Do Saving Nudges Cause Borrowing? Evidence from a Mega Study

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  Direct policy relevance, specially in light of credit card debt puzzle: co-holding of high interest debt and low interest savings (Sussman and O'brien, 2016; Telyukova, 2013; Haliassos and Reiter, 2005) among others)

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- Rich panel data of individual credit cards and checking accounts transactions and balances
  - We measure rolled-over debt (actual borrowing) and not only credit card balances (Beshears et al., 2019; Chetty et al., 2014), as well as spending with credit and debit cards and ATM withdrawals

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- We provide new facts about the simultaneous holding of high interest debt and low interest savings
- We uncover significant treatment effect heterogeneity using ML for causal inference

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  - Select customers in the top quartile of the predicted treatment effect distribution (ranking based on cross-fitted predictions over two folds Chernozhukov et al. (2018))
- Were increased savings accompanied by an increase in borrowing? changes in spending or credit card repayment behavior?

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- Reduction in spending (measured by ATM withdrawals and card spending)

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- We find no significant increases in credit card interest
- No significant increases in credit card repayment following the intervention $\rightarrow$ saving nudges exacerbated the credit card debt puzzle
- Saving decisions are uncorrelated with the probability of rolling-over credit card debt and with credit card interest rates

Experimental design

- Field experiment: 3,054,438 customers (374,893 in control group) were sent (bi-)weekly savings messages
- The intervention lasted 7 weeks from September 13 to October 27, 2019
- Encouragements to save were sent via SMS and on ATM screens at the end of a transaction

Experimental pool

- Random sample from the universe of Banorte customers satisfying the following characteristics:
  1. Had a valid payroll account with Banorte.
  2. Kept an average daily balance of at least 50 MXN over the 2 months previous to the intervention
  3. Valid cell phone number to receive SMS

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- Experimental pool selected with minimal constraints: can study heterogeneous treatment effects overcoming implicit selection of experimenting only with those for whom the treatment is expected to work (Athey et al., 2021)

Treatment messages

- Messages about savings more generally
  - "Congratulations. Your average balance over the last 12 months has been great! Continue to increase your balance and strengthen your savings."
  - "Join customers your age who already save 10% or more of their income. Commit and increase the balance in your Banorte Account by $XXX this month."
  - "Increase your balance this month by $XXX and reach your dreams. Commit to it. You can do it by saving only 10% of your income."
- $XXX is a personalized amount: 10% of monthly income

Treatment messages

- Messages focused on short-term savings
  - "The holidays are coming. Commit to saving \$XXX In your Banorte Account and see your wealth grow!"
  - "Increase the balance in your Banorte Account and get ready today for year-end expenses!"
  - "Be prepared for an emergency! Commit to leaving 10% more in your account. Don't withdraw all your money on payday."
- Message alluding to money box and "locking away the money"
  - "In Banorte you have the safest money box! Increase your account balance by \$XXX this payday and reach your goals."

Data: summary statistics in MXN (For USD PPP $\sim$ divide by 9.2)

Table: Descriptive Statistics

All Individuals (N= 3,054,503)					
	Mean	Std dev	P25	P50	P75
Age (years)	44.72	16.35	31.00	43.00	56.00
Monthly Income	13,499.86	13,711.68	6,116.67	9,866.88	15,005.78
Tenure (months)	81.67	73.16	22.00	59.33	125.37
Checking Account Balance	19,384.03	52,565.83	729.00	2,295.69	10,402.39
Fraction with Credit Card	0.12	0.32	0.00	0.00	0.00
Credit Card Interest	20.04	120.24	0.00	0.00	0.00
Credit Card Balance	3,879.84	16,602.93	0.00	0.00	0.00
Credit Card Limit	17,168.81	67,247.74	0.00	0.00	0.00
Individuals with Credit Cards (N=362,223)					
	Mean	Std dev	P25	P50	P75
Age (years)	43.15	13.04	33.00	42.00	53.00
Monthly Income	19,744.77	18,653.78	9,071.32	13,912.75	22,718.28
Tenure (months)	103.65	73.12	43.27	86.43	148.53
Balance Checking Account	32,191.10	70,646.63	1,581.29	5,157.02	23,069.07
Credit Card Interest	168.91	311.01	0.00	0.00	170.01
Credit Card Balance	21,914.28	34,666.06	85.17	6,055.66	25,297.75
Credit Card Limit	102,277.57	137,313.20	14,000.00	40,000.00	123,999.00

