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ABSTRACT

We study whether savings nudges have the unintended consequence of additional borrowing in high-interest credit. We use data from a pre-registered experiment that encouraged 3.1 million bank customers to save via SMS messages and train a machine learning algorithm to predict individual-level treatment effects. We then focus on individuals who are predicted to save most in response to the intervention and hold credit card debt. We find that these individuals save 5.7% more (61.84 USD per month) but do not change their borrowing: for every additional dollar saved, we can rule out increases of more than two cents in interest expenses.

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1 Introduction

A vast number of policies aimed at increasing savings are currently in place, especially via so-called nudges (Benartzi et al., 2017). When policymakers or researchers evaluate these interventions, they often focus on the immediate savings outcome and do not consider other margins of adjustment (Beshears and Kosowsky, 2020). However, we may be interested in the effects of savings nudges on short-term unsecured debt. After all, if individuals were to borrow more at high interest to finance the additional savings, they would be worse off. To date, however, limited evidence exists on whether or not individuals respond with increased borrowing when they are nudged to save. Clearly, this question is of central importance for policymakers and researchers alike in order to evaluate whether savings nudges or even more forceful policies should be implemented.

We empirically evaluate and quantify whether or not savings nudges that are followed by actual increases in savings also increase high-interest unsecured borrowing in general and specifically for individuals who were already rolling over credit card debt. To do so, we use a large-scale field experiment paired with comprehensive and very accurate panel data of individual credit cards and checking accounts. We obtain this data from one of the largest banks in Mexico, Banorte. The bank ran a randomized experiment with 3,054,438 customers, out of which 374,893 were selected as the control group. Clients in the treatment group received ATM and SMS messages suggesting that they save. The intervention lasted 7 weeks, from September 13 to October 27, 2019.

To meaningfully test if saving causes borrowing, we focus the analysis on individuals whose observable pre-treatment characteristics predict a strong response to the savings nudge. To do so, we study the behavior of individuals with the largest treatment effects as predicted by machine learning techniques. Specifically, we estimate a causal forest model as discussed in Athey and Imbens (2015) and Athey et al. (2019). Using a rich set of pre-treatment covariates, the algorithm recursively estimates heterogeneous treatment effects for different sub-populations and then predicts for each individual an estimated average treatment effect. In turn, we focus on the subsample of customers in the top quartile of the predicted treatment effect distribution who have a credit card. For this group of individuals, we ask whether the increased savings were accompanied by an increase in borrowing.

It is important to note that this approach does not suffer from overfitting problems, which would lead us to incorrectly infer large treatment effects for arbitrary sub-populations. Searching over many possible partitions and estimating treatment effects for each of them in the same sample would be problematic; any one sample observation sharing certain covariates could exhibit a larger treatment effect by pure chance or due to other idiosyncratic shocks. In contrast, the predicted treatment score from the random forest is calculated using 2,000 repeated sample splits to figure out which pre-treatment covariates predict a large response to the savings treatment (holding all pre-treatment observable characteristics constant across treatment and control through explicit orthogonalization). This procedure eliminates the possibility that pre-treatment covariates predict a large treatment effect by pure chance or as a result of idiosyncratic shocks that could also affect other outcomes.

We first focus on individuals who are in the top quartile of the predicted treatment effects and have a credit card. For them, we estimate that the treatment is associated with an increase in savings of 6.01% on a baseline savings of 31,681 MXN in the control group (1,489 USD), that is, an increase of 1,904 MXN (89 USD). On average, this group decreased their interest payments by 1.71% from a basis of 230 MXN with a standard error of 3.34%. We can thus rule out an increase in borrowing costs of more than 11 MXN with 95% statistical confidence. We can compare this to the increase in savings and conclude that, for every 1 MXN in savings, we can rule out an 11/1,904 or 0.006% increase in borrowing costs.

We then focus on individuals with a credit card who roll over debt as measured by their interest payments in the 6 months previous to the intervention. For them, we see an increase in savings of 5.67% on a baseline value of 23,080 MXN, that is, 1,316 MXN (62 USD). In turn, we can rule out a 6.64% increase in credit card borrowing with 95% confidence (an increase of 26.68 MXN in borrowing costs). To conclude, for every 1 MXN in savings, we can thus rule out a 27/1,409 or larger than 1.9 cent increase in credit card borrowing costs.

To further illustrate the pitfalls of overfitting and how the causal forest overcomes it, we compare our results with the estimates for saving and borrowing for sub-populations with the largest ex-post observed treatment effects. We identify individuals who belong to the experimental blocks with the largest observed average treatment effects. Individuals in this group could have increased their savings due to idiosyncratic shocks that also affect their borrowing. Indeed, for them, we find treatment effects on borrowing that are large and negative. This suggests that individuals who responded a lot to the treatment were actually cleaning up their finances and thus also reduced their borrowing.

Individuals in the top quartile of the predicted treatment effects who were carrying credit card interest at the time of the intervention exhibited a large response to the savings nudge. While this response did not come at the expense of increases in credit card debt, we find no evidence that these savings were used to pay off credit card debt in the billing cycles following the savings nudges, thus exacerbating the simultaneous co-holding of low-interest savings and high-interest debt.

