The limits of self-commitment and private paternalism

Appendix – For Online Publication

Isaac Meza Joyce Sadka Enrique Seira

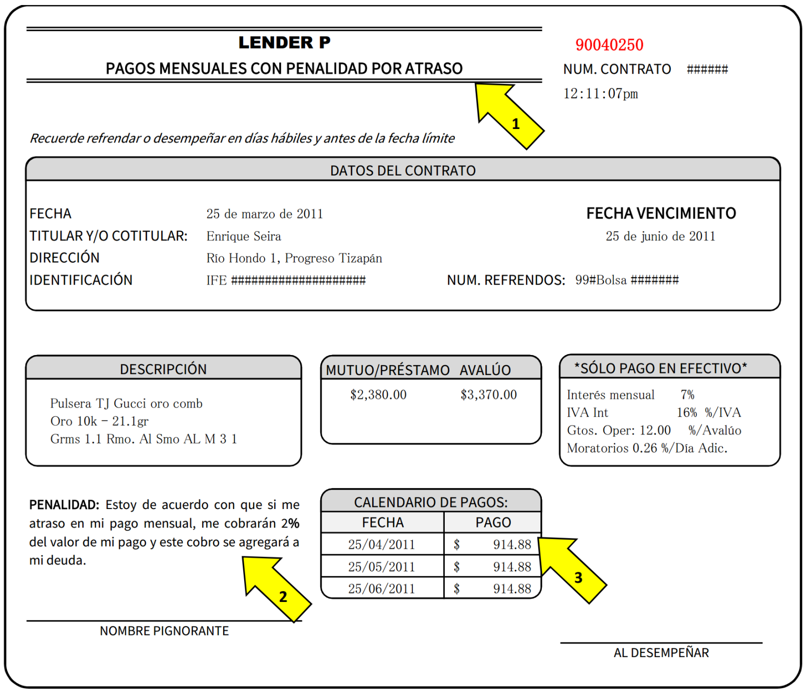
Contents

Appendix A. Further results

A.1 Some materials

Figure OA-1: Contract Terms Summary, and Promise Slip

(a) Receipt for client



LENDER P

PAGOS MENSUALES CON PENALIDAD POR ATRASO

90040250

NUM. CONTRATO ######

12:11:07pm

1

Recuerde refrendar o desempeñar en días hábiles y antes de la fecha límite

DATOS DEL CONTRATO

FECHA 25 de marzo de 2011

TITULAR Y/O COTITULAR: Enrique Seira

DIRECCIÓN Río Hondo 1, Progreso Tizapán

IDENTIFICACIÓN IFE ####################

FECHA VENCIMIENTO 25 de junio de 2011

NUM. REFRENDOS: 99#Bolsa #######

DESCRIPCIÓN

Pulsera TJ Gucci oro comb

Oro 10k – 21.1gr

Grms 1.1 Rmo. Al Smo AL M 3 1

MUTUO/PRÉSTAMO	AVALÚO
$2,380.00	$3,370.00

SÓLO PAGO EN EFECTIVO

Interés mensual 7%

IVA Int 16% %/IVA

Gtos. Oper: 12.00 %/Avalúo

Moratorios 0.26 %/Día Adic.

PENALIDAD: Estoy de acuerdo con que si me atraso en mi pago mensual, me cobrarán 2% del valor de mi pago y este cobro se agregará a mi deuda.

2

CALENDARIO DE PAGOS:

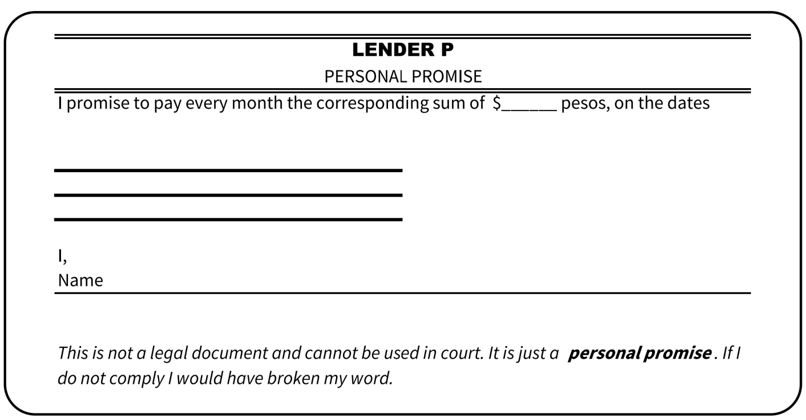
FECHA	PAGO
25/04/2011	$ 914.88
25/05/2011	$ 914.88
25/06/2011	$ 914.88

3

NOMBRE PIGNORANTE

AL DESEMPEÑAR

(b) Personal promise signed by client



LENDER P

PERSONAL PROMISE

I promise to pay every month the corresponding sum of $______ pesos, on the dates

I,

Name

This is not a legal document and cannot be used in court. It is just a ***personal promise****. If I do not comply I would have broken my word.*

The top of this figure is a sample receipt that was given to clients that got assigned to the fee-forcing contract (the font and format were changed to protect Lender's P identity). We want to highlight the salience of some items. First the title clearly indicated which contract the client has (arrow 1). Second, in the case of the fee contract it clearly indicates that there is a fee for paying late equivalent to 4% of the value of the monthly payment (arrow 2). Third, there is a calendar for payments clearly specifying the dates and amounts to pay each month. The bottom panel of the figure shows a "promise slip", the paper that those who were assigned (or chose) to the monthly payment with promise had to sign to make the promise salient. It emphasizes that the client is giving his word, and that the promise is not a legal document.

A.2 Pictures

Figure OA-2: Some Pawnshops

(a) Appraiser/tellers inside a pawnshop

(b) Pawnshop

(c) Pawnshop

(d) Lost pawns which are for sale

This figure shows pictures of pawnshops in Mexico city. They do not necessarily coincide with Lender P for confidentiality.

Figure OA-3: Gold buyers next to pawnshops

(a) Gold buyer next to pawnshop 1

(b) Gold buyer next to pawnshop 1

This figure shows pictures of gold buyers next to pawnshops in Mexico city. They do not necessarily coincide with Lender P for confidentiality.

A.3 Surveys

Table OA-1: Survey's non-response balance

	Panel A : Entry Survey				Panel B : Exit Survey		
	Overall	No Response	Response	p-value	No Response	Response	p-value
Loan amount	2145.46	2262.14	2145.46	0.08	2157.15	2367.62	0.17
	(31.81)	(59.21)	(35.45)		(30.93)	(154.83)	
Monday	0.18	0.18	0.18	0.95	0.18	0.19	0.71
	(0.02)	(0.03)	(0.02)		(0.02)	(0.04)	
Number of branch-day pawns	33.03	32.13	33.33	0.61	32.83	35.66	0.51
	(1.04)	(2.08)	(1.2)		(1.07)	(4.18)	
Obs	13444	3007	10437		12539	905	

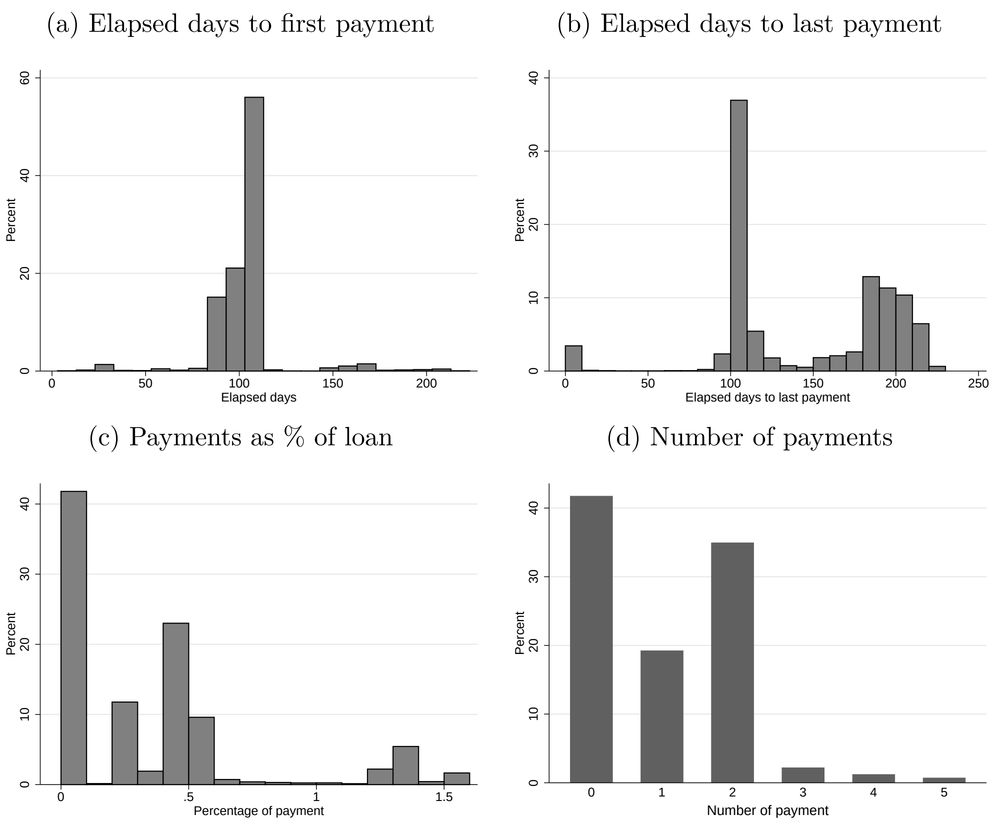
This table shows whether the means of variables in the administrative dataset are different for those that respond the baseline survey vs those that do not. We use this as an assessment of external validity. Internal validity is guaranteed because the baseline survey was implemented before treatment assignment and therefore response rates are orthogonal to treatment assignments. Panel A studies the baseline survey, while Panel B focuses on the exit survey. The columns labeled "p-values" report p-values for the test that the means of the respective variable are the same for those that responded did not respond the survey.