Data: covariate balance

Table: Covariate Balance

	Control	Treatment	P-value of Difference
Age (Years)	44.73	44.71	0.1604
Monthly Income	13,506.49	13,497.15	0.7030
Tenure (Months)	87.75	80.94	0.3950
Checking Account Balance	19,322.25	19,394.21	0.3629
Ln (Checking Account Balance)	8.02	8.02	0.3180
Credit Card Interest	20.31	20.23	0.2849
Ln(Credit Card Interest)	0.26	0.25	0.3760
Credit Card Balance	3,858.71	3,884.17	0.3526
Ln(Credit Card Balance)	1.32	1.33	0.6653
Credit Card Limit	17,203.11	17,199.28	0.7031
N	357,567	2,696,936	

Aggregate treatment effects

$$Y_i = \alpha_s + \beta * treatment_i + \varepsilon_i$$

Table: Aggregate Effect of the Intervention

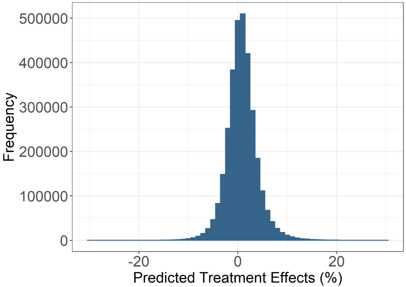
	All Individuals	Individuals with a Credit Card	
	Log of Checking Acct. Balance +1	Log of Checking Acct. Balance +1	Log of Credit Card Interest +1
Any treatment	0.006*	0.014**	-0.005
	(0.004)	(0.007)	(0.004)
Observations	3054503	362223	362223
Mean of Dep. Var in Control Group	17393.63	24331.63	213.84

Method: heterogeneous treatment effects identified by causal forest

- Causal forest with 2,000 trees: "honest estimation" (Athey et al., 2019).

  First with all 161 covariates, and then on the 52 most relevant

  Athey and Wager (2019).



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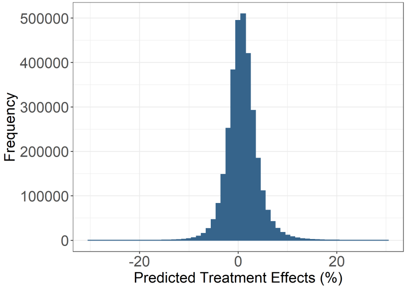
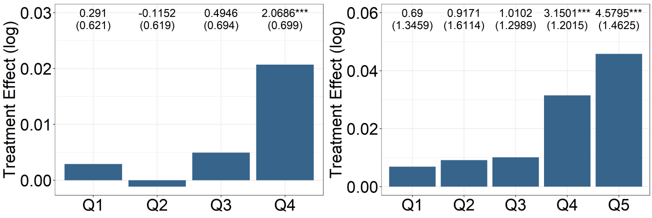


- Calibration test (Chernozhukov et al., 2018) confirms heterogeneity

Results: treatment effects by quantiles of predicted treatment effects

- Ranking into quartiles based on cross-fitted predictions over 2 folds.



(a) Quartiles (b) Quintiles (top quartile)

Figure: Treatment effect on checking account balances, as a function of predicted treatment effects.