Households in Mexico and in the US tend to co-hold liquid savings and credit card debt. In our sample, the average credit card interest rate is 35.2% and checking accounts pay 0% interest. Despite the large price differences, we find that 26% of individuals who pay credit card interest keep average daily balances higher than 50% of their income in their checking accounts (over the 6 months previous to the intervention). Similarly, in the 2001 US Survey of Consumer Finances (SCF), 27% of households reported revolving an average of 5,766 USD in credit card debt with an APR of 14% and simultaneously holding an average of 7,338 USD in liquid assets with a return of around 1%. 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).

The literature proposes different explanations for why households that accumulate credit card debt may not use their liquid savings to pay it off. Telyukova (2013) argues that this occurs because households anticipate needing that money in situations where credit cards cannot be used, such as making mortgage or rent payments or unexpected home and auto repairs. Haliassos and Reiter (2005) argue that individuals who accumulate credit card debt do not pay it off with their savings because they want to constrain their impatience or spendthriftness of their spouses. If the debt were to be repaid, the impatient party would simply accumulate credit card debt again, effectively spending the household's savings.

A key distinction between transaction-convenience models and preference-based explanations for the co-holding puzzle is the following: in a transaction-convenience model, increases in savings would cause increases in debt, whereas that is not true in a model of co-holding based on self-control. In the transaction-convenience model, individuals set aside money for transaction purposes, knowing that it will be available in the future; thus, if they are nudged to save more, to maintain their consumption, they borrow against those savings. In contrast, in preference-based models, individuals keep two separate mental accounts, one for savings and one for borrowing. By keeping savings on a separate mental account, individuals effectively remove a certain amount of money (labeled as savings) from their consumption-borrowing problem and simply split whatever resources are left to smooth consumption. In turn, setting more money aside as savings should reduce consumption rather than increase borrowing. By testing whether saving causes borrowing, we thus test a key prediction to distinguish between these two theories. We argue that our findings are consistent with individuals choosing to hold credit card debt and savings simultaneously in order to cope with self-control problems, as in Haliassos and Reiter (2005).

To provide further evidence for a preference-based explanation behind the co-holding puzzle, we show that those individuals who co-hold, defined as holding more than 50% of their income in their checking accounts and paying credit card interest, overlap most strongly with the highest quartile of the predicted savings score: that is, the co-holding individuals are also most responsive to the savings nudge without increasing their credit card borrowing in response. Additionally, the message that talks about "the safest money box" carries a large treatment effect.

2 Literature Review

Our paper is related to a large literature on the savings effects of automatic (as opposed to opt-in) enrollment into 401(k) savings plans. This literature generally finds that a 1% increase in default savings rates increases total savings by 0.5% to 0.8% (see, e.g., Choi et al., 2004; Chetty et al., 2014). Implicitly, this research assumes that individuals do not offset the increased savings with additional borrowing. To the best of our knowledge, the only research paper evaluating whether nudges to save increase borrowing is Beshears et al. (2019). The authors look at a natural experiment in which the US army started to automatically enroll all newly hired employees into their retirement savings plan. In response, employees saved more and borrowed about 1% of their income more in secured credit such as auto loans and first-time mortgages. In this paper, credit card borrowing is measured via biannual snapshots of balances from a credit bureau. However, a biannual snapshot of credit card balances does not reveal how much high-interest unsecured debt is actually rolled over. In our study, we instead look at the high-frequency responses in credit card borrowing using bank account transactions and balances. Additionally, we see whether individuals roll over debt in the first place. We observe credit limits to ensure that individuals would have the ability to borrow.

Similarly, the literature on savings nudges via SMS or Fintech apps (Karlan et al., 2016; Gargano and Rossi, 2020; Akbaş et al., 2016; Rodríguez and Saavedra, 2015) has documented effects of varying magnitude but has not in general studied potential increases in borrowing.

We also contribute to a growing literature looking at unintended effects of nudges in different domains, ranging from financial accounts (Beshears et al., 2015; Goldin et al., 2017; Keys and Wang, 2019; Medina, 2020; Medina and Negrin, 2021) to health outcomes (Wisdom et al., 2010) to energy conservation (Costa and Kahn, 2013; Allcott and Kessler, 2019).

Our paper relates to the literature on credit card borrowing. Laibson et al. (2003) argue that credit card debt constitutes "a puzzle" for standard life-cycle models in which fully rational agents would rather forgo the benefits of consumption smoothing than borrow at prevailing credit card interest rates. Laibson et al. (2012) examine the coexistence in household portfolios of credit card debt and retirement assets. The authors explain this behavior with time-inconsistent decision making by households, which makes them patient in the long run but impatient in the short run. Thus, households want to lock away their wealth in retirement assets to keep from consuming it. Kaplan and Violante (2014) explain the same phenomenon in a fully rational model in which households save at a higher return in their illiquid assets and then borrow in response to income fluctuations. Retirement assets in these models are illiquid because they involve a significant penalty for early withdrawal, which is not the case for savings accounts. Analyzing whether liquid savings result in borrowing may provide us with a lower bound for the borrowing response to illiquid savings.