Table OA-2: Baseline survey

	Baseline Survey
1	**Your pawn was:** (a) Inherite, (b) a gift, (c) bought by me, (d) lend to me, (e) other ___________
2	**Mark with an "X" in the line below how likely is that you recover your pawn. Where 0 is impossible and 100 is completely certain**
3	**How much would you sell the item you want to pawn for? _____________ pesos**
4	**Gender**
5	**Age**
6	**Civil Status** (a) married, (b) single, (c) divorced, (d) widowed
7	**Work status** (a) employed, (b) own business, (c) houseshores, (d) don't work, (e) retired, (f) study
8	**Education** (a) no formal education, (b) primary, (c) middle school, (d) highschool, (e) more than highschool
9	**In the last month, did a friend or family member asked you for money?** (a) yes (b) no
10	**What would you like to have: 100 pesos tomorrow or 150 pesos in one month?**
11	**How often do you feel stressed by your economic situation?** (a) always, (b) very often, (c) sometimes, (d) never
12	**What is the main reason you want to pawn?** (a) Need the money because somebody in my family lost his/her job (b) Need the money to pay for a sickness in the family (c) Need the money for an urgent expense (d) Need the money for some non urgent expense.
13	**How stressed do you feel from the situation that led to to pawn?** (a) very stressed, (b) somwhat stressed, (c) a little stressed, (d) not stressed
14	**In 3 months, I expect to have a _______________ situation** (a) better, (b) similar, (c) worse
15	**Have you panwned before?** (a) yes (b) no
16	**How many times have you pawned on a Lender P branch?** (a) NO___ (b) 1-2 times ___ (c) 3-5 times____ (d) More than 5____
17	**If you are saving money and a family member wants to use it for something** (a) I would only give him the money for an urgent expenze (b) I would give him the money even if it was not an urgent expense (c) I would not give him/her the money regardless (d) No one would ask me for my money
18	**Do you make an expenses budget for the month ahead of time?** (a) always, (b) very often, (c) sometimes, (d) never
19	**Do you have other items you could pawn?** (a) yes (b) no
20	**Do you have savings?** (a) yes (b) no
21	**Do you participate in a ROSCA?** (a) yes (b) no
22	**Is it common that family or friends ask for money?** (a) yes (b) no
23	**How much did you spend to come to the branch today? $_____________ pesos**
24	**How much time does it usually take to come to this branch? ___________**
25	**How much does your family spend in a normal week? $_____________ pesos**
26	**How much do you manage to save in a normal week? $_____________ pesos**
27	**Does it happen to you that you spend more than you wanted because you fall into temptation?** (a) never, (b) almost never, (c) sometimes, (d) very often
28	**In the last 6 months, has it happened that at some point you lacked money to pay** (a) rent? (b) food (c)food (d) medicine (e) electricity (f) heating (g) telephone (i) water
29	**What would you like to have: 100 pesos in 3 months or 150 pesos in four months?**
30	**Would you like to receive (free) reminders for upcomming payments?** (a) yes (b) no

A.4 Some more evidence of overconfidence

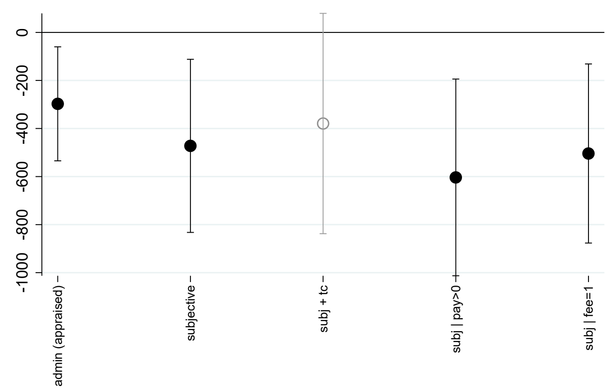
Figure OA-4: Behavior of those who lost pawn



This figure describes behavior for the subsample of clients whose pawn was not recovered (in the control group). Panel (a) shows days elapsed from the pawn to the first payment, while panel (b) displays the days elapsed to last payment. Some people pay after the day 105 when the grace period ends because the can "restart" the loan if they pay all interest owed. It amounts to starting a new loan with the same conditions and same pawn. Panel (c) shows the fraction of the loan that they paid (even when they ended up losing the pawn). Panel (d) displays the number of times they went to the branch to pay.

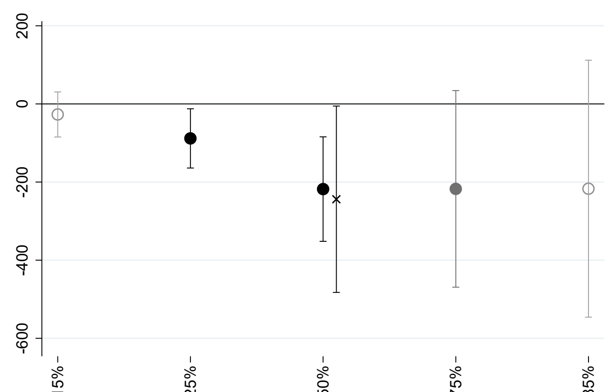
A.5 Main treatment effects: Additional material

Figure OA-5: FC as % of loan - treatment effect



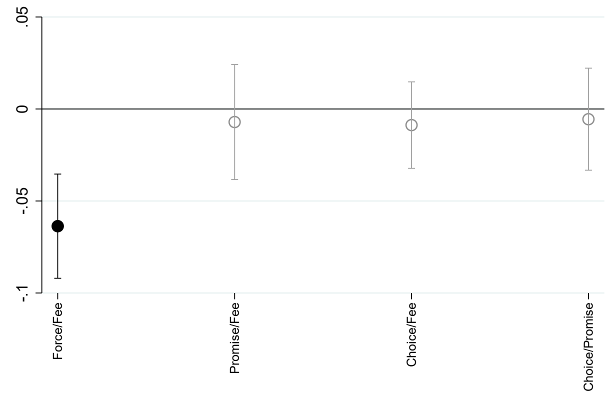
This figure is the same as in Figure 4 Panel (a), but with the subsample restricted to the first 115 days.

Figure OA-6: Financial cost effect: charging all fees



This figure is the analogous to Figure 4(b), except that for the fee-forcing contract we pretend that all clients incurred in their late fees, and therefore inflate the financial cost by summing those fees. This is intended as a kind of worse case scenario for the financial cost of the fee-forcing contract. The circles indicate the quantile treatment effects, while the cross is the (OLS) mean. We still find that the financial cost of will be smaller under the fee-forcing contract in spite of artificially inflating it.

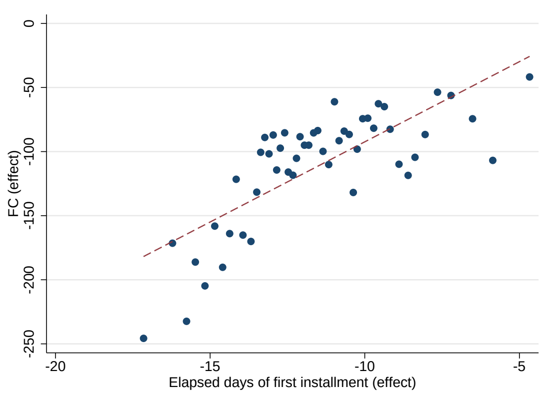
Figure OA-7: FC as % of loan - treatment effect



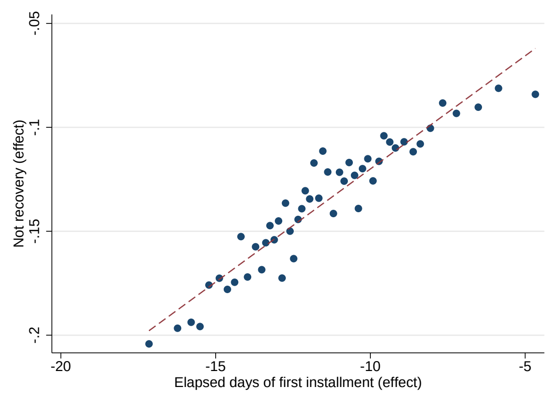
This figure shows the estimated treatment effect of all arms against the status quo, but normalizing the dependent variable by the value of the loan.

Figure OA-8: Relationship between treatment effects

(a) Induced to pay earlier vs Induced Lower FC

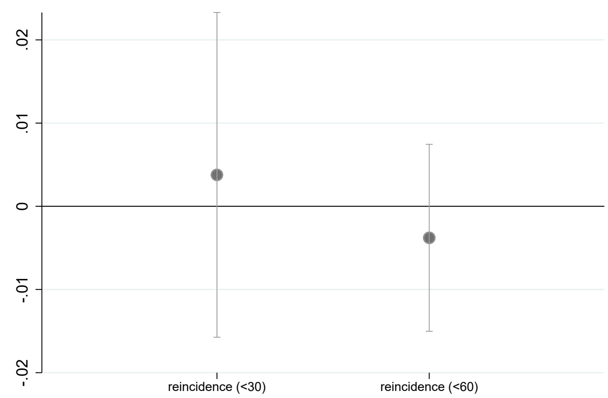


(b) Induced to pay earlier vs Induced Recovery



This figure plots relationships between *treatment effects*. Both Panels (a) an (b) have the same X-axis, which displays the estimated heterogeneous treatment effect on the outcome "elapsed days of first payment", that is how many days elapsed from the day the loan was awarded to the first payment the client made. The treatments effects were calculated using Athey *et al.* (2019). In Panel (a) the Y-axis is the *treatment effect* on financial cost. In Panel (b) the Y-axis is the *treatment effect* on losing their pawn. Panel (a) shows that those induced to pay earlier are also those that have larger savings in financial cost as a result of "forcing" the frequent payment commitment contract compared to the status-quo (control). Panel (b) shows that those induced to pay earlier are also those that have a larger increase in recovery.