Results: saving and borrowing in the top quartile of predicted treatment effects

Table: Treatment Effects on Savings and Credit Card Borrowing

Dep.Var	(1)	(2)	(3)	(4)	(5)	(6)
	Ln Checking Account Balance +1	Ln Credit Card Balance (Banorte) +1	Ln Credit Card Balance (Credit Bureau) +1	Ln Credit Card Interest +1	Paid Interest {0,1}	Ln Credit Card Payments +1
Panel A: All Clients with Credit Cards						
TE	0.0614***	-0.0141	-0.0066	-0.0145	-0.0044	-0.0221
	(0.0137)	(0.0107)	(0.0060)	(0.0353)	(0.0067)	(0.0176)
Mean of Dep. Var in Control Group (MXN)	31,701.61	17,119.74	43,191.72	222.42	0.46	9,472.50
N= 126571						
Panel B: Clients who Paid Credit Card Interest at Baseline						
TE	0.0557**	-0.0120	-0.0085	-0.0191	-0.0034	-0.0286
	(0.0257)	(0.0095)	(0.0057)	(0.0422)	(0.0097)	(0.0213)
Mean of Dep. Var in Control Group (MXN)	23,244.40	22,945.46	51,401.71	410.38	0.73	7,948.76
N= 58497						

Error term | Prob. interest | Interest rate | By message | Weekly | Utilization

Results: saving and borrowing in the top quartile when Banorte is main bank

Table: Treatment Effects on Savings and Credit Card Borrowing for Individuals for whom Banorte is their Main Bank

Dep.Var	(1)	(2)	(3)	(4)	(5)
	Ln Checking Account Balance +1	Ln Credit Card Balance (Banorte) +1	Ln Credit Card Interest +1	Paid Interest {0,1}	Ln Credit Card Payments +1
Panel A: All Clients with Credit Cards					
TE	0.0607***	-0.0107	-0.0028	-0.0016	-0.0112
	(0.02)	(0.01)	(0.04)	(0.01)	(0.02)
Mean of Dep. Var in Control Group (MXN)	34,395.46	12,884.18	226.60	0.70	10,314.65
N= 89899					
Panel B: Clients who Paid Credit Card Interest at Baseline					
TE	0.0526**	-0.0097	-0.0191	-0.0014	-0.0096
	(0.02)	(0.01)	(0.05)	(0.01)	(0.03)
Mean of Dep. Var in Control Group (MXN)	28,271.85	19,272.32	399.34	0.69	8,888.42
N= 41223					

Results: treatment effects on deposits, ATM withdrawals, and spending (top quartile)

	(1)	(2)	(3)
Dep.Var.	Ln Deposits	Ln ATM Withdrawals	Ln Spending with Credit or Debit Card
Panel A: Clients With Credit Card			
TE	-0.0086	-0.0511***	-0.0467***
	(0.0098)	(0.0101)	(0.0107)
Mean of Dep. Var	28184.53	12634.46	15615.62
N=126571			
Panel B: Clients With Credit Card Who Paid Interest At Baseline			
TE	-0.0063	-0.0712***	-0.0394***
	(0.0099)	(0.0167)	(0.0107)
Mean of Dep. Var	23199.13	14008.18	21063.06
N=58947			

The credit card debt puzzle

- In our sample, the average credit card interest rate is 35.2%, and checking accounts pay 0%. Nevertheless, 13.5% of individuals who pay credit card interest keep more than 50% of their income as the minimum balance in their checking accounts over the previous 6 months

The credit card debt puzzle

- Several explanations:
  - Liquidity management:
    - Transaction-convenience Telyukova (2013); Debt becomes more expensive in bad times Fulford (2015); others.
  - Mental accounting (Bertaut et al., 2009; Sussman and O'brien, 2016). In the presence of self-control:
    - Spending up to a certain personal limit on credit card
    - If savings are used to pay-off debt: free up credit limit, catch upon debt, spend savings
    - **Mental accounting motivated by self-control: Liquid savings are de-facto iliquid, not available for consumption**