Households may hold not only credit card debt and illiquid retirement assets simultaneously but also perfectly liquid assets. Previous literature on the credit card debt or co-holding puzzle began with Gross and Souleles (2002), who documented the phenomenon and note that the transaction demand for liquidity may contribute to it. Maki (2002) studied whether households may run up credit card debt strategically in preparation for a bankruptcy filing, to be discharged during the filing while keeping assets in liquid form in order to convert them to exemptible assets. However, Telyukova (2013) indicates that most puzzle households are unlikely to file for bankruptcy. Beyond the models in Telyukova (2013) and Haliassos and Reiter (2005), proposed explanations for the co-holding puzzle include financial literacy (Gathergood and Weber, 2014), mental accounting (Gathergood and Olafsson, 2020), or the variability of credit limits (Fulford, 2015) .

A number of authors from different fields such as marketing or consumer psychology have argued in favor of spending or self-control considerations in borrowing behavior. Hoch and Loewenstein (1991) argue that self-control problems occur when the benefits of consumption are experienced earlier and are dissociated from the costs. The findings of Shefrin and Thaler (1988), Prelec and Simester (2001), and Wertenbroch (2001) suggest that liquidity enhances both the probability of making a purchase and the amount one is willing to pay for a given item being purchased over and above any effects due to the relaxation of liquidity constraints. Soman and Cheema (2002) present experimental and survey evidence that consumers interpret available credit lines as indications of future earning potential when deciding consumption expenditures.

3 Background on the Mexican Credit Card Market

The Mexican credit card market has expanded rapidly. As of June 2017, there were 17.9 million general-purpose credit card accounts in good standing holding a positive balance in a population of 124 million, whereas only 13 million cards were in circulation in 2009. In spite of this trend, credit card penetration in Mexico has remained low relative to other countries. In 2014, only 18% of adults had credit card accounts, while the equivalent figures in Brazil, Argentina, and the US were 32%, 27%, and 60%, respectively. Furthermore, the number of credit cards per individual cardholder remains relatively low compared to the US. According to a nationally representative survey, the average credit cardholder has 1.27 cards. Among individuals reporting to have at least one credit card, 79% have only one credit card, 15% have 2, and the rest have more than 2 cards.[1] Interest rates are high compared with those in the US. By the end of 2017, the average credit card interest rate in Mexico had a spread of 26.4% above the federal short-term interest rate, which was 7.17%. Banorte's average credit card interest is 35.2%.

The credit card market in Mexico is not too competitive, similar to the US (Herkenhoff and Raveendranathan, 2020). There are 16 banks participating in the credit card market, offering 140 products. The five largest banks hold 85% of the market, the two largest products hold more than 25% of the market, and the six largest products cover just above 50%. Credit cards represent 22% of the consumer credit portfolio measured by balance, inclusive of mortgage debt at the end of 2015.[2]

4 Experimental Design and Data Description

4.1 Experiment

We analyze the results of a large-scale experiment to promote savings with the Mexican bank Banorte. The experimental pool consists of 3,054,438 customers, out of which 374,893 were

[1] INEGI, Encuesta Nacional de Inclusion Financiera, 2018.
[2] Refer to Banco de Mexico, multiple reports.

selected randomly to be in a control group. Clients in the control group received no messages. Clients in the treatment group were randomly assigned to receive 1 of 7 messages that proved to be effective in previous experiments nudging individuals to save. Half of the treated customers were cross-randomized to receive the messages on a weekly basis, while the other half were assigned a bi-weekly frequency.[3] The intervention lasted 7 weeks, from September 13 to October 27, 2019.

The treatment messages were as follows:

> **Message 1:** “Congratulations. Your average balance over the last 12 months has been great! Continue to increase your balance and strengthen your savings."
>
> **Message 2:** “Increase the balance in your Banorte Account and get ready today for year-end expenses!”
>
> **Message 3:** “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.”[4]
>
> **Message 4:** “In Banorte, you have the safest money box! Increase your account balance by $XXX this payday and reach your goals."
>
> **Message 5:** “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.”
>
> **Message 6:** “The holidays are coming. Commit to saving $XXX in your Banorte Account and avoid money shortfalls at year-end!”
>
> **Message 7:** “Be prepared for an emergency! Commit to leaving 10% more in your account. Don’t withdraw all your money on payday.”

[3]Users in the treatment group were further cross-randomized across two additional dimensions. First, half of them would stop receiving the messages for 2 weeks after 2 months of receiving them, and then the messages would resume. Second, half of the consumers in the treatment group would receive the same message throughout the duration of the intervention, and the other half would receive alternating messages every 4 weeks. Due to logistical considerations, these last two treatment variations were not implemented.

[4]XXX was a personalized amount representing 10% of the balance in the last 3 months.

For each customer in the experimental pool, we observe all information routinely collected by the bank, including transactions and balances on checking accounts and credit cards, information from the credit bureau, income, and other demographic characteristics.

4.2 Descriptive Statistics

Table 1 shows descriptive statistics for treatment and control groups with and without credit cards. We can see that the average age is 45 years, the average monthly after-tax income is approximately 13,500 MXN (635 USD), and the clients have banked with the bank for 7 years on average.[5] Additionally, their average checking account balance is approximately 19,384 MXN and about 30% of credit cardholders pay credit card interest.

Beyond showing these descriptive statistics for all individuals, we also show them separately for the ones who have a credit card with Banorte. These individuals have about 30% more income and 60% higher checking account balances than the average client. Their average credit card balance is 21,914 MXN (1,030 USD). The average individual with a credit card pays 169 MXN (8 USD) in interest costs per month (this average includes individuals who do not pay any interest). Individuals also have substantial borrowing capacity on their cards, 102,278 MXN on average.

