Do Saving Nudges Cause Borrowing? Evidence from a Mega Study

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Motivation

Several policies in place aimed at increasing savings, a growing number use nudges (Benartzi et al., 2017)
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- Based on the assumption that savings are financed with decreases in consumption (Thaler, 1994)
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- Based on the assumption that savings are financed with decreases in consumption (Thaler, 1994)
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- This paper: Do saving nudges cause borrowing?
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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)
This paper

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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
This paper

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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
What we do: Overview

- Focus on individuals whose observable characteristics predict a large treatment effect
- Causal forest to predict for each individual a treatment effect using all pre-treatment covariates (no-overfitting (Athey et al., 2019))
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- Were increased savings accompanied by an increase in borrowing? changes in spending or credit card repayment behavior?
Findings in a nutshell

- For this individuals who had a credit card, the increase in savings estimate is 6.1% on a baseline savings of 31,702 MXN in their control group, i.e., an increase of 1,948 MXN
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- There are no significant changes in credit card interest –For every $1 increase in savings, we can rule out a $0.01 increase in borrowing cost.
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- For this individuals who had a credit card, the increase in savings estimate is 6.1% on a baseline savings of 31,702 MXN in their control group, i.e., an increase of 1,948 MXN.
- There are no significant changes in credit card interest – For every $1 increase in savings, we can rule out a $0.01 increase in borrowing cost.
- Reduction in spending (measured by ATM withdrawals and card spending).
Findings in a nutshell

- For individuals who had a credit card and paid interest at baseline, we find a 5.6% increase in savings (1295 MXN per month)
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- We find no significant increases in credit card interest
Findings in a nutshell

- For individuals who had a credit card and paid interest at baseline, we find a 5.6% increase in savings (1295 MXN per month)
- We find no significant increases in credit card interest
- No significant increases in credit card repayment following the intervention → saving nudges exacerbated the credit card debt puzzle
Findings in a nutshell

- Saving decisions are uncorrelated with the probability of rolling-over credit card debt and with credit card interest rates
Findings in a nutshell

- Saving decisions are uncorrelated with the probability of rolling-over credit card debt and with credit card interest rates
- No evidence of heterogeneity in borrowing response
Experimental design

- Field experiment: 3,054,438 customers (374,893 in control group) were sent (bi-)weekly savings messages
- The intervention lasted 7 weeks in the fall of 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.
Experimental pool

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  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.

- 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."
Aggregate treatment effects

\[ Y_i = \alpha_s + \beta \times \text{treatment}_i + \varepsilon_i \]

Table: Aggregate Effect of the Intervention

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

- 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

<table>
<thead>
<tr>
<th>Dep. Var</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ln Checking Account Balance +1</td>
<td>Ln Credit Card Balance (Banorte) +1</td>
<td>Ln Credit Card Balance (Credit Bureau) +1</td>
<td>Ln Credit Card Interest +1</td>
<td>Paid Interest {0,1}</td>
<td>Ln Credit Card Payments +1</td>
</tr>
<tr>
<td>TE</td>
<td>0.0614***</td>
<td>-0.0141</td>
<td>-0.0066</td>
<td>-0.0145</td>
<td>-0.0044</td>
<td>-0.0221</td>
</tr>
<tr>
<td></td>
<td>(0.0137)</td>
<td>(0.0107)</td>
<td>(0.0060)</td>
<td>(0.0353)</td>
<td>(0.0067)</td>
<td>(0.0176)</td>
</tr>
<tr>
<td>Mean of Dep. Var in Control Group (MXN)</td>
<td>31,701.61</td>
<td>17,119.74</td>
<td>43,191.72</td>
<td>222.42</td>
<td>0.46</td>
<td>9,472.50</td>
</tr>
<tr>
<td>N= 126571</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel A: All Clients with Credit Cards

<table>
<thead>
<tr>
<th>Dep. Var</th>
<th>(1)</th>
<th>(2)</th>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
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<td>Paid Interest {0,1}</td>
<td>Ln Credit Card Payments +1</td>
</tr>
<tr>
<td>TE</td>
<td>0.0557**</td>
<td>-0.0120</td>
<td>-0.0085</td>
<td>-0.0191</td>
<td>-0.0034</td>
<td>-0.0286</td>
</tr>
<tr>
<td></td>
<td>(0.0257)</td>
<td>(0.0095)</td>
<td>(0.0057)</td>
<td>(0.0422)</td>
<td>(0.0097)</td>
<td>(0.0213)</td>
</tr>
<tr>
<td>Mean of Dep. Var in Control Group (MXN)</td>
<td>23,244.40</td>
<td>22,945.46</td>
<td>51,401.71</td>
<td>410.38</td>
<td>0.73</td>
<td>7,948.76</td>
</tr>
<tr>
<td>N= 58947</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Clients who Paid Credit Card Interest at Baseline
Results: treatment effects on deposits, ATM withdrawals, and spending (top quartile)