The credit card debt puzzle: our findings in perspective

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    - Shock to patience? $\rightarrow$ reduction in debt
    - Show to precautionary motive? $\rightarrow$ increases in debt
    - **Mental accounting? $\rightarrow$ no changes in debt**

The credit card debt puzzle: our findings in perspective

- The puzzle group has a strong overlap with the top quartile of predicted treatment effects
  Puzzle group
- Message based on mental accounting had a large effect TE by message
- Savings response is uncorrelated with credit card interest rates and with the probability of carrying interest Interest rate
- No heterogeneity in borrowing response $\rightarrow$ borrowing and saving behavior are predicted with different variables

Conclusion

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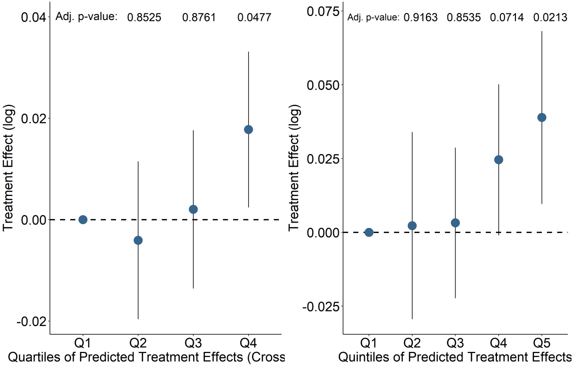
  - They don't observe rolled over debt or spending data
* Large scale experiment to jointly study saving and borrowing decisions:
  - Savings out of nudges are not financed with new debt, but with reductions in consumption
  - Nudges lead to net increases in savings regardless of pre-existing levels of debt
  - For some individuals this is second best $\rightarrow$ better-off paying existing debt
  - Suggest that saving and borrowing decisions are processed in different mental accounts.

Results: treatment effects by quantiles of predicted treatment effects

- Differences to the bottom quantiles with Romano Wolf p-values ⏩ Characteristics



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Results: heterogeneity in borrowing

Table: Calibration Test. Causal Forest for Borrowing Heterogeneity

Models	(1)	(2)	(3)
Mean Forest Prediction	1.3702*	1.1483**	1.1062*
	(0.9114)	(0.6123)	(0.7014)
Differential Forest Prediction	-0.2240	0.0761	-0.0495
	(0.2918)	(0.1852)	(0.1975)
N= 362223			

The first model considers all 161 available variables. The second model considers only those with variable importance greater than 1 percent, according to the first model. The third model considers variables with variable importance greater than 1 percent, according to the causal forest for savings (used throughout the paper).

Why causal forest?

- Causal forests have been successfully applied in the fields of education (Carlana et al., 2022), labor (Davis and Heller, 2020) and development economics (Ashraf et al., 2020)
- Our paper - one of the first applications in the household finance literature (Burke et al., 2020)
- In our setting, a substantially larger sample size allow us to use these methods in two novel ways
  - Powered enough to study treatment effects on sub-populations of interest identified by the causal forest
  - Able to compare causal forests and other methods for treatment effect heterogeneity based on experimental strata, to illustrate the risk of over-fitting bias

Why causal forest? Experimental strata may not capture heterogeneity

Table: Heterogeneous Treatment Effects by Experimental Strata

	Dep. Var: Ln (Checking Account Balances +1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Any Treatment	-0.006	0.009	0.013*	0.006	0.002	0.008*	0.006	0.007*	0.005
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Any Treatment*Group$_1$	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Any Treatment*Group$_2$	0.012	0.001	-0.013	0.001	0.002	-0.010	0.000	-0.003	0.009
	(0.01)	(0.01)	(0.01)	(0.007)	(0.007)	(0.009)	(0.010)	(0.010)	(0.007)
Any Treatment*Group$_3$	0.010	0.014	-0.002			-0.001			
	(0.01)	(0.01)	(0.01)			(0.009)			
Any Treatment*Group$_4$	0.024**	0.002	-0.013						
	(0.01)	(0.01)	(0.01)						
Group Definition	Quartiles of Checking Acct. Balance	Quartiles of Income	Quartiles of Age	Median of Tenure with Banorte	Median of ATM Withrawals	Median of Debit Card Transactions	Is Digital?	Main Bank?	Has Credit Card?
Observations	3054503	3054503	3054503	3054503	3054503	3054503	3054503	3054503	3054503