Figure OA-9: Repeat purchase before 30/60 days



This figure shows the estimated treatment effect of repeat purchase before 30 & 60 days.

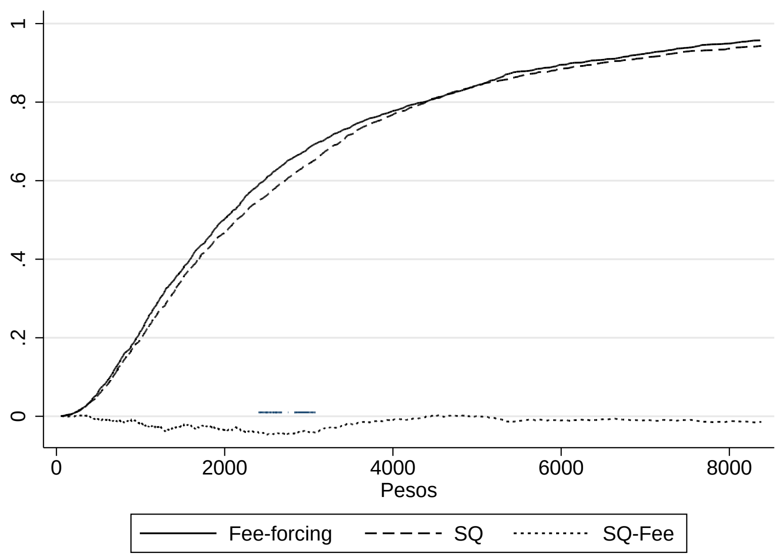
Table OA-3: Intermediate outcomes

	Days to 1st pay.	# of pay.	Size of pay.	Days to rec.	+ pay.	% of pay.	
Panel A: No choice / Fee							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Arm	-8.54	0.19	34.0	-8.52	-0.0068	0.081	-0.017
	(1.03)	(0.044)	(51.2)	(2.68)	(0.018)	(0.025)	(0.028)
Arm#Rec							-0.0042
							(0.030)
Recovered							0.88
							(0.017)
Observations	4996	5085	5085	2490	5085	5062	5062
Panel B: No choice / Promise							
	(1)	(2)	(3)	(5)	(6)	(7)	(8)
Arm	-2.97	0.17	-72.6	-1.45	-0.021	-0.0049	-0.012
	(1.13)	(0.051)	(46.5)	(3.21)	(0.020)	(0.026)	(0.028)
Arm#Rec							0.0060
							(0.028)
Recovered							0.88
							(0.017)
Observations	4655	4757	4757	2073	4757	4733	4733
Panel C: Choice / Fee							
	(1)	(2)	(3)	(5)	(6)	(7)	(8)
Arm	-2.40	0.13	-53.7	0.98	-0.0077	0.0026	-0.013
	(0.97)	(0.048)	(42.6)	(2.89)	(0.015)	(0.020)	(0.019)
Arm#Rec							0.013
							(0.020)
Recovered							0.88
							(0.017)
Observations	5922	6037	6037	2639	6037	5997	5997
Panel D: Choice / Promise							
	(1)	(2)	(3)	(5)	(6)	(7)	(8)
Arm	-1.06	0.049	-90.2	-3.00	-0.021	-0.015	-0.0049
	(0.94)	(0.042)	(53.4)	(3.14)	(0.017)	(0.023)	(0.025)
Arm#Rec							-0.0080
							(0.026)
Recovered							0.89
							(0.017)
Observations	5253	5368	5368	2334	5368	5346	5346
Control Mean	90.0	1.18	830.5	92.7	0.75	0.73	0.73

This table explores treatment effects in "intermediate variables". Each column represents a different dependent variable in an OLS regression, and each panel represents a different treatment arm-control comparison. All regressions include fixed effects for branch, day of week fixed effects, number of pawns at the time of pawning this particular one, number of different treatment arms experienced before pawning this particular one. R^2 are not reported, they were less than 0.04 for all but the last column which had R^2's close to 0.6. The last row shows the mean of the dependent variable for the control group. Dependent variables are as follows: Column (1) measures the number of days elapsed from the pawning date to the first payment done. Column (2) records the number of payments done within 230 days of the pawn. Column (3) is the average size of the payments for each client in pesos. Column (4) is self-reported cost to get to the branch plus the imputed loss of a whole day of salary (using the minimum wage in Mexico) multiplied by the number of visits to the branch. Column (5) measures the number of days it took to recover the pawn, conditional on recovering. The dependent variable in Column (6) is a dummy =1 if the client paid any positive amount within 230 days of the pawn. For Columns (7) and (8) the dependent variable it is the sum of total payments done within 230 days of the pawn divided by the size of the loan, but column (8) includes as regressors a dummy=1 if the client recovered her pawn, and its interaction with treatment.

A.6 FOSD: fee forcing vs status quo financial cost distributions

Figure OA-10: Empirical CDF of Financial Cost: fee-focing vs status-quo



This figure plots the empirical cumulative distribution of financial cost. It does this separately for the fee-forcing contract and for the status-quo contract. The doted line at the bottom is the difference of the status-quo CDF minus the fee-focing CDF. It shows that the CDF of the status quo contract is always below that of the fee-forcing (and this difference is significant for the points indicated by the blue line), and therefore that the former first-order stochastically dominates the later for weakly decreasing utility functions; see Proposition 2.

Table OA-4: Clients who should prefer fee-forcing financial cost distribution

Sub-population	Dominance	Log-normality (AD/KS)	Obs
Fee-forcing	$\succeq_1^*$	*/* — */*	5034
Low-loan	$\succeq_1^*$	/ — /	2508
High-loan	$\succeq_1^*$	/ — /	2526
Low-subj. prob.	$\succeq_1^*$	*/* — */*	1083
High-subj. Prob.	$\succeq_1^*$	*/* — */*	2590
Low-income index	$\succeq_1$	*/* — */*	1047
High-income index	$\succeq_1$	*/* — */*	948
Male	-	*/* — /*	755
Female	$\succeq_1$	*/* — */*	2158
Pawn before	$\succeq_1$	*/* — */*	2475
Family doesn't ask	$\preceq_1$	*/* — */*	1826
Family asks	$\succeq_1^*$	*/* — */*	987
No savings	$\preceq_1$	*/* — */*	1353
Has savings	$\succeq_1^*$	*/* — */*	717
Not rosca	$\succeq_1^*$	*/* — */*	1270
Rosca	$\preceq_1$	*/* — */*	795
Low-education	$\succeq_1$	*/* — /*	906
High-education	$\succeq_1$	*/* — */*	1797
Overconfident	$\succeq_1$	*/* — /*	1626
Not PB	$\succeq_1$	*/* — */*	1438
PB	$\succeq_1^*$	*/* — /*	226
Doesn't make budget	$\succeq_1$	*/* — */*	1054
Makes budget	$\succeq_1$	*/* — */*	1689
Not tempted	$\succeq_1$	*/* — /*	875
Tempted	$\succeq_1$	*/* — */*	1872
High-transp. cost	$\succeq_1$	*/* — */*	1352
Low-transp. cost	$\succeq_1$	*/* — */*	1343
High-transp. time	$\succeq_1$	*/* — */*	1260
Low-transp. time	$\succeq_1^*$	*/* — */*	1442

This table does two things. First, it tests whether the observed empirical distribution of financial cost is well approximated by a log normal. It does this using two tests, the Anderson-Darling and the Kolmogorov-Smirnoff tests. Second, it fits a log normal distribution by maximum likelihood to observed empirical distribution of financial cost, separately for the fee-forcing arm and the status-quo arm. Using the fitted log normal, it tests whether the fee-forcing financial cost distribution would be preferred by any expected utility agent using Proposition 1 below. The different rows of the table do this for different sub-populations. The first row of the table does it for every client in the fee forcing and status quo arms. The "*" show that we cannot reject at the 5% level that both distribution are log normal for any of the two tests. The column entitled "Dominance" shows whether any client that dislikes higher cost would prefer the fee-forcing cost distribution over the status quo one, with $\succeq_1$ meaning he should (with $\succeq_1^*$ indicating the difference is statistically significant). It turns out to be the case that for the overwhelming majority of sub-populations, the conditions of preferring the fee-forcing distribution hold.

Proposition 1. *Let F and G be the cumulative distributions of two alternative log-normal prospects. The following are equivalent:*

(a) For every weakly decreasing utility function u: $E_F(u(FC)) \leq E_G(u(FC))$

(b) $E_F \log(FC) \geq E_G \log(FC)$ and $Var_F \log(FC) = Var_G \log(FC)$

Proof. See Theorem 4 in Levy (1973). $\square$

Proposition 2. *This is a standard result.*
The following are equivalent:

(a) For every weakly decreasing utility function u: $E_{sq}(u(FC)) \leq E_{fee}(u(FC))$

(b) $F_{sq}(FC) \leq F_{fee}(FC)$

Proof.
$[(a) \implies (b)]$ Suppose (b) does not hold. So there exists FC^* such that $F_{sq}(FC^*) > F_{fee}(FC^*)$, Define $u := \mathbb{1}_{FC \leq FC^*}$. Then

$$E_{sq}(u(FC)) = \int u(FC) dF_{sq} = F_{sq}(FC^*) > F_{fee}(FC^*) = \int u(FC) dF_{fee} = E_{fee}(u(FC))$$

which contradicts (a).

