

# Does Saving Cause Borrowing?

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# Motivation

- ▶ When and how do people accumulate high-interest unsecured debt?
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  - ▶ Holding savings and consumer debt – the credit card debt puzzle. Haliassos and Reiter (2005), and Bertaut et al. (2009a)

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- ▶ A household in the SCF puzzle group loses, on average, 734 USD per year from the costs of revolving debt, which amounts to 1.5% of its total annual after-tax income (Telyukova, 2013)
- ▶ Several explanations:
  - ▶ Transaction-convenience: Telyukova (2013)
  - ▶ Preferences: mental accounting and self-control: Haliassos and Reiter (2005), and Bertaut et al. (2009a)



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- Does Saving Cause Borrowing?
- ▶ Policy implications: We may not want to nudge individuals to save, or we may want to target nudges.
  - ▶ Unique setting: We are able to measure rolled-over debt (actual borrowing) and not only credit card balances (Beshears et al., 2019)

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  - ▶ Focus on customers in the top quartile of the predicted treatment effect distribution and ask whether the increased savings was accompanied by an increase in borrowing
- ▶ No reverse-endogeneity or over-fitting

## Findings in a nutshell

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- ▶ We can thus rule out an increase in borrowing cost of more than 11 MXN with 95% statistical confidence
- ▶ Compare this to the increase in savings: for every \$1 increase in savings, we can rule out a \$0.01 increase in borrowing
- ▶ For individuals that also paid credit card interest at baseline, we can rule out a larger than \$0.02 increase in credit card borrowing for every dollar in savings.



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- ▶ The intervention lasted 7 weeks from September 13 to October 27, 2019

# Treatment messages

- ▶ “Congratulations. Your average balance over the last 12 months has been great! Continue to increase your balance and strengthen your savings.”
- ▶ “Increase the balance in your Banorte Account and get ready today for year-end expenses!”
- ▶ “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.”

# Treatment messages

- ▶ “In Banorte you have the safest money box! Increase your account balance by \$XXX this payday and reach your goals.”
- ▶ “Increase your balance this month in \$XXX and reach your dreams. Commit to it. You can do it by saving only 10% of your income.”
- ▶ “The holidays are coming. Commit to saving \$XXX on your Banorte Account and see your wealth grow!”
- ▶ “Be prepared for an emergency! Commit to leaving 10% more in your account. Don't withdraw all your money on payday.”

# Data: summary statistics pre-intervention

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: saving and borrowing

**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

Decile	<i>All Clients with Credit Card</i>					<i>Clients Paying Credit Card Interest</i>		
	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

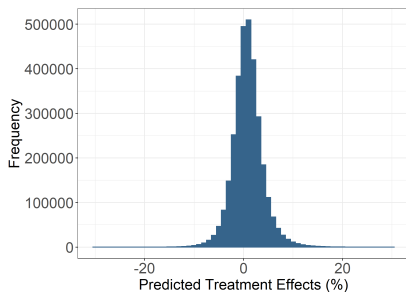
# Data: covariate balance

Table: Covariate balance

Variable	Control	Treatment	Difference
Age (Years)	44.73	44.72	-0.01 (0.01)
Monthly Income (\$)	13506.49	13498.98	-7.51 (19.71)
Tenure (months)	81.75	81.66	-0.08 (0.1)
Checking Acct. Balance (\$)	19322.25	19392.22	69.95 (76.91)
Credit Card Balance (\$)	3858.71	3882.64	23.94 (25.76)
Credit Card Limit (\$)	17203.11	17164.27	-38.84 (101.91)

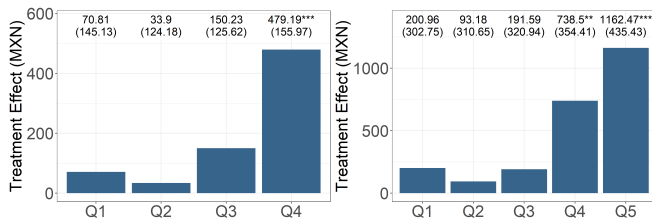


# Causal forest: predicted treatment effect distribution



- ▶ By chance people with some characteristics just ended up having higher savings during that period (but not in all 2,000 random samples, and not consistently showing large effects) —> No "reverse endogeneity"

# Results: treatment effects by quantiles 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: characteristics of individuals in top and bottom quartiles

**Table:** Differences between top and bottom quartiles of the distribution of predicted treatment effects

Variable	Bottom 25%	Top 25%	Difference
Age (Years)	43.92	45.28	1.37 (0.03)
Monthly Income (\$)	12924.95	14655.87	1730.96 (23.45)
Tenure (months)	73.95	87.14	13.19 (0.12)
Checking Acct. Balance (\$)	15791.01	21340.95	5549.94 (84.40)
Credit Card Balance (\$)	2688.76	6391.20	3702.43 (29.36)
Credit Card Limit (\$)	10408.82	28641.07	18238.25 (117.17)

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

**Table:** Treatment effect on savings 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*** (0.0177)	-0.0155 (0.0116)	-0.0077 (0.0062)	-0.0171 (0.0334)	-0.0037 (0.0054)	-0.0159 (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) <sup>1</sup>		123.54	195.50	11.12	0.0068	127.79
Upper Confidence Interval (MXN) <sup>1</sup> 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*** (0.0251)	-0.0102 (0.0082)	-0.0091 (0.0072)	-0.0242 (0.0453)	-0.004 (0.007)	-0.0133 (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) <sup>1</sup>		133.97	262.18	26.68	0.0097	210.99
Upper Confidence Interval (MXN) <sup>1</sup> divided by increase in Savings (MXN)		0.10	0.20	0.02	0.0000074	0.16
N= 58485						

# Robustness: treatment effects on deposits, ATM withdrawals and spending

**Table:** Treatment Effects on Deposits, ATM Withdrawals and Spending

	(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 (0.0091)	-0.0602*** (0.0090)	-0.0422*** (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 (0.0097)	-0.0737*** (0.0094)	-0.0346*** (0.0073)
Mean of Dep. Var.	23271.71	13997.47	20984.16

# Robustness: borrowing and saving when Banorte is main bank

**Table:** Treatment effect on savings and on credit card borrowing for whom Banorte is their main bank

Dep.Var.	(1) Ln Checking Account Balance	(2) Ln Credit Card Balance (Banorte)	(3) Ln Credit Card Interest	(4) Paid Interest {0,1}	(5) Ln Credit Card Payments
Panel A: all clients with credit cards					
ATE	0.0568*** (0.0181)	-0.0106 (0.0128)	-0.0029 (0.0371)	-0.0021 (0.0059)	-0.0108 (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) <sup>1</sup>		186.74	14.93	0.0095	232.24
Upper Confidence Interval (MXN) <sup>1</sup> 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** (0.0226)	-0.0091 (0.0090)	-0.0197 (0.0498)	-0.0015 (0.0077)	-0.0093 (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) <sup>1</sup>		164.13	33.82	0.01	314.77
Upper Confidence Interval (MXN) <sup>1</sup> divided by increase in Savings (MXN)		0.11	0.02	0.0000061	0.21
N=41226					

# Why causal forest? Sorting without sample splitting 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

Dep.Var.	Observed Average Treatment Effects				Individual Treatment Effects predicted by Causal Forest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	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*** (0.0072)	-0.0197*** (0.0037)	-0.0142*** (0.0048)	763,625	0.0220*** (0.0072)	-0.0023 (0.0048)	-0.0019 (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*** (0.0148)	-0.0991*** (0.0095)	-0.1089*** (0.0083)		0.0601*** (0.0177)	-0.0171 (0.0334)	-0.0155 (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*** (0.0114)	-0.1109*** (0.0094)	-0.1946*** (0.0092)		0.0567** (0.0251)	-0.0242 (0.0453)	-0.0102 (0.0082)
Mean of dep var (MXN)		14994.75	410.8639	19585.27		23194.21	413.31	23080.11

# 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
- \* We document 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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