cooperating bank. As can be seen the interest rate and the MTP are displayed, but not too saliently.

Dear XXXXX,

Based on your credit behavior, we have detected that your credit card has the following **probability of default:**



Congratulations!

You form part of our group of clients with very good payment behavior.

Continue to enjoy the benefits from your credit card by keeping your finances healthy.

Figure 12: Low Risk Message.

Dear XXXXX,

We want our clients to have healthy finances. That's why we have analyzed the credit behavior of a group of cardholders.

With respect to this group **your debt** is:

HIGHER

than the average of

people similar to

yourself*

Figure 13: High Debt Message.

References

Benjamini, Y. and Y. Hochber, "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing," *Journal of the Royal Statistical Society*, 1995, *57.*