$[(a) \impliedby (b)]$ On the other hand for u weakly decreasing,

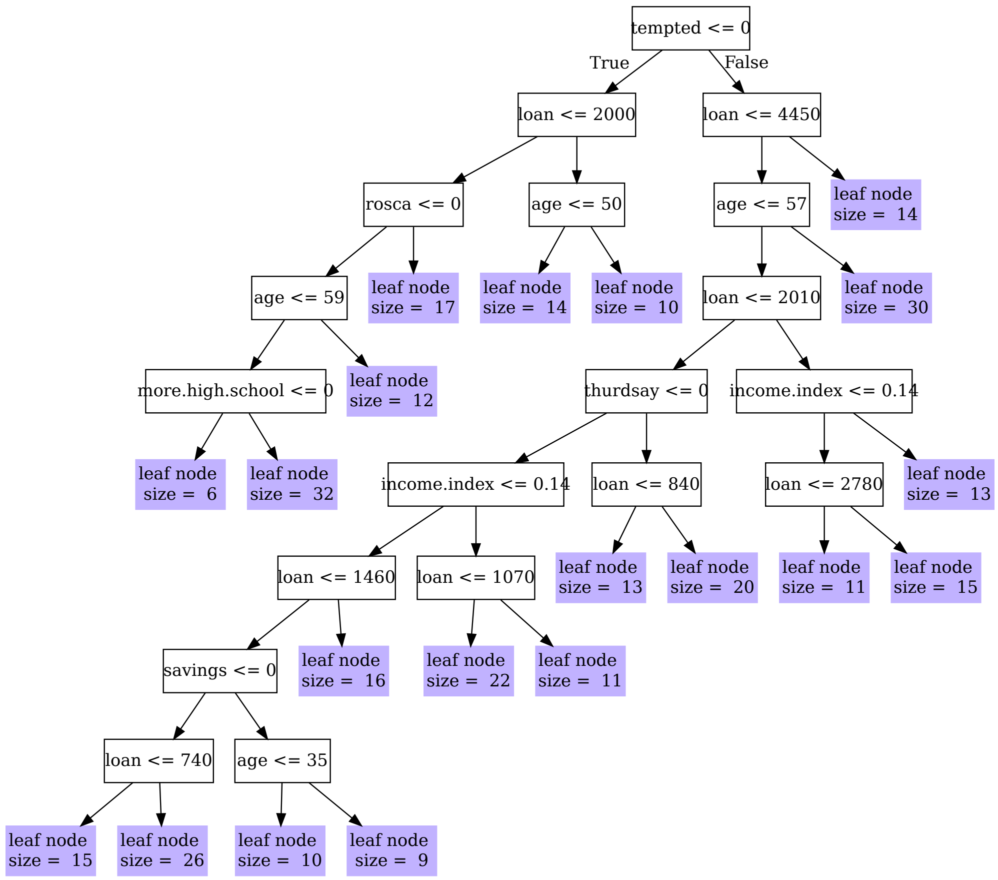
$$\int u(y(FC)) dF_{sq}(y(FC)) = \int u(y(FC)) dF_{fee}(FC) \leq \int u(FC) dF_{fee}(FC)$$

with $y(FC) = F_{sq}^{-1} F_{fee}(FC)$. □

Note the proof was done in the case of absolutely continuous and strictly increasing distribution functions F_{sq} and F_{fee}.

A.7 Causal Random Forest and HTE

Figure OA-11: Honest causal tree for the fee forcing contract heterogenous treatment effects

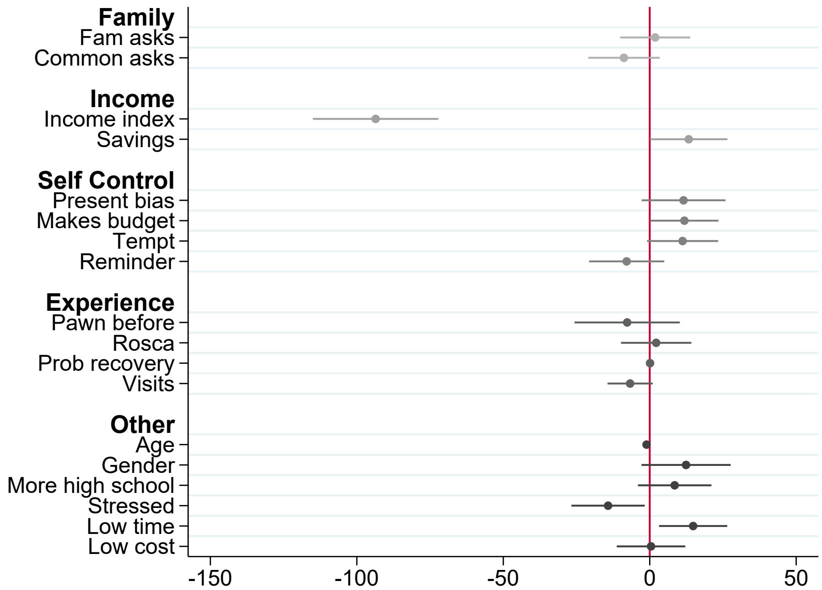


This is one(it is chosen such that it minimizes the pruned cost, that is it is the tree with the smallest root-node impurity) of the honest causal trees in the random forest we use for the estimation of the heterogeneous treatment effect of the fee-forcing contract. It is meant only as an example of how these trees look like. The forest was such that there are as many estimated treatment effects as there are clients.

We use Athey *et al.* (2019) `causal_forest` of the `grf` library in *R*. The parameters used were: *causal_forest(X, Y, W, Y.hat = NULL, W.hat = NULL, num.trees = 2000, sample.weights = NULL, clusters = NULL, equalize.cluster.weights = FALSE, sample.fraction = 0.5, mtry = min(ceiling(sqrt(ncol(X)) + 20),ncol(X)), min.node.size = 5, honesty = TRUE, honesty.fraction = 0.5, honesty.prune.leaves = TRUE, alpha = 0.05, imbalance.penalty = 0, stabilize.splits = TRUE, ci.group.size = 2, tune.parameters = "none", tune.num.trees = 200, tune.num.reps = 50, tune.num.draws = 1000, compute.oob.predictions = TRUE, orthog.boosting = FALSE, num.threads = NULL)*

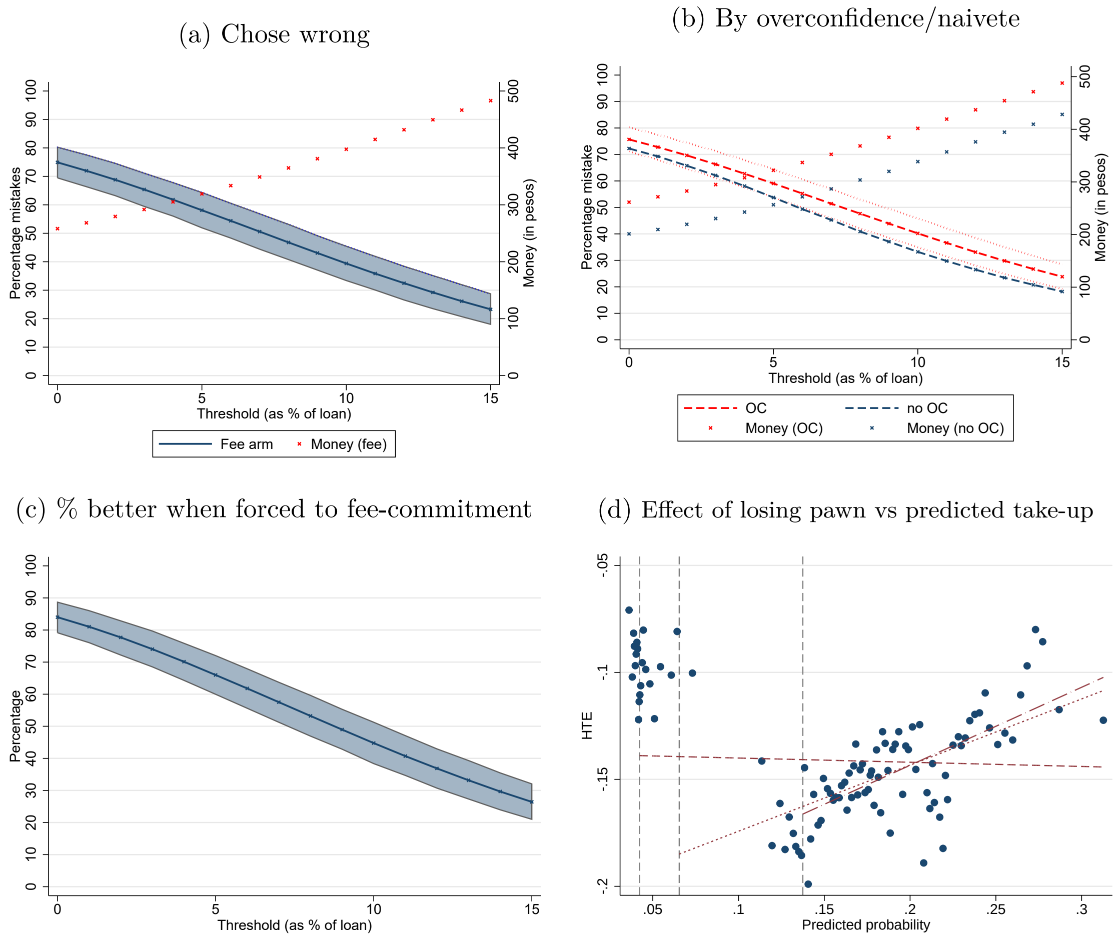
Figure OA-12: Heterogeneous Treatment Effect: Fee-forcing contract

(a) Determinants of effects



This figure estimates bivariate regressions of the estimated client-level heterogeneous treatment effects against the respective covariate from the baseline survey $\widehat{hte_i} = \alpha + \beta\, X_i + \epsilon_i$. The regressors X_i include (e.g if the family asks for money, if they have savings, if they are overconfident using the definition the text, etc. See this Appendix for a transcription of the survey).

