Do Savings Nudges Cause Borrowing? Evidence from a Megastudy

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Motivation: Analysis of Savings Nudges

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- May be interested in the effects of savings nudges on short-term unsecured debt
  - Many people co-hold savings and credit card debt
  - If individuals were to borrow more at high interest to finance the additional savings, they would be worse off

Bigger topic: credit card borrowing

- Why and how do people accumulate high-interest unsecured debt?
  - "Over the last 50 years, household credit has risen dramatically [...] and, particularly in developing countries, [non-mortgage] consumer credit accounts for much of this growth." (Müller, 2018)

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- Yet, use of consumer debt is puzzling
  - Levels of consumer debt – a debt puzzle (Laibson et al., 2000)
  - Holding savings and consumer debt simultaneously – co-holding puzzle (Haliassos and Reiter, 2005; Telyukova, 2013)

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- Identify the mechanisms behind simultaneous savings and consumer debt: key distinctive empirical prediction
  - If individuals hold credit card debt and savings optimally, increasing savings should increase credit-card debt: Telyukova (2013)
  - Otherwise it would not: Haliassos and Reiter (2005), Laibson et al. (2007), and Bertaut et al. (2009a)

Experimental design

- Pre-registered field experiment: 3,054,438 customers (374,893 control) were sent (bi-)weekly savings messages in Fall 2019, randomized within 6,104 experimental strata based on pre-treatment covariates such as income quartiles, age, savings, and ATM, debit, versus credit card transactions

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  - No over-fitting or "reverse-endogeneity" concerns

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 mental accounting 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 pre-intervention

Table: Descriptive statistics: to get numbers in USD, divide by 200

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: saving and borrowing

- We define the co-holding puzzle group as having more than 50% of their monthly income in checking account balances as well as holding credit card debt

Table: Checking, and credit card account balances for individuals who have a credit card– by deciles of average daily balance on checking accounts, over income

		All Clients with Credit Card				*Clients Paying Credit Card Interest*		
Decile	N	Checking Account Balance over Income (Average)	Fraction Of Clients with non-zero Credit Card Balance	Fraction Of Clients Paying Credit Card Interest	N	Checking Account Balances (Average)	Credit Card Balances (Average)	Credit Card Interest (Average)
All	362223	1.81	0.61	0.31	111999	27,818.18	32,929.68	1,120.90
1	36223	0.01	0.62	0.42	15141	340.20	29,917.08	1,018.99
2	36222	0.05	0.56	0.37	13445	1,086.67	24,165.70	854.02
3	36222	0.08	0.59	0.37	13351	2,054.23	26,525.30	956.52
4	36223	0.13	0.61	0.36	13115	3,204.63	27,805.94	1,001.48
5	36222	0.20	0.64	0.35	12546	5,293.93	31,556.76	1,107.03
6	36222	0.33	0.64	0.32	11475	8,467.78	35,507.68	1,215.31
7	36223	0.58	0.63	0.28	10054	15,266.06	38,101.32	1,280.91
8	36222	1.16	0.62	0.24	8757	29,971.89	42,637.44	1,366.57
9	36222	2.81	0.59	0.21	7529	66,548.62	43,713.88	1,381.63
10	36222	12.73	0.58	0.18	6586	295,446.99	45,925.31	1,463.94

Results: aggregate treatment effects

We estimate

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

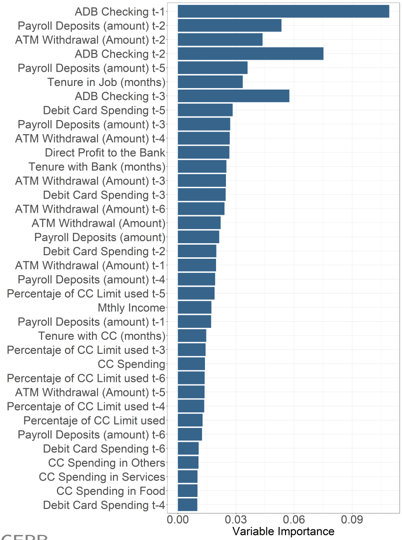
where α_s represents strata fixed effects and β identifies the ITT(=ATE) effect of treatment i

Table: ITT(=ATE) effects of the intervention: pooling all treatment messages and frequencies

	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: each divided into three subsamples