Why causal forest? Sorting without thinking about overfitting leads to biased estimates

Table: Average treatment effects for users in groups with the highest observed average treatment effect and for users with the highest individual treatment effects predicted by the causal forest

	Observed Average Treatment Effects				Individual Treatment Effects predicted by Causal Forest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	N	Ln Checking Account Balance	Ln Credit Card Interest	Ln Credit Card Balance (Banorte)	N	Ln Checking Account Balance	Ln Credit Card Interest	Ln Credit Card Balance (Banorte)
Panel A: All Clientes	763,511							
ATE		0.2401***	-0.0197***	-0.0142***	763,625	0.0220***	-0.0023	-0.0019
		(0.0072)	(0.0037)	(0.0048)		(0.0072)	(0.0048)	(0.0041)
Mean of dep var (MXN)		18283.47	66.66463	4161.451		21872.15		
Panel B: Clients with Credit Card	126,468				126,458			
ATE		0.4403***	-0.0991***	-0.1089***		0.0601***	-0.0171	-0.0155
		(0.0148)	(0.0095)	(0.0083)		(0.0177)	(0.0334)	(0.0116)
Mean of dep var (MXN)								
		21623.82	241.41	15077.12		31681.46	230.39	17097.99
Panel C: Clients with Credit Card who paid interest at baseline	61,204				58,485			
ATE		0.5167***	-0.1109***	-0.1946***		0.0567**	-0.0242	-0.0102
		(0.0114)	(0.0094)	(0.0092)		(0.0251)	(0.0453)	(0.0082)

Results: characteristics of individuals in top and bottom quartiles

Table: Differences Between Top and Bottom Quartiles of the Distribution of Predicted Treat-ment Effects

	Bottom 25%	Top 25%	P-value of Difference
Age (Years)	44.18	46.35	0.0054
Monthly Income	14,118.44	15,109.87	0.0000
Tenure (Months)	74.60	88.69	0.0000
Checking Account Balance	16,017.05	21,338.30	0.0000
Credit Card Balance	2,435.53	6,038.65	0.0000
Credit Card Limit	10,812.16	29,933.66	0.0000

Back

Results: saving and borrowing for individual with low credit line utilization

Table: Treatment Effects on Savings and Credit Card Borrowing for Individuals Below the Median Credit Line Utilization

Dep.Var	(1)	(2)	(3)	(4)	(5)	(6)
	Ln Checking Account Balance +1	Ln Credit Card Balance (Banorte) +1	Ln Credit Card Balance (Credit Bureau) +1	Ln Credit Card Interest +1	Paid Interest {0,1}	Ln Credit Card Payments +1
Panel A: Clients with Credit Line Utilization Lower Than the Median						
TE	0.0595***	0.0030	-0.0041	0.0035	0.0056	0.0071
	(0.0230)	(0.0173)	(0.0072)	(0.0495)	(0.0089)	(0.0193)
Mean of Dep. Var in Control Group (MXN)	43,152.85	8,701.33	19,045.70	98.62	0.23	6,013.95
N= 63286						

Back

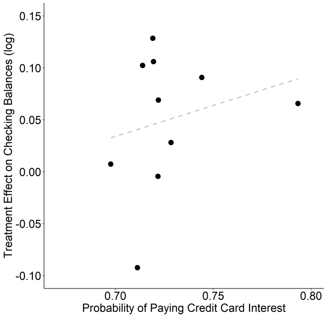
Results: Treatment effects by message

Table: Treatment Effects on Saving and Credit Card Borrowing: Individuals in the Top Quartile of Predicted Treatment Effects who Have a Credit Card ⏩ Back