Figure OA-13: Choice of contracts and treatment effects



In Panel (a) we estimate what the treatment effect of the commitment contract *would have been* for all subjects in the choice arm if they had been forced into the fee-commitment contract. To do this we proceed in two steps. First, we estimate treatment effects in the forcing arm by comparing the fee-forcing arm against the status quo arm. We let these effects be heterogeneous as a function of our x's using Athey *et al.* (2019)'s methodology of causal forests. Second, we extrapolate these treatment effects based on the choice arm using the same x's. Once we have personalized counterfactual treatment effects in the choice arm we calculate what fraction of subjects in the choice arm incurred in financial costs that are $> z\%$ than if they had chosen the opposite contract of what they actually chose, were $z\%$ is defined as a fraction of the loan. $z\%$ is a level of tolerance we can vary and we plot it in the X-axis. The left Y-axis measures the fraction of subjects that would have been better by a margin of $z\%$ if they changed their choice, and the right Y-axis measures the amount of money "left on the table". We use bootstrap to tighten the confidence intervals (CIs). Athey *et al.* (2019)'s heterogeneous treatment effect using GRF is asymptotically normal. We compute the HTE (μ) together with standard errors (σ) . For every pledge, we draw a random effect from a normal distribution with parameters (μ,σ^2), and compute via bootstrap the percentage that choose wrong, along normal-approximation CIs (results are robust if we use instead percentile CIs or bias-corrected CIs) . This allows us to estimate a distribution for the upper and lower bound CIs, which we then use to obtain a 95% CI. Panel (b) is analogous to Panel (a) except that it does the exercise separately for clients we classified as overconfident ($OC_i := \mathbb{1}(P_i^s - \widehat{P_i(X_i)} > 0)$) and those we classified as not overconfident. Panel (c) simulates what percentage would be better by at least z if we forced everybody of those in the fee-choice arm into the fee-commitment contract. Panel (d) asks whether it is the case that people with larger causal savings from the fee-forcing contract would be more likely to select that contract. To do this we proceed in two steps as well. First we estimate a flexible model of take-up of the fee commitment contract *in the choice arm* using random forests, and from this model obtain a probability $P(x_i)$ of choosing the fee-forcing contract for a client with characteristics x_i. We extrapolate this model to clients in the fee-forcing arm to estimate what would they have chosen if we had given them choice. Figure (d) plots $\widehat{P(x_i)}$ in the X-axis using a binscatter that splits the X-axis in 100 percentile bins. The Y-axis plots the heterogeneous treatment effects of the fee forcing contract on the probability of losing the pawns (more negative means then more likely to recover it), averaged for the respective x-axis bin. Positive assortative selection would mean a negative relationship: those who benefit more by treatment and lose the pawn less are more likely to choose it. Using all bins we estimate a slope of zero in the relationship. Using the 80 right most points, we estimate a *positive* relationship.

A.8 Take up

Table OA-5: Predicting Take-up: Goodness-of-Fit

(a) Take up: Choice-fee Arm

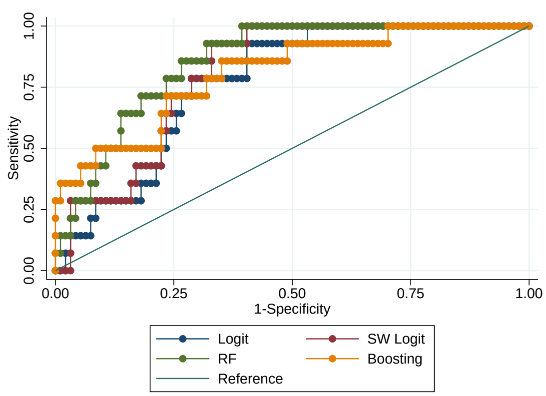
	Choice-Fee Arm			
GOF measures	Logit	SW-Logit	RF	Boosting
AUC (out of sample)	0.76	0.8	0.85	0.81
	(0.05)	(0.04)	(0.04)	(0.06)
AUC (in sample)	0.83	0.82	0.92	0.96
	(0.02)	(0.02)	(0.02)	(0.01)
Accuracy	0.74	0.76	0.85	0.86

(b) Take up: Choice-promise Arm

	Choice-Promise Arm			
GOF measures	Logit	SW-Logit	RF	Boosting
AUC (out of sample)	0.63	0.63	0.7	0.72
	(0.06)	(0.06)	(0.06)	(0.06)
AUC (in sample)	0.83	0.82	0.9	0.97
	(0.02)	(0.02)	(0.01)	(0.01)
Accuracy	0.62	0.67	0.65	0.7

Figure OA-14: Out of sample ROC curve

(a) Take-up in Fee Arm



(b) Take-up in Promise Arm

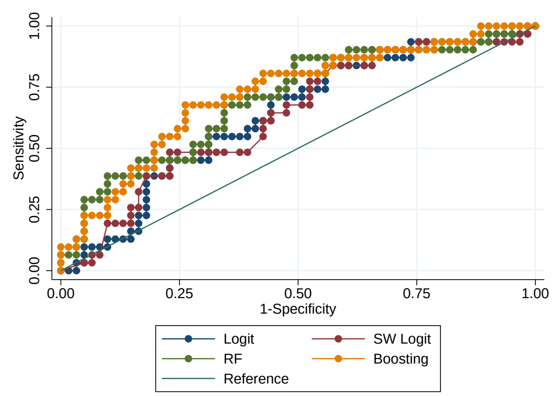
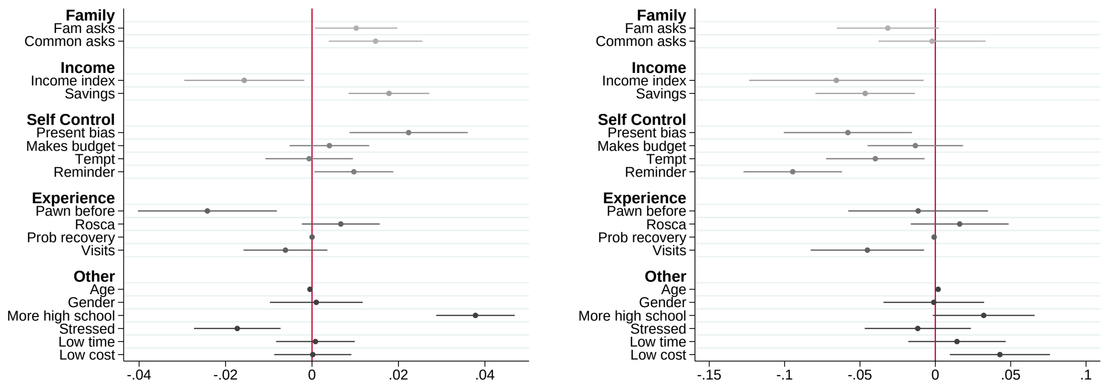


Figure OA-15: Predictors of commitment contract take-up

(a) with Fee Arm (b) with Promise Arm

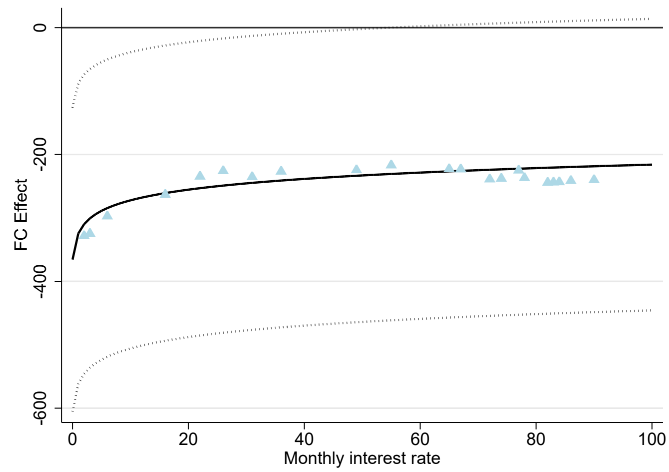


This figure reports bivariate regressions of the form $\widehat{TakeUp} = \alpha + \beta\, X_i + \epsilon_i$, where $\widehat{TakeUp}$ is the prediction using random forests. The figure reports the β coefficients for different X_i's along with 95% confidence intervals. Panel (a) focuses on take up in the arm where clients could chose among the fee-commitment contract and the status quo contract. Panel (b) focuses on the arm where clients could chose among the promise-commitment contract and the status quo contract. Using random forests we can predict who takes up the fee-forcing contract with 85% accuracy out of sample.[45] Which suggests that choice among contracts is not purely random. This figure shows that the more educated, those that report that their family typically asks for money, those that make a monthly budget of expenses, and those that ask for a remainder of their due payments (and marginally those we classify as present-biased) are more likely to chose the fee-commitment contract if given the choice. The opposite holds for clients that are more economically vulnerable (can barely pay for food, electricity, etc) and those that report being more stressed.

[45] Correcting for the fact that most chose the status-quo contract using the method of SMOTE, Chawla *et al.* (2002) we find an accuracy rate of 75%.