<table>
<thead>
<tr>
<th>Dep.Var.</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln Deposits</td>
<td>-0.0086</td>
<td>-0.0511***</td>
<td>-0.0467***</td>
</tr>
<tr>
<td></td>
<td>(0.0098)</td>
<td>(0.0101)</td>
<td>(0.0107)</td>
</tr>
<tr>
<td>Ln ATM Withdrawals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln Spending with</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit or Debit</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel A: Clients With Credit Card

| TE    | -0.0063      | -0.0712***   | -0.0394***   |
|       | (0.0099)     | (0.0167)     | (0.0107)     |

Mean of Dep. Var
N=126571

Mean of Dep. Var
N=58947

Panel B: Clients With Credit Card Who Paid Interest At Baseline
The credit card debt puzzle

In our sample:

- The average credit card interest rate is 35.2%, and checking accounts pay 0%.
- 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.
- Co-holding costs them 5% of monthly income.
The credit card debt puzzle

Several explanations:

- Liquidity management:
  - Transaction-convenience: Telyukova (2013)
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  - Individuals with limited self control spend up to a certain personal limit on their credit card
  - If savings are used to pay-off debt: free up credit limit and with limited self-control catch up on debt effectively spending your savings
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- Liquidity management:
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  - Individuals with limited self control spend up to a certain personal limit on their credit card
  - If savings are used to pay-off debt: free up credit limit and with limited self-control catch up on debt effectively spending your savings

- Mental accounting: Liquid savings are de-facto illiquid, not available for consumption
The credit card debt puzzle: responding to a savings nudge

Saving nudges as a shock to patience

- Predictions of liquidity management models:
The credit card debt puzzle: responding to a savings nudge

Saving nudges as a shock to patience

- Predictions of liquidity management models:
  - Liquidity needs already covered, open line of credit is cheaper than cash holding → saving through debt repayment
    - No increases in checking account balances
    - Reductions in debt
The credit card debt puzzle: responding to a savings nudge

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Saving nudges as a shock to patience

- Predictions of liquidity management models:
  - Liquidity needs already covered, open line of credit is cheaper than cash holding $\rightarrow$ saving through debt repayment
    - No increases in checking account balances
    - Reductions in debt

- Predictions of mental accounting models:
  - Shock to preferences of long-term self: repaying debt would lead to increases in spending
    - Increases in checking account balances
    - No changes in debt
The credit card debt puzzle: responding to a savings nudge

Saving nudges as exogenous increase in cash balances

- Predictions of liquidity management models:
  - New cash holdings are available for future consumption. Consumption smoothing $\rightarrow$ more debt

- Predictions of mental accounting models:
  - New cash holdings not considered in consumption decision $\rightarrow$ no changes in debt
39% of individuals carrying credit card debt are in the top quartile of predicted treatment effects:

6% increase in savings, no changes in debt.

Savings: ↑
Debt: -

<table>
<thead>
<tr>
<th></th>
<th>Liquidity Management</th>
<th>Mental Accounting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shock to patience</td>
<td>Checking -&lt;br&gt;Debt ↓</td>
<td>Checking ↑&lt;br&gt;Debt -</td>
</tr>
<tr>
<td>Shock to cash</td>
<td>Checking ↑&lt;br&gt;Debt ↑</td>
<td>Checking ↑&lt;br&gt;Debt -</td>
</tr>
</tbody>
</table>
The credit card debt puzzle: our findings in perspective

- The puzzle group overlaps with the top quartile of predicted treatment effects
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- Message based on mental accounting ("lock away your savings") carries a large effect.
The credit card debt puzzle: our findings in perspective

- The puzzle group overlaps with the top quartile of predicted treatment effects
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- Savings response is uncorrelated with interest rates and with probability of carrying interest → consistent with separate accounts
The credit card debt puzzle: our findings in perspective

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- Message based on mental accounting ("lock away your savings") carries a large effect.