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln Checking Account Balance +1	Increase in Savings (MXN)	Ln Credit Card Interest +1	Upper Confidence Interval of Credit Card Interest (MXN)	Upper Confidence Interval for Interest Charges Divided by Increase in Savings	N
All messages	0.0601*** (0.0177)	1904.37	-0.0171 (0.0336)	11.12	0.006	126458
Msg 1 Congratulations	0.0265 (0.0228)	839.56	-0.0055 (0.0336)	13.90	0.017	38802
Msg 2 Year end expenses	0.1170*** (0.0228)	3705.46	-0.0183 (0.0336)	10.96	0.003	38775
Msg 3 Join others your age	0.0413* (0.0228)	1306.86	-0.0142 (0.0336)	11.90	0.009	38822
Msg 4 Money box	0.0979*** (0.0229)	3102.57	-0.0256 (0.0339)	9.41	0.003	38700
Msg 5 Reach your dreams	0.0623*** (0.0237)	1974.71	-0.0348 (0.0350)	7.79	0.004	38803
Msg 6 Money shortfalls	0.0338 (0.0253)	1069.25	-0.0291 (0.0374)	10.20	0.010	38752
Msg 7 Prepared for emergency	0.042 (0.0298)	1330.94	0.008 (0.0440)	21.72	0.016	38590

Results: treatment effects on savings and probability of rolling-over credit card debt

Figure: Correlation between the Fraction of Individuals Paying Credit Card Interest and the Treatment Effect of the Intervention on Checking Account Balances. Based on observations in the top 25% of predicted treatment effects, which are further split into deciles.



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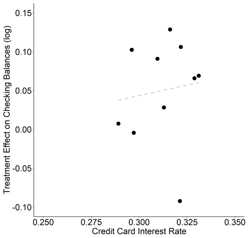
Debt Puzzle

Results: treatment effects on savings and credit card interest rates

Figure: Correlation between Credit Card Interest Rates and the Treatment Effect of the Intervention on Checking Account Balances. Based on observations in the top 25% of predicted treatment effects, which are further split into deciles of predicted treatment effects.



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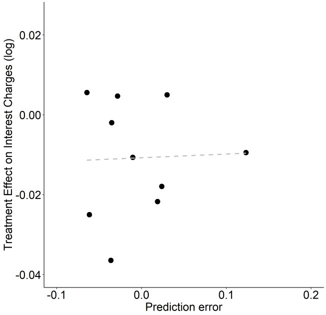
Debt Puzzle

Results: treatment effects on borrowing and prediction errors

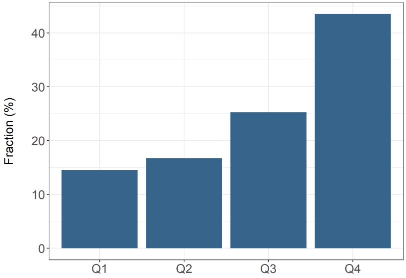
Figure: Correlation between between Prediction Errors and Treatment Effects on Borrowing. Based on observations in the top 25% of predicted treatment effects, which are further split into deciles



Main result

Distribution of the Puzzle Group by Quartiles of Predicted Treatment

Figure: Distribution of the Puzzle Group by Quartiles of Predicted Treatment Effects



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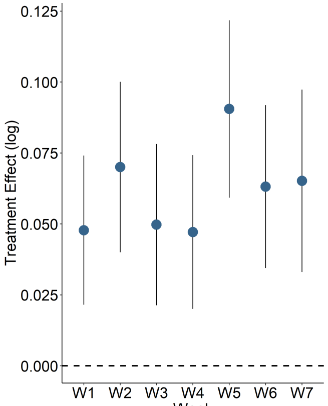
Results: treatment effects on savings week-by-week

Figure: Treatment Effect on Savings by Week, for Individuals with Credit Card who are in the Top Quartile of the Distribution of Predicted Treatment Effects



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