A.9 New results

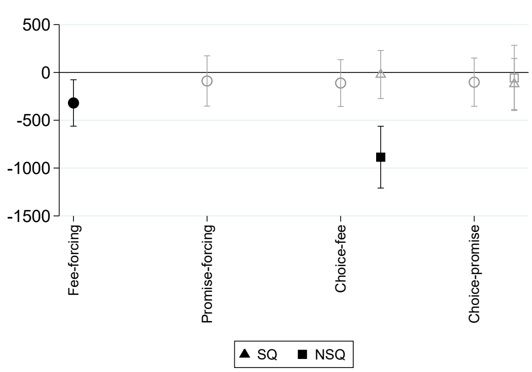
Figure OA-16: Financial cost for different discount rates



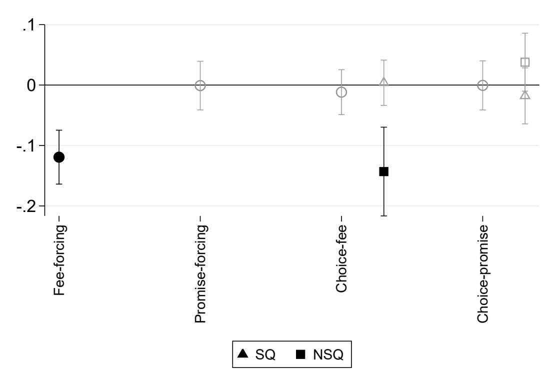
This Figure estimates the treatment effect on financial cost with different discount rates.

Figure OA-17: Treatment effects pooling all arms

(a) Financial Cost

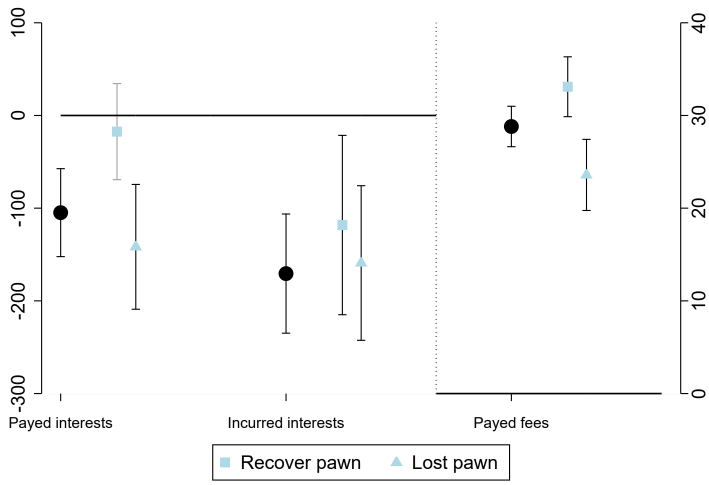


(b) Lost Pawn



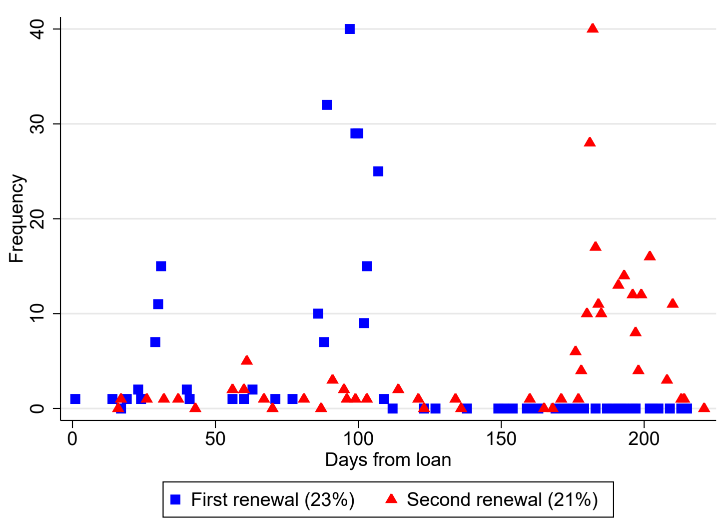
This Figure shows the treatment effects for the main outcomes when pooling all arms in the same regression.

Figure OA-18: Treatment effect decomposition of the Financial Cost



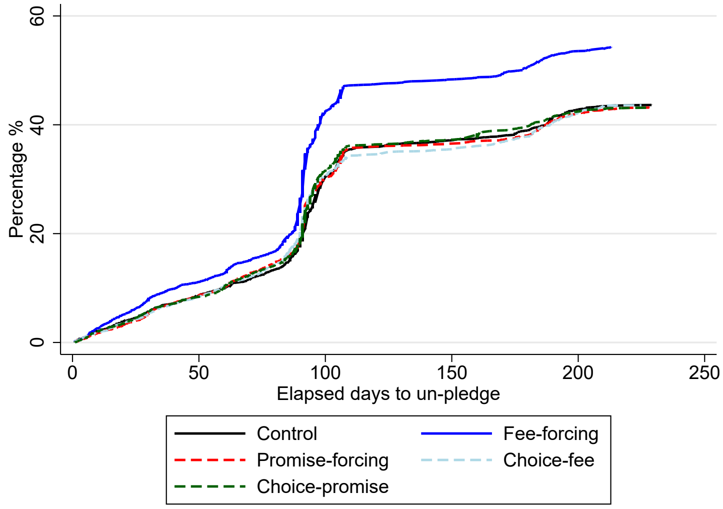
This Figure is a "close-up" for the estimates found in Figure 4 - Panel (a). It shows the treatment effects on payed & incurred interest, the former defined as the actual interest payed, and the latter is the sum of all potential interests (for those pawns that were lost we calculate the interest generated until day 230). In the right axis we show the treatment effect on the payed fees. Finally, we analyze this effect for the subsamples that recovers or loses the pawn.

Figure OA-19: Frequency of renewals



This Figure shows the occurrence and frequency of renewals. It locates in time, respective to the day the loan started, when the renewal occurs for both the first and second renewal. Note that the first renewal is concentrated around 100 days, while the second is concentrated around the 200 days, corresponding to the first and second cycle.

Figure OA-20: Probability of recovery by arm



This Figure shows the accumulated percentage of recovery in time by treatment arm.

Appendix B. Observational analysis

The objective of this Appendix is to conduct one test aiming to assess if there is learning in choosing the frequent payment FP) contract. In particular if being endogenously induced to have a FP contract causes the client to chose a FP in subsequent pawn. The identification strategy is not as strong as in a randomized control trial —having to rely on an instrumental variable strategy using changes in the supply of the FP contract– and this is why we chose to locate it in a separate Appendix. However we believe we find a strong case for learning causing higher demand for the FP contract.

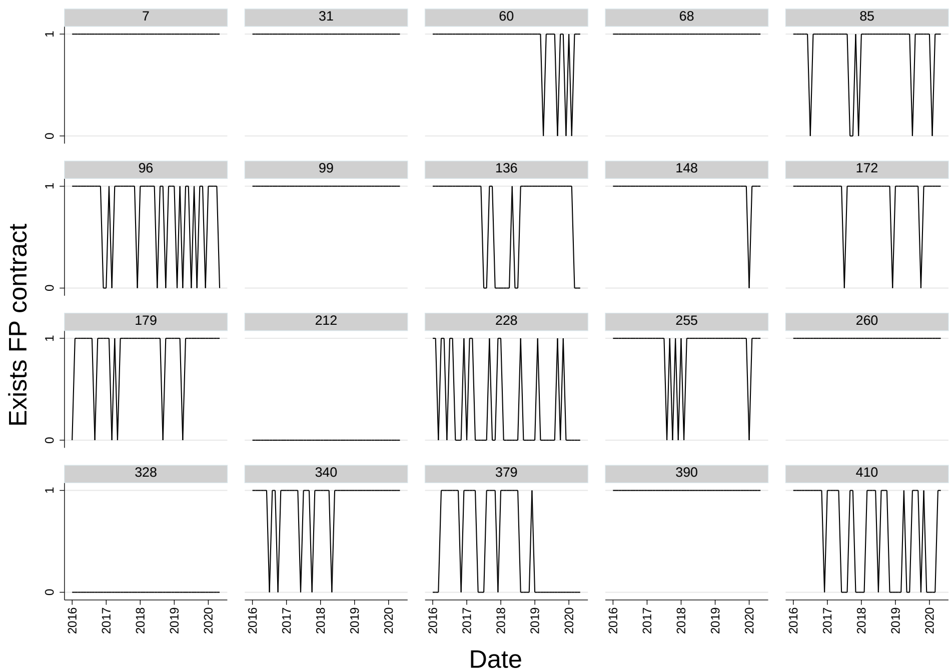
In what follows we will describe the identifying variation and use the richness of the observational data to control for possible confounds. We will use hundreds of branches and hundreds of thousands of pawns covering more than 4 years to estimate (under the identification assumptions) the causal effect of having had a FP on the conditional demand for the FP type of contract.

B.1 Variation in branches' use of frequent payment contract

After our experiment ended, Lender P started offering frequent payment contracts along their traditional ones. We were not able to get data for the dates of the first expansion, but we have data for the period January 2016 through May 2020. During this period some branches where offering the frequent payment contract while others were just starting to do this. Some branches also stopped offering the frequent payment contracts. Out of all branches 2% never offered the FP contract, 29% always offered it, while 69% offered for only part of our sample period. Our identification strategy will mostly rely on these later group, as we include branch fixed effects in our regressions.

To show the reader a glimpse of this variation in availability of the contract we randomly selected 20 branches and plotted which months had a frequent payment contract active in their IT system. Figure OA-21 shows a time plot for each branch, where each observation is a month. The Y-axis takes the value of 1 if in that month the FP contract was available in that branch and zero otherwise. So it is a "supply side" variable.