4.2.1 Randomization checks

The experiment was stratified along a number of dimensions: income quartiles, age quartiles, median of tenure with the bank, quartiles of baseline savings, dummy for clients for whom Banorte is the main bank, dummy for clients considered predominantly digital (30% or less of debit card charges made through cash withdrawals), median of ATM transactions, terciles of debit card transactions, and a dummy variable indicating if an individual had a credit card. The baseline refers to the 6 months previous to the intervention. Table 2 shows that there is covariate balance across a number of variables of interest. More specifically, Table 2 shows the same descriptive statistics

[5] As mentioned, over our sample period, 1 MXN corresponded to 0.047 USD on average. A rough estimate for the USD value can thus be obtained by subtracting one decimal point and dividing by 2.

separately for the treatment and control groups and also shows the results of the randomization check. The randomization appears successful, as none of the differences between the two groups are statistically significant except for age: the treatment group is 1 month younger than the control group, a difference we argue is due to chance and not economically meaningful.

4.2.2 Descriptive Statistics of Simultaneous Credit Card Debt and Liquid Savings

In terms of the credit card debt puzzle, Table 3 shows the fraction of individuals who pay credit card interest and their balances on checking accounts, credit cards, and interest payments by deciles of savings over income. Here, we restrict the sample to only individuals who have a credit card. We can see that, even among those individuals in the higher deciles of checking account balances, 20% to 30% pay credit card interest. We are concerned about the individuals with both savings and credit card debt. The 30% of individuals with the highest checking account balances could repay their entire credit card debt and save around 1,300 MXN per month (60 USD). After all, as mentioned, Banorte's average credit card interest is 35.2% and the return on checking accounts is 0%.

We now look at all individuals rolling over credit card debt and define the savings and credit card debt puzzle group as individuals holding more than 50% of their income in their checking accounts and paying credit card interest (hereafter referred to as the puzzle group). About 26% of individuals who pay credit card interest are in the puzzle group. This corresponds to about 8% of all individuals who have a credit card. In turn, Table 4 compares individuals in the puzzle group to the rest of those who pay credit card interest. The puzzle group is slightly older but has similar monthly income and tenure with the bank. They mostly differ in their checking account and credit card balances and seem to roll over more debt.

Note that, individuals appear to hold debt persistently: there is a correlation of 80% between rolling over debt in any given month and doing so in the previous month.

While having credit cards in the first place and co-holding are not as common in the overall population of Mexico relative to the US, the size of our experiment will provide sufficient statistical power to analyze this sub-population.

5 Methodology

For every customer, we observe the daily balances in their checking accounts at the end of each day. We calculate the average of daily checking account balances over the 7-week treatment period as our main dependent variable. Note that, we also observe savings account balances but they are rarely used and most individuals do not have one. We then analyze the effects of the experiment using two approaches. First, we evaluate the effects of the savings nudges on checking account balances for the entire population. For this, we use standard ordinary least squares (OLS) specifications comparing treatment to control outcomes, as this is standard to measure treatment effects in field experiments.

Then, we use machine learning techniques to predict individual treatment effects. Specifically, we estimate a causal forest, as discussed in Athey and Imbens (2016) and Athey et al. (2019). In turn, we look at the frequency distribution of the individual treatment effects and identify the sub-population with the largest predicted treatment effects on savings. For them, we will study the borrowing consequences of saving by looking at average treatment effects on savings and credit card outcomes.

5.1 Estimating Heterogeneous Treatment Effects

5.1.1 Overfitting and Heterogeneous Treatment Effects in High-Dimensional Settings

The typical way to estimate heterogeneous treatment effects in low-dimension settings is by interacting a variable that captures a heterogeneity of interest (for example, a dummy variable for observations above or below the median age) with the treatment indicator. The interaction coefficient then identifies the incremental effect of the treatment on individuals above or below the median age. If there are several potential explanatory variables, the dimensionality of the model grows significantly, since one would need to interact all variables of interest with each other and with the treatment variable. Researchers then run the risk of overfitting or capturing spurious heterogeneous treatment effects, that is, an interaction shows up as significant by pure chance. The causal forest algorithm allows us to identify heterogeneity in treatment effects without concern about invalidating inference due to overfitting or multiple hypothesis testing problems. This method is tailored to efficiently predict the causal effects of a treatment for a rich set of different sub-populations through three distinctive features: sample splitting, orthogonalization, and optimization designed to capture treatment effect heterogeneity.

5.1.2 Causal Forests

Causal forests are based on causal trees, and their relation is analogous to the relation between widely known random forests and regression trees. Regression trees predict an individual outcome Y_i using the mean Y of observations that share similar covariates, X. To define what counts as similar, regression trees partition the covariate space into disjoint groups of observations called 'leaves.' Within each leaf, all observations share values (or belong to the same value interval) of certain Xs. A tree starts with a training sample, that is treated first as a single group and then recursively partitioned. For each value $X_j = x$, the algorithm forms candidate splits, placing all observations with $X_j \leq x$ in a left leaf and all observations with $X_j > x$ in a right leaf. The split is implemented if it minimizes a certain loss criterion, such as mean squared error ($\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$). This criterion is evaluated in the sample, that is, the same observations used to define where to split are also used to calculate the mean value of the outcome in each leaf. The algorithm then repeats the process for each of the two new leaves and so on until it reaches a stopping rule. Using the final set of leaves, the tree provides out-of-sample predictions by figuring out in which terminal leaf a certain observation falls based on its covariate values and assigning a predicted value equal to the average value of all observations in that leaf in the training sample.