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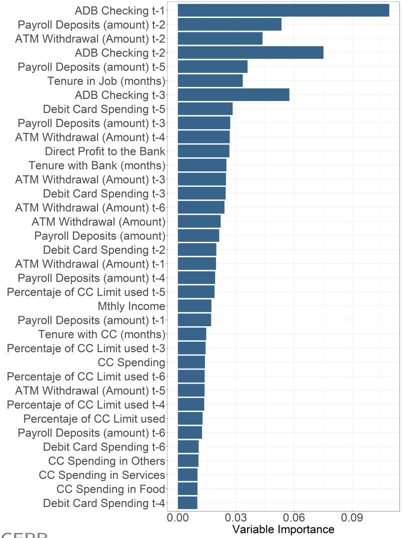

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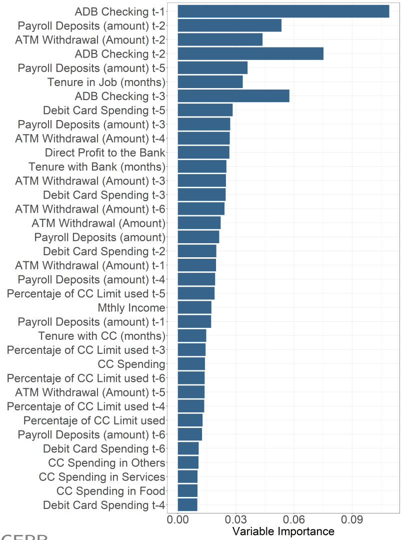

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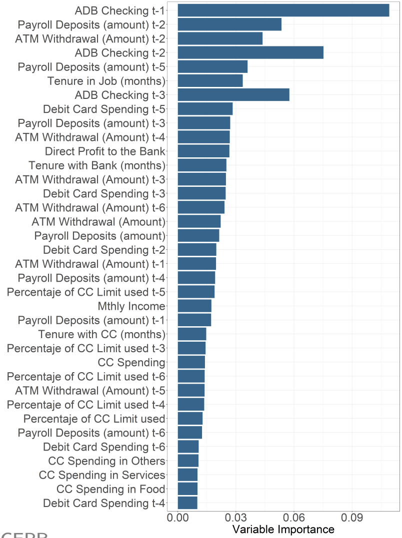
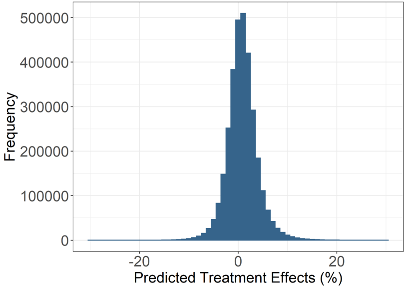
3. Cross validate in test sample



Results: causal forest variable importance and predicted treatment effect distribution

- By chance people with some characteristics end up saving in response to the treatment during that period (but not in all 2,000 random samples, and not consistently showing large effects)



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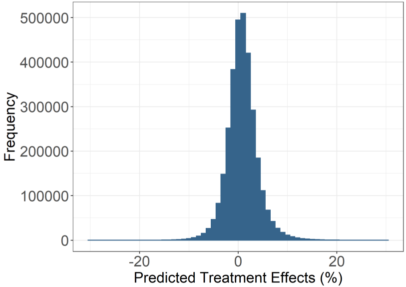
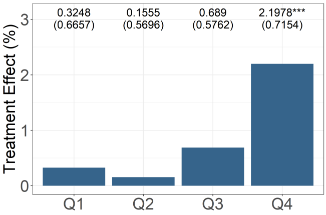
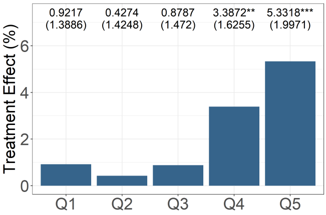


Results: treatment effects by quartiles (quintiles of top quartile) of predicted treatment effects



(a) Quartiles



(b) Quintiles (top quartile)

Figure: Treatment effect on checking account balances, as a function of predicted treatment effects. Individuals in the top quartile of the distribution of predicted treatment effects are further split in to quintiles