Figure OA-21: Existence of FP per branch



This Figure shows the presence of the frequent payment (FP) contract in 20 randomly chosen branches of Lender P for a span of more than 4 years. A y value = 1 means that in that month the FP contract was available in that branch.

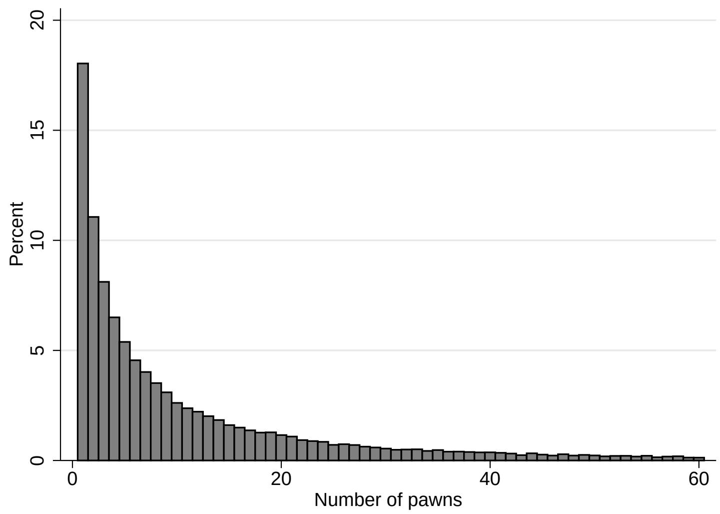
In conversations with Lender P about this variability they said that it is driven by three things: the expansion of the frequent payment product is done gradually, the IT system of a branch sometimes fails, and they often do experiments themselves turning on and off the existing of the frequent payment contract as this was a relatively new type of contract.[46] We did verify that there are no frequent payment contracts when they said it was turned off in their IT system.

Orthogonality of FP supply. We will use the availability of the FP contract as an instrument for the client choosing a FP contract when she pawns. Clearly one cannot choose a FP when it does not exist, so that this instrument allows would-be-FP choosers to obtain a FP contract. We verify that indeed it has a statistically powerful first statge. One may be concerned that this instrument may not satisfy the exclusion restriction however. As we will explain below we will use this instrument in an specification that controls for branch and client fixed effects, taking into advantage that many clients do pawn repeatedly (See Figure OA-22 below). These control for any characteristic of the client that is fixed across time, and therefore is a strong control for selection of clients across branch or across contracts. We also control for calendar of the month fixed effects, thereby absorbing common time trends that affect all clients, like macroeconomic shocks. We

[46]Unfortunately the had no documentation on how these experiments were implemented.

describe the exact specification below, but for now we want to note that we need only for the exogeneity of the instrument to hold conditional on these extensive set thousands of fixed effects.

Figure OA-22: Number of pawns per client



This figure plots a histogram of the number of pawns per client during our sample period (January 2016 through May 2020). A large fraction of clients have more than one pawn, and many have several pawns. We use these repeat clients to identify learning below.

Having said this, in Table OA-6 we assess to what extent we can predict whether a given branch activates the FP contract in its IT system in a given week or a given month. It turns out that we cannot predict in which weeks a given branch uses the FP contract with our observables controlling for branch fixed effects. The observables include fraction female clients last week (or last month), the age of these clients, number of pawns last week (or last month), average size of those loans, the percentage of pawns last week (or last month) that were jewelry, the percentage of loan recoveries –the opposite of default– last week (or last month). The same is true if we use one month prior instead of one week. The R^2 shows that the *additional* variance explained by the covariates beyond branch and calendar week fixed effects is low: going from 0.154 to 0.157 when we add all regressors. The AUC and the *Accuracy Rate* give a similar picture, with out-of-sample AUC around 0.72 and Accuracy rates around 66%.[47]

Quantitatively the correlations are small: an increase of 1 years of the mean age of clients is associated with an increase of 0.008 percentage points in introducing FP, an increase in the size of the loan by 1000 pesos increases it by 0.002, an increase of 10 pawns per day increases it by less than 0.0002 percentage points. Having 10% less women as clients in the past increases it by

[47]Castellanos *et al.* (2020) say that for predicting loan default for instance AUC's from 0.80 to 0.95 are common.

1 percentage point. This result of low correlation between important observable variables and the supply of FP contract in a given branch makes us more comfortable with the assumption that the instrument satisfies the exclusion restriction. The presence of the FP contract in a given week in a given branch seems almost random from this perspective.

Table OA-6: Predicting the supply of FP contracts within branch across time

	Branch j had FP in week t		
	Last week		Last month
	(1)	(2)	(3)
% women		0.11	0.11
		(0.052)	(0.051)
Mean age		0.0082	0.0065
		(0.0019)	(0.0019)
Mean loan		-0.0000021	-0.0000035
		(0.0000018)	(0.0000020)
Number of pawns		0.00015	0.00035
		(0.00016)	(0.00017)
% jewels		-0.024	0.071
		(0.045)	(0.045)
% recovery - lag 4		-0.060	-0.096
		(0.046)	(0.048)
% recovery - lag 5		-0.10	-0.041
		(0.049)	(0.050)
% recovery - lag 6		-0.093	-0.021
		(0.049)	(0.050)
% recovery - lag 7		0.0062	0.015
		(0.050)	(0.050)
% recovery - lag 8		-0.012	-0.0044
		(0.048)	(0.049)
Mean appraise		-0.012	-0.011
		(0.0016)	(0.0017)
Branch FE	✓	✓	✓
Number of week FE	✓	✓	✓
p-value Branch = 0	0	0	0
p-value week = 0	0.006	0.014	0.003
R-sq	0.154	0.158	0.157
Adjusted R-sq	0.15	0.15	0.15
DepVarMean	0.44	0.43	0.43
AUC	0.72	0.72	0.72
Accuracy	0.66	0.65	0.66

This table uses OLS regressions to predict whether branch j in week t had a FP available. So the dependent variable is an indicator for this event $\mathbb{1}(\text{Branch Had FP})_{jt}$, and the explanatory variables are measures of performance of that branch and the characteristics of the clients either the week previous to t or 4 weeks previous to week t. We allow for two time periods since the branch manager or central offices may take time to react to information. Column 1 includes branch and week fixed effects, while Column 2 adds the covariates displayed measured the week previous to t. Column 3 is analogous to column 2 except that the values of the displayed covariates are averaged across the 4 weeks prior to week t. The bottom panel shows measures of predictive power like R^2, as well as area under the ROC curve (AUC), and the Accuracy Rate. It also shows F-test of the null hypothesis that the branch (week) fixed effects, or the other regressors have coefficients equal to zero.

B.2 Experiencing FP causes future demand for FP to increase

This subsection uses the existence of a FP contract in the branch as an instrument for a client *having* a FP contract if she visited that branch that week to pawn. Using this instrumental variable strategy we estimate the effect of having had a FP in the previous pawn. More concretely, Table OA-7 reports results from a two-stage least squares estimate of the effect of having a FP contract on subsequent demand for FP contracts. We estimate the following regression:

$$\mathbb{1}(\text{Has FP})_{ijt} = \alpha_i + \gamma_t + \beta \mathbb{1}(\text{Had FP previously})_{ijt} + \epsilon_{ijt} \tag{2}$$

where i, j, t index client, branch, and week respectively. $\mathbb{1}(\text{Has FP})_{ijt}$ is an indicator for client i pawning in branch j in week t using a FP contract, given that both FP and traditional contracts were available at the branch at the time of pawning, so that there is a choice to be made among these.[48] Moreover we restrict the sample to pawns where the immediate previous pawn is already closed at the moment of opening the new one[49]. We estimate a regression with calendar week fixed effects (we have 212 weeks) γ_t, and also include client fixed effect α_i. The variable of interest is denoted by $\mathbb{1}(\text{Had FP previously})_{ijt}$, and is an indicator for the client's immediate previous loan[50] being FP loan.

Having client fixed effects in the regression means that we only use variation across time (across subsequent pawns) to identify the effect of experience, and avoid the selection problems that come from comparing across clients. That is, they control for the fact that different types of clients may select different types of contracts. Repeat pawning is common and this helps for identification. Figure OA-22 shows a histogram of the fraction of clients that had $1, 2, 3, \ldots, 60$ pawns in our sample. We have more than one hundred thousand clients that got two loans within 3 or less months from each other[51], and for 37% of those clients the immediately sequentially preceding loan was taken when the branch had FP available.

However, even with client fixed effects, idiosyncratic unobserved shocks across time may induce spurious correlation between choosing a FP last week and choosing FP today. The variable $\mathbb{1}(\text{Had FP previously})_{ijt}$ is therefore still potentially endogenous. To deal with this we instrument $\mathbb{1}(\text{Had FP previously})_{ijt}$ with the *availability* of the contract in branch j when the client previously went to pawn the immediately prior pawn with respect to t, $\mathbb{1}(\text{FP Avail})_{ijt}$. This is basically using a supply shifter to identify demand. We showed above that availability of FP contracts has close to a zero correlation to a battery of observables. The IV strategy assumes that availability of the

[48] When a FP is not available in branch j in week t the variable takes the value of missing, and is therefore not considered in the regression. That is, we only include observations when the client had a choice between FP and traditional contracts.

[49] We do this to avoid making the conclusion that clients are re-pawning in order to meet their past debt.

[50] We consider only the immediate previous loan, following a "Markov's" assumption, in which only the present state determines the future.