Random forests are an ensemble of n trees in which n random subsamples of the data are taken and each subsample is used to train a causal tree. Predictions for each observation in a test sample (which could be the full original dataset) are defined as the average across n predictions, obtained by pushing that one observation down each of the n trees.

In contrast to regular random forests that predict individual outcomes Y_i, causal forests want to predict conditional average treatment effects ($E[Y_1 - Y_0|X = x]$ in a potential outcomes framework), to measure how causal effects vary for different sub-populations. Standard loss criteria such as goodness-of-fit measures are not available because we do not observe the treatment effect $Y_1 - Y_0$ for any one individual. Athey and Imbens (2016) show that maximizing the expected mean squared error of predicted treatment effects instead of the infeasible mean squared error itself is basically equivalent to maximizing the variance of treatment effects across leaves. Thus, this defines a new criterion for sample splitting that is specifically designed to identify treatment effect heterogeneity. They also show that, to reduce overfitting bias, the training sample should be further split into a splitting and an estimation sample so that the observations used to choose where to create new leaves are not the same ones used to calculate treatment effects within each leaf. In addition, Athey et al. (2019) argue for the importance of orthogonalization: in other words, the treatment effect estimation in the next sample (the estimation sample) has to balance covariates between the treatment and control groups.

Thus, causal forests are different from off-the-shelf machine learning methods in three ways: 1) they estimate treatment effects with a repeated split sample method by which one sample is used to identify splitting rules and a different sample is used to estimate treatment effects (this is referred to as "honest estimation" (Athey and Imbens, 2016)), 2) the splitting rule for the trees is defined to find sub-populations with different treatment effects instead of predicting levels of the outcome of interest in the treatment and control groups separately, and 3) orthogonalization methods are used to ensure covariate balance across multiple sub-populations. A.1 provides additional details on the intuition behind causal forests as well as the specific implementation of causal forests in conjunction with the generalized random forest algorithm developed by Athey et al. (2019).

We will further discuss the rationale and findings of applying a causal forest in our setting in Subsection 6.2.

6 Results

6.1 Aggregate Effects of the Intervention

We study the treatment effect of the intervention on saving for the entire experimental pool as well as the treatment effect on saving and borrowing for individuals who have a credit card. To do so, we estimate Equation (1).

$$Y_i = \alpha_s + \beta * treatment_i + \epsilon_i \tag{1}$$

where α_s represents fixed effects for randomization blocks and β identifies the treatment effect of the intervention as the difference in outcomes between the treatment and control groups. Note that these average treatment effects are intention-to-treat (ITT) effects because individuals may or may not have seen the messages; if they do see the messages, they then choose how much to respond. The fact that we find a positive and significant effect in a randomized setting implies that at least some individuals saw the messages and that their behavior was affected by them.

Table 5 shows the average treatment effects across all treatments by treatment message and treatment frequency. Column 1 shows that, on average, there is a significant 0.6% increase in savings from a basis of 21,867 MXN. Column 2 displays the effects by treatment message, showing that only Message 2, individually, has a positive treatment effect. Column 3 shows that only the treatment with weekly messages has a positive treatment effect on its own. That said, even though not all treatments lead to significant effects on their own, all treatment messages and frequencies have similar coefficients that are not statistically significantly different from each other.

Columns 4 and 5 show the average treatment effect for individuals who have a credit card. In this column, we again pool all treatments into one single dummy variable that takes the value of one if a given individual was assigned to any of the treatments. Here, we find a significant 1.4% increase in savings from a basis of 24,331 MXN, which represents an increase in savings of 340 MXN. We then explore if there is any increase in credit card interest payments but do not find a significant effect. This null effect is tightly estimated: We can rule out an increase in credit card interest of more than 0.3% with 95% statistical confidence on a basis of 213.84 MXN, that is, we can rule out an increase of more than 0.64 MXN in borrowing costs. Thus, in this aggregate specification, for every 1% increase in savings, individuals with credit cards incurred less than a 0.64/340 or 0.19% increase in borrowing costs.

Consistent with the previous literature on savings nudges via SMS, the documented impact is relatively small (Karlan et al., 2016). The fact that there was a stronger effect on savings among credit cardholders suggests that there may be some sub-populations with a stronger response than others. We thus study heterogeneity of treatment effects in the following section looking at both saving and borrowing.

6.2 Heterogeneous Effects and Sub-Population Analysis

We pay special attention to heterogeneous treatment effects for two reasons. First, previous work has found moderate effects of nudging interventions via SMS on savings. We argue that this occurs because the average effect masks heterogeneities, with some individuals responding strongly while others remain unaffected. Our setting allows us to characterize sub-populations who indeed respond to savings nudges and provide insights on how to perform targeted interventions. Second, any meaningful test of the effect of savings nudges on borrowing requires nudges to first have a strong effect on savings. Testing the impact of savings nudges on borrowing where there is a small effect on savings would be of limited use. In contrast, testing the effect of savings nudges on borrowing for individuals who indeed responded to the savings nudge and experienced meaningful increases of savings is relevant for both policy and testing theoretical explanations of the credit card debt puzzle.

Our heterogeneity analysis allows us to study the borrowing response of individuals who indeed increased their savings significantly as a result of a savings nudge. To identify individuals with the highest response to the treatment, we use a causal forest.

6.2.1 Characterizing Individuals with the Largest Predicted Responses to Savings Nudges

As described, the causal forest produces individual predictions of treatment effects for each observation in the sample (both treatment and control groups). Following Athey and Wager (2019), we first train a pilot causal forest with 2,000 trees using all 161 pre-treatment variables available for the analysis. These variables include past financial behavior (for example, for checking and credit card balances and interest, we include 6 monthly lags), demographic variables, and a number of geographic dummies. We then train a second forest only on the 52 variables with higher importance, that is those which saw the largest number of splits in the first estimation. For this second causal forest estimation, Figure 2 shows the 27 variables with the highest variable importance, and Figure 1 shows the distribution of the predicted treatment effects at the individual level, listing the 52 final pre-treatment variables in the caption. This will be the basis for our subsequent analysis.

Figure 1 shows the distribution of predicted treatment effects. We use individual predictions as a "score" value that ranks observations according to their predicted treatment effects (Chernozhukov et al., 2018), and we split the sample of users into quartiles according to each individual's score value. Figures 2 and 3 show how the treatment effects on savings are larger for individuals with larger scores, suggesting that the predicted treatment effects are a valid measure of the actual treatment effects. We can see that the top 5% of individuals in the sample have a treatment effect of 5.33% (1,162.5 MXN). A.1.1 provides a formal test for the validity of individual treatment effects as a measure for the actual treatment effects (Chernozhukov et al., 2018) in Table A1.

Table A2 compares the baseline characteristics of individuals in the top and bottom quartiles of the distribution of the predicted treatment effects. By design, these groups of individuals are not the same. Compared to individuals in the bottom quartile of the distribution of the predicted treatment effects, individuals with the highest predicted response are about one year older and have a higher income, longer tenure with the bank, larger checking account balances, and larger credit card balances and credit card limits.

6.2.2 Addressing Overfitting Concerns

We now focus on individuals in the top quartile of the predicted treatment effects who have a credit card. For them, we calculate the treatment effect on savings and then borrowing. We note that the individual predictions produced by the causal forest are based on pre-treatment covariates and result from a procedure based on sample splitting and orthogonalization. We do not search for large treatment effects over multiple partitions of the entire dataset, since, in that case, our analysis would suffer from a type of "reverse endogeneity" overfitting (that is, we would pick a group of individuals who displayed large savings in response to the treatment, but something else might have been happening with this subsample). Instead, our predictions are based on 2,000 causal trees, each trained with a different sample, which is further split into a splitting sample and an estimation sample. Heuristically, individuals in the top quartile of the predicted treatment effects are those who consistently showed high treatment effects across the multiple training samples.

6.2.3 Ensuring Covariate Balance

Furthermore, since the top quartile of the predicted treatment effects is an arbitrary sample cut from the perspective of the experimental design, covariate balance between the treatment and control groups is not ensured. Therefore, instead of calculating average treatment effects with a simple regression of treatment status on the outcome, we adjust our treatment effect estimates by treatment propensity or covariate imbalance using a variation of the Adjusted Inverse Probability Weighted (AIPW) estimator of Robins et al. (1994), as implemented by Athey et al. (2019) in the grf package of R. AIPW estimators are based on calculating the propensity to be in the treatment group given observable characteristics (Glynn and Quinn, 2010). Under perfect covariate balance, treatment propensity is constant across all observable characteristics. But while successful randomization guarantees that this is true on average, perfect covariate balance is not necessarily present across all partitions of the sample. AIPW effectively controls for these imbalances, thus improving the precision of our estimates.

6.3 Results for the Top Quartile of Predicted Treatment Effect Individuals

6.3.1 Effects on Saving and Borrowing

Table 6 shows the average treatment effects on saving and borrowing for individuals in the top quartile of the predicted treatment effects who have credit cards. Panel A considers all individuals who have a credit card, while Panel B focuses on the subset of individuals paying credit card interest.

We first discuss the results in Panel A. In Column (1), we can see the savings results for the top quartile of predicted treatment effect individuals who have a credit card. Here, the estimated increase in savings is 6.01% on a baseline savings of 31,681 MXN, that is, 1,904 MXN. On average, this group of individuals decreased their credit card balances by 1.55% from a basis of 17,097 MXN and a standard error of 1.16%, as can be seen in Column (2). We can thus rule out an increase in borrowing of more than 124 MXN with 95% statistical confidence. Similarly, in Column (4), we can see that interest payments decreased by 1.71% from a basis of 230 MXN. Column (3) shows a standard error of 3.34%. We can thus rule out an increase in borrowing costs of more than 11 MXN with 95% statistical confidence.

We can compare this to the increase in savings and conclude that, for every 1 MXN in savings, we can rule out a 124/1,904 or 11/1,904 increase in borrowing or borrowing costs, respectively. In other words, we can rule out a 0.06% increase in borrowing or a 0.01% increase in borrowing costs in response to a 1% increase in savings.

In Column (3), we can see the effect of credit card balances from the credit card bureau, which also includes non-Banorte credit cards. The coefficient estimate and standard errors paint a similar picture. For each 1% increase in savings, we can rule out a very small increase in borrowing with statistical confidence. Note that the credit bureau reports the credit card balances at the end of the month, whereas we use the average daily balances for Banorte credit cards. Nevertheless, the fact that we tightly estimate small effects reassures us that individuals do not borrow using other cards instead of their Banorte credit cards. Furthermore, comparing our Banorte results for credit balances versus actual rolled-over debt as measured by interest payments, we conclude that the balances are indicative of the actual rolled-over debt.

In Column (5), we can see the estimated effect for the likelihood of paying interest in a given month. Here, we can rule out an increase of 0.68% on a baseline probability of 42%. Thus, for every 1 MXN in savings, the increase in the likelihood to borrow is only 0.0068/1,904, or 0.0000036%.

Finally, in Column (6), we report results for credit card payments, that is, individuals repaying their outstanding credit card balances or rolled-over credit card debt. Here, we also document a very small and tightly estimated treatment effect. Individuals save more but do not repay more of their outstanding credit card balances or debt.

We now turn to the results in Panel B of Table 6, which corresponds to individuals that pay credit card interest at baseline, that is, we observe average positive interest payments in the 6 months previous to the intervention, and are in the top quartile of the predicted treatment effects. For this group, we have an increase in savings of 5.67% (1,315 MXN) on a baseline of 23,194 MXN. In turn, we can rule out an increase of 133.97 MXN in credit card borrowing or 26.68 MXN in borrowing costs. To conclude, for every 1 MXN in savings, we can thus rule out increases larger than 10 cents (134/1,315) or 2 cents (27/1,315) in credit card borrowing and borrowing costs, respectively.

Table A3 shows the increases in saving and borrowing for five quintiles of the treatment effect score for the group of individuals who have a credit card. To be clear, the table conditions are based on the top quartile of the predicted treatment effect for savings and then further splits the sample into quintiles. Additionally, the table shows the respective increases in borrowing costs and the likelihood to borrow. We can see that, for all of the predicted treatment effect quintiles, the increases in borrowing are very small. Table A4 shows the same for individuals with a credit card who pay interest at baseline.

Figure A6 shows in a graph the treatment effect on interest charges for consumers with credit cards and separately for those consumers who pay credit card interest at baseline. We can see that the negative effect is concentrated in the first quintile of the predicted savings effect, but all quintiles' estimates are insignificant and small.

6.3.2 Effects on Spending and Income

We want to know whether individuals increased their savings without increasing their borrowing by decreasing their spending or increasing their income. Table 7 shows the treatment effects on deposits, ATM withdrawals, and spending for the top quartile of the predicted treatment scores. We can see that the treatment effect appears to work through a 6.0% decrease in monthly ATM withdrawals and a slightly smaller but still significant 4.2% decrease in debit card spending. This is true for all individuals with a credit card and also for the subset of those paying credit card interest. We thus conclude that a decrease in spending, and in particular discretionary spending that may be financed by cash, was responsible for the increase in savings.

6.3.3 Customers with Banorte as their Main Bank

Finally, we also replicate the analysis for individuals for whom Banorte is likely to be their main bank. After all, it could be that individuals who have other bank accounts offset their additional savings using those other accounts. We say that Banorte is likely to be the main bank of a given individual when the following three conditions are satisfied: she receives her payroll on a Banorte payroll account (identified as such by the Mexican transaction system), she has a credit card with Banorte, and she has no credit (of any type) outside of Banorte, according to the credit bureau records. Table 8 shows the saving and borrowing results for this group. Panel A shows the results for all clients in the top quartile of the predicted treatment effects and for whom Banorte is likely to be their main bank (who therefore have a credit card). We can rule out increases of more than 10 cents in credit card balances or 1 cent in borrowing cost for every additional MXN saved as a result of the savings nudge. Panel B shows the results for the subset of individuals who also incurred credit card interest at baseline. For them, we can rule out increases of 11 cents in credit card balances or 2 cents in borrowing cost for every additional 1 MXN saved.

6.3.4 Effects by Treatment Message

We now want to understand whether the effects on saving and borrowing differ across treatment messages. To explore the relationships between saving and borrowing across each of the seven messages included in the experiment, we focus on the 126,458 individuals in the top quartile of the predicted treatment effects who had a credit card. For them, we calculate the average treatment effect of receiving each specific message on their saving and borrowing.

Table A5 shows that the savings effect was concentrated for Messages 2, 3, 4, and 5 (the messages are displayed in Subsection 4.1). The borrowing effect is small and tightly estimated for all messages. This finding is important for the interpretation of our results. The effect does not seem to be constrained to messages alluding to short-term savings motives. Message 2, "[...] get ready for year-end expenses," is the only significant one that alludes to saving for the short term, whereas the other significant messages do not. Additionally, Message 6 "[...] avoid money shortfalls at year-end." and Message 8 "[...] emergency [...]" did not have significant effects, even though they refer to specific short-term savings goals.

Because we do not find differences between messages alluding to short-term versus long-term savings, we may be in a position to extrapolate our specific savings nudge experiment to other savings nudges or more forceful measures aimed to increase savings for the longer term.

Finally, Message 4 "[...] you have the safest money box [...] reach your goals" carried a large average treatment effect and alluded to the safeness of the savings and reaching general goals. This message and its effect are in line with the behavioral hypothesis of mental accounting and constraining oneself to save more.

6.4 Analysis of Methods to Identify Sub-Populations with Large Treatment Effects Subject to Overfitting Problems

We study heterogeneous treatment effects using a causal forest (Athey et al., 2019). This method allows us to derive valid inferences for the treatment effects of the intervention across different sub-populations and to identify the sub-population with the largest treatment effect without concerns of overfitting. We now contrast this method with methods of identifying heterogeneous treatment effects based on randomization strata or ex-post observed treatment effects. Both methods are subject to overfitting concerns.

6.4.1 Heterogeneity by Experimental Strata

A standard way to study heterogeneous treatment effects is to split the sample based on strata from the experimental design. Table 9 shows the average treatment effects on savings across the experimental strata. We find limited heterogeneity across the sub-populations that were pre-selected for heterogeneity analysis before the experiment was run. Individuals with pre-treatment checking account balances in the top quartile are the ones with the largest treatment effects. For them, we find a 1.8% increase in savings (-0.006 + 0.024).

Looking at experimental strata is a useful approach to estimate how a treatment affects a sub-population of interest that is specified before the experiment takes place. However, this method is inappropriate when trying to identify the sub-population with large treatment effects. We thus replicate our base saving and borrowing analysis focusing on individuals in the top quartile of pre-treatment checking account balances who have a credit card. After all, pre-treatment checking account balances had high variable importance, as seen in Figure 4. For them, Table A6 shows that there is no treatment effect on savings or borrowing. Pre-treatment checking account balances are a coarse predictor of treatment effects, and they could be bundling together individuals with large and small responses to the treatment. We thus conclude that, on average, individuals in the top quartile of pre-treatment checking account balances have a large and significant response to the savings nudge, but individuals with a credit card who had pre-treatment checking account balances in the top quartile did not show a statistically significant increase in savings.

Comparing treatment effects across experimental strata thus appears inefficient when searching for the group with the largest effects because it is based on very coarse partitions of the covariate space. Instead, one could split the sample based on the ex-post observed treatment effects. For example, one could further split the sample of individuals in the top quartile of pre-treatment checking account balances by overlaying strata dimensions and ultimately calculating the treatment effects for each strata block.[6] However, we now show that such attempts to perform more granular partitions without adjusting for overfitting (as the causal forest does) leads to substantial bias.

6.4.2 Heterogeneity by Observed Treatment Effects at the Strata-Block Level

Specifically, we split the sample into 6,104 non-empty mutually exclusive groups defined by the interaction of all experimental strata. For each group, we calculate average treatment effects, and we assign to each observation in the group the average treatment effect of its group. We then split the sample into quartiles based on the average treatment effect assigned to each observation. The top quartile corresponds to the 25% of observations which belong to strata blocks with the highest observed average treatment effect. For them, we calculate treatment effects on checking account balances, credit card interest, and credit card balances regressing the corresponding outcome variable on a treatment indicator.

The results are presented in Table 10. Column 1 shows the number of observations included in this section of the analysis. Columns 2 to 4 show the treatment effects for individuals in strata blocks with the largest observed average treatment effects. We see that the increases in savings are very large. When considering all individuals, we find a 24% increase in savings. When considering only individuals with a credit card, we find a 44% increase in savings. When considering only individuals who have a credit card and who paid interest at baseline, we find a 52% increase. Additionally, these individuals show large decreases in borrowing, measured both in terms of interest (Column 3) and balances (Column 4). In contrast, Columns 5 to 8 show the results obtained from the causal forest. Column 5 shows the number of observations included in this part of the analysis. Column 6 shows that, as described before, the increases in savings are in the order of 2 to 6%. Columns 7 and 8 show the corresponding treatment effects on borrowing and borrowing

[6] We note that this is not the standard way in which people calculate heterogeneous treatment effects (and we are not aware of any study that has done so), but we use this as a limiting case of what would happen when trying to find heterogeneous treatment effects with a rich set of explanatory variables without adjusting for the risk of overfitting.

cost. These estimates, which are free of overfitting bias, are significantly smaller than the ones in Columns 2 to 4. The large overestimation we find is consistent with the discussion of Abadie et al. (2018), who also found that sample splitting reduces bias in the context of endogenous stratification.

In Table A7, we compare the overlap between the observations assigned to quartiles of predicted individual treatment effects calculated with the causal forest and the observations assigned to quartiles of the observed average treatment effects, calculated for each strata block. We conclude that there is little overlap.

We conclude that causal forests, or more generally double machine learning algorithms, are the appropriate method to identify sub-populations with the largest treatment effects. And we use this as our preferred method for identifying responsive sub-populations.

7 Explanations for the Credit Card Debt Puzzle

One important empirical finding is that some individuals who are paying credit card interest respond to savings nudges with substantial increases in savings. These savings are not used to pay off credit card debt over the two billing cycles subsequent to receiving the nudge (as documented in Table 6), thus exacerbating the co-holding of low-interest savings and high-interest debt. As we discussed, the literature proposes different explanations for this behavior.

In A.5, we outline a toy model to demonstrate that a null effect on credit card borrowing after an increase in savings is inconsistent with the predictions of rational models explaining the credit card debt puzzle, e