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

Table: Treatment effect on saving and on credit card borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	Ln Checking Account Balance	Ln Credit Card Balance (Banorte)	Ln Credit Card Balance (Credit Bureau)	Ln Credit Card Interest	Paid Interest {0,1}	Ln Credit Card Payments
Panel A: All clients with credit cards						
ATE	0.0601***	-0.0155	-0.0077	-0.0171	-0.0037	-0.0159
	(0.0177)	(0.0116)	(0.0062)	(0.0334)	(0.0054)	(0.0150)
Mean Dep. Var in Control Group (MXN)	31681.46	17097.99	43136.75	230.39	0.42	9500.24
Increase in Savings (MXN)	1904.37					
Upper Confidence Interval (MXN)[1]		123.54	195.50	11.12	0.0068	127.79
Upper Confidence Interval (MXN)[1] divided by increase in Savings (MXN)		0.06	0.10	0.01	0.0000036	0.07
N= 126458						
Panel B: Clients who paid credit card interests at baseline						
ATE	0.0567**	-0.0102	-0.0091	-0.0242	-0.004	-0.0133
	(0.0251)	(0.0082)	(0.0072)	(0.0453)	(0.007)	(0.0202)
Mean Dep. Var in Control Group (MXN)	23194.21	23080.11	51491.24	413.31	0.71	8012.99
Increase in Savings (MXN)	1315.58					
Upper Confidence Interval (MXN)[1]		133.97	262.18	26.68	0.0097	210.99
Upper Confidence Interval (MXN)[1] divided by increase in Savings (MXN)		0.10	0.20	0.02	0.0000074	0.16
N= 58485						

Robustness: saving and borrowing when Banorte is the main bank

Table: Treatment effect on saving and borrowing: individuals for whom Banorte is their main bank in the top quartile of the predicted treatment effect distribution

	(1)	(2)	(3)	(4)	(5)
Dep.Var.	Ln Checking Account Balance	Ln Credit Card Balance (Banorte)	Ln Credit Card Interest	Paid Interest {0,1}	Ln Credit Card Payments
Panel A: all clients with credit cards					
ATE	0.0568***	-0.0106	-0.0029	-0.0021	-0.0108
	(0.0181)	(0.0128)	(0.0371)	(0.0059)	(0.0170)
Mean Dep. Var in Control Group (MXN)	34391.41	12889.39	213.8667	0.3539553	10312.63
Increase in Savings (MXN)	1953.43				
Upper Confidence Interval (MXN)[1]		186.74	14.93	0.0095	232.24
Upper Confidence Interval (MXN)[1] divided by increase in Savings (MXN)		0.10	0.01	0.0000048	0.12
N=89904					
Panel B: clients who paid credit card interests at baseline					
ATE	0.0531**	-0.0091	-0.0197	-0.0015	-0.0093
	(0.0226)	(0.0090)	(0.0498)	(0.0077)	(0.0228)
Mean Dep. Var in Control Group (MXN)	28281.41	19264.42	434.08	0.68	8897.35
Increase in Savings (MXN)	1501.74				
Upper Confidence Interval (MXN)[1]		164.13	33.82	0.01	314.77
Upper Confidence Interval (MXN)[1] divided by increase in Savings (MXN)		0.11	0.02	0.0000061	0.21
N=41226					

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)
Mean of dep var (MXN)		14994.75	410.8639	19585.27		23194.21	413.31	23080.11

Mechanism: treatment effects on deposits, ATM withdrawals, and spending

Table: Treatment effects on deposits, ATM withdrawals, and spending for individuals in the top quartile of the predicted treatment effect distribution

	(1)	(2)	(3)
Dep.Var.	Ln Deposits	Ln ATM Withdrawals	Ln Spending with Credit or Debit Card
Panel A: Clients With Credit Card			
ATE	-0.0083	-0.0602***	-0.0422***
	(0.0091)	(0.0090)	(0.0077)
Mean of Dep. Var.	28271.71	12733.68	15788.43
Panel B: Clients With Credit Card Who Paid Interest At Baseline			
ATE	-0.0071	-0.0737***	-0.0346***
	(0.0097)	(0.0094)	(0.0073)
Mean of Dep. Var.	23271.71	13997.47	20984.16

Mechanism: implications for the co-holding puzzle

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- Individuals increase savings by cutting discretionary spending specifically (ATM withdrawals)
- The "lock away your savings" message carries a large treatment effect
- None of the messages focusing on short-term saving have large treatment effects

Conclusion and open questions

* What's new here?
  - To the best of our knowledge, only one study looks at whether savings nudges increases borrowing (Beshears et al., 2019)
  - The study cannot look at rolled-over credit card debt but only snapshots of balances
  - Other studies on savings nudges cannot estimate a tight zero for borrowing

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  - Other studies on savings nudges cannot estimate a tight zero for borrowing
* Huge pre-registered experiment to show that individuals do not borrow more in response to savings nudges
  - Important for understanding whether or not we should nudge people to save
  - And to understand mechanisms behind high interest borrowing: self control and/or intra-household agency conflicts may explain why we see so much borrowing (Laibson et al., 2000; Bertaut et al., 2009b)

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