[51] We give a small lower bound to keep the identity of Lender P confidential

FP contract in a given week in a given is uncorrelated with ϵ_{ijt} — i.e. that after conditioning on thousands of client, branch and week fixed effects and the client having pawned recently, there is no omitted variable driving both: the branch having FP contracts on, and the client subsequent pawn using a FP contract. Note that including branch fixed effects means that identification comes from a given branch sometimes having the FP and sometimes not.

The exclusion restriction for an instrument is untestable, but note that we are comparing clients that go to the same branch, who have the same pawning frequency, but where one of them arrived to the branch to pawn on a week where the FP contract was available and the other arrived on a week where the same branch had no FP contract available.The exclusion restriction could be violated for example if the branch manager makes FP available as a function of clients that will come in that week and therefore reaches a certain type of client that is more likely in-and-of themselves to prefer FP contracts now and in the future. We find this unlikely. It is hard to predict who will come on a given week and if they are more likely to like the FP contract: Table OA-6 strongly suggests that the branch manager is not turning the FP contract on and off as result of which clients are coming to the branch or how the branch is doing. Having said this, we acknowledge that the exclusion restriction could be violated even in this very tightly controlled specification.

Table OA-7 shows the first and the second stage regressions for equation 2. All columns have branch, and calendar week fixed effects, and standard errors are clustered by client. Columns 1 and 4 show strong first stages (t-stats above 50). The availability and unavailability of the FP contract has an incidence on its use. Under our identification assumptions, Columns 2-3 (and 5-6) show strong causal effects: having been induced by the instrument to have a FP contract in the previous loan causes the client to a FP for her subsequent pawn by 50 percentage points (column 2). The difference between columns 2 and 3 (and 4-5) is the sub-sample considered: in the first one we only condition the immediate previous pawn to be closed at the time of opening a new one, the second one not only considers previous pawns being closed, but having at least one week closed.

Table OA-7: Experience with frequent payment contract raises future demand for it

	OLS			FE		
	FS	IV - 0	IV - 1	FS	IV - 0	IV - 1
	(1)	(2)	(3)	(4)	(5)	(6)
FP available	0.020			0.0100		
	(0.00065)			(0.00084)		
Had FP in the past		0.49	0.42		0.30	0.25
		(0.071)	(0.076)		(0.18)	(0.21)
Residual		-0.015	0.016		-0.51	-0.48
		(0.070)	(0.075)		(0.18)	(0.21)
Observations	$>$100000	$>$100000	$\sim$100000	$>$100000	$>$100000	$\sim$100000
R-sq	0.012	0.086	0.078	0.010	0.035	0.041
DepVarMean	0.012	0.043	0.041	0.012	0.043	0.041
Calendar week FE	✓	✓	✓	✓	✓	✓
Branch FE	✓	✓	✓	✓	✓	✓
Client FE				✓	✓	✓

This table shows resulting estimates of variants of equation 2 above. They regress a dummy for the client choosing a frequent payment contract (when both the traditional one and the FP are available) on whether the previous loan was under a FP contract. All columns have branch, and calendar month fixed effects, and the standard errors are clustered by client. The main regressor of interest is having had a FP loan in the immediate past of t which measures experiencing a FP contract. Columns 1 and 4 report the result of first stage where the supply side instrument is an indicator for the branch having had a FP available when the client showed to pawn the previous pawn. Column 2 & 5 presents the two-stage least square estimate. Columns 3 & 6 are analogous, but instead of looking clients whose previous pawn is already closed, it looks at those whose previous pawn has at least one week of being closed. We do not report the exact number of observations to keep Lender P identity confidential and instead give a lower bound.

Appendix C. A simple model

We use the model of John (2020) and refer the reader to that paper for more detail, justification of assumptions and some of the proofs. The model has three periods and linear utility.[52] Period $t = 0$ is a planning period where the client is either allocated to the status quo, the fee-forcing contract, or a choice between the two. Period $t = 1$ is the saving-for-the-monthly-payment period, and $t = 2$ in the pawn recovery (loan payment) period. In period 1 the client receives her income $y_1 = 1$, or gets zero with probability λ. She can consume (c_1) or save (s_1) part that income. In period 2 the client gets her savings from period 1, and again receives income of either $y_2 = 1$, or zero with independent probability λ. In this last period, she decides whether to use income and savings for consumption c_2 and/or for paying back the loan of size $p \in (1, 2)$ to recover the pawned piece valued at $b > p$. In this simple set up we model the fee-commitment contract as a contract that imposes a fee of size F if the client fails at $t = 1$ to save $s_1 = p - 1$ pesos, which is what is needed to pay the loan back when there are no shocks. In period $t = 0$ she evaluates her welfare as $E[c_1 + c_2]$, were for simplicity we have set the time discount to one. We also assume the interest rate is one. We introduce present biased preferences by assuming the following utility function $U_t = c_t + \beta \sum_{k=t+1}^{2} E[c_k]$, with $\beta < 1$ indicating present bias. A naive client perceives she is not so present biased and instead of β uses $\hat{\beta} \in (\beta, 1]$.

Note that under these assumptions it is efficient at $t = 0$ to recover the loan since $b > p$ and since there is no discounting at $t = 0$. Because $b > 1$, paying back the loan requires that there is no negative shock in any period and that $s_1 > 0$. Because $\beta < 1$ at $t = 1$ the client will not send savings in excess of what is needed to recover the loan: $s_1 = p - 1$. This parsimonious model implies the following results:

Result 1: Present biased clients default more. Under the status-quo contract, absent shock realizations, present biased clients (sophisticated or naive) with $\beta < \beta_{SQ} < 1$ will lose their pawn, while clients with no present bias will not.[53]

Result 2: Forcing present-biased clients into the fee-commitment contract reduces default. Imposing a fee $F > 0$ for late payments weakly decreases default (for present biased clients only). It strictly decreases default if $F > F_{min}(\beta) := (p - 1) - \beta[\lambda(p - 1) + (1 - \lambda)(b - 1)]$. The larger the present bias the larger the F required to induce pawn recovery.[54]

Result 3: Demand for commitment. Given $F > 0$, (a) Neoclassical clients will never demand

[52]This does not map perfectly to our 3 period contract, but it is enough to generate the results we need. We also assume that the amount of the loan is used up to pay for the emergency. John (2017) provides a more general treatment.

[53]$\beta_{SQ} = \frac{p-1}{\lambda(p-1)+(1-\lambda)(b-1)}$. See Proposition 1 in John (2020).

[54]$F_{min}(\beta)$ is derived from the incentive compatibility constraint needed to generate savings at $t = 1$ to recover the pawn can be written as $1 - (p - 1) + \beta[\lambda(p - 1) + (1 - \lambda)(b - 1)] \geq 1 - F + \beta(1 - \lambda)$.

commitment. (b) Present-biased sophisticated clients will prefer the fee-forcing contract over the status quo contract $\iff \lambda F < (1-\lambda)^2(b-p)$ and $F > F_{min}(\beta)$, that is $\iff \beta \in [\beta_{min}, \beta_{SQ}]$.[55] (c) Analogously, naive clients will demand commitment $\iff \hat{\beta} \in [\widehat{\beta_{min}}, \beta_{SQ}]$, where $\widehat{\beta_{min}} < \beta_{min}$. So strongly naive clients will on the one hand demand more commitment than sophisticated clients since they believe (incorrectly) that a smaller fee will motivate them to pay. On the other hand they may demand less commitment since they think they can save and pay on their own. Whether they demand more or less than sophisticated clients depends on the empirical distribution of β and $\hat{\beta}$.

Result 4: Overconfidence. Only naive clients will be overconfident about the probability of recovery. This will be true whether they have the status quo or the fee-forcing contract. Overconfidence is increasing in $\hat{\beta}$.

Result 5: Welfare. (a) Neoclassical consumers' welfare strictly decreases when we force clients into the fee-commitment contract instead of the status quo contract because of the risk of them not being able to pay for the installment, and does not change when we offer a choice between them. (b) The welfare of sophisticated present biased consumers weakly increases when we give them choice, and it strictly increases $\iff \beta \in [\beta_{min}, \beta_{SQ}]$, that is when they would choose the fee-commitment contract themselves. Forcing them into the fee-commitment contract increases welfare $\iff \beta \in [\beta_{min}, \beta_{SQ}]$, otherwise it strictly decreases it. So choice is better than forcing for sophisticates. (c) Forcing can be welfare improving for the naive. Indeed if $\hat{\beta} > \beta_{SQ} > \beta$ then forcing the fee-commitment contract increases welfare, and if $\hat{\beta} \in (\widehat{\beta_{min}}, \beta_{min})$ then forcing the status quo contract increases welfare.[56] We want to highlight that only under certain parameters will forcing installment payments improve welfare, and that welfare will likely decrease for those with no present bias and the sophisticated present biased consumers.

Result 6: Welfare and ex-post observed behavior. If for a naive client i the fee-forcing contract causes higher pawn recovery, then we know the fee F made her IC constraint binding, and therefore that $\hat{\beta}_i > \widehat{\beta}_{min}$. If in addition if it was the case that $\beta_i < \beta_{SQ}$. then the fee-forcing contract would have increased welfare for the naive. That is, our finding that the fee-forcing contract increases pawn recovery is a sign of higher welfare (although not a sufficient condition).[57]

[55] β_{SQ} was determined in Result 1. β_{min} is such that $F = F_{min}(\beta_{min})$.

[56] This result is different from that in John (2020). Her context has individuals choosing the size of the fee. In that context naive clients will *always* chose the wrong fee size and default later, therefore choice is always decreasing for the naive. In our context F is fixed at 2% of the balance due, and this implies that choice could be welfare improving for some naifs.

[57] It is not sufficient since ex-ante the commitment F may have been too expensive given the income shocks, i.e. if $\lambda F > (1-\lambda)^2(b-p)$.