- Savings response is uncorrelated with interest rates and with probability of carrying interest. 
  Consistent with separate accounts.

- No heterogeneity in borrowing response. Borrowing and saving not predicted by same variables.
To the best of our knowledge, only one study looks at saving nudges and credit outcomes (Beshears et al., 2019)

- They don’t observe rolled over debt or spending data
Conclusion

* To the best of our knowledge, only one study looks at saving nudges and credit outcomes (Beshears et al., 2019)
  ▶ 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
  ▶ 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

![Graph showing treatment effects by quantiles](image)

(a) Quartiles  (b) Quintiles (top quartile)
Results: heterogeneity in borrowing

Table: Calibration Test. Causal Forest for Borrowing Heterogeneity

<table>
<thead>
<tr>
<th>Models</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Forest Prediction</td>
<td>1.3702*</td>
<td>1.1483**</td>
<td>1.1062*</td>
</tr>
<tr>
<td></td>
<td>(0.9114)</td>
<td>(0.6123)</td>
<td>(0.7014)</td>
</tr>
<tr>
<td>Differential Forest Prediction</td>
<td>-0.2240</td>
<td>0.0761</td>
<td>-0.0495</td>
</tr>
<tr>
<td></td>
<td>(0.2918)</td>
<td>(0.1852)</td>
<td>(0.1975)</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>3054503</td>
<td>3054503</td>
<td>3054503</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th>Dep.Var.</th>
<th>ATE</th>
<th>Observed Average Treatment Effects</th>
<th>Individual Treatment Effects predicted by Causal Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1) (2) (3) (4) (5) (6) (7) (8)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>N</td>
<td>Ln Checking Account Balance</td>
</tr>
<tr>
<td>Panel A: All Clientes</td>
<td>763,511</td>
<td>0.2401***</td>
<td>-0.0197***</td>
</tr>
<tr>
<td>ATE</td>
<td>(0.0072)</td>
<td>(0.0037)</td>
<td>(0.0048)</td>
</tr>
<tr>
<td>Mean of dep var (MXN)</td>
<td>18283.47</td>
<td>66.66463</td>
<td>4161.451</td>
</tr>
<tr>
<td>Panel B: Clients with Credit Card</td>
<td>126,468</td>
<td>0.4403***</td>
<td>-0.0991***</td>
</tr>
<tr>
<td>ATE</td>
<td>(0.0148)</td>
<td>(0.0095)</td>
<td>(0.0083)</td>
</tr>
<tr>
<td>Mean of dep var (MXN)</td>
<td>21623.82</td>
<td>241.41</td>
<td>15077.12</td>
</tr>
<tr>
<td>Panel C: Clients with Credit Card who paid interest at baseline</td>
<td>61,204</td>
<td>0.5167***</td>
<td>-0.1109***</td>
</tr>
<tr>
<td>ATE</td>
<td>(0.0114)</td>
<td>(0.0094)</td>
<td>(0.0092)</td>
</tr>
</tbody>
</table>
Results: characteristics of individuals in top and bottom quartiles

**Table: Differences Between Top and Bottom Quartiles of the Distribution of Predicted Treatment Effects**

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

<table>
<thead>
<tr>
<th>Dep.Var</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ln Checking Account Balance +1</td>
<td>Ln Credit Card Balance (Banorte) +1</td>
<td>Ln Credit Card Balance (Credit Bureau) +1</td>
<td>Ln Credit Card Interest +1</td>
<td>Paid Interest {0,1}</td>
<td>Ln Credit Card Payments +1</td>
</tr>
<tr>
<td>TE</td>
<td>0.0595***</td>
<td>0.0030</td>
<td>-0.0041</td>
<td>0.0035</td>
<td>0.0056</td>
<td>0.0071</td>
</tr>
<tr>
<td></td>
<td>(0.0230)</td>
<td>(0.0173)</td>
<td>(0.0072)</td>
<td>(0.0495)</td>
<td>(0.0089)</td>
<td>(0.0193)</td>
</tr>
<tr>
<td>Mean of Dep. Var in Control Group (MXN)</td>
<td>43,152.85</td>
<td>8,701.33</td>
<td>19,045.70</td>
<td>98.62</td>
<td>0.23</td>
<td>6,013.95</td>
</tr>
</tbody>
</table>

N= 63286
## 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

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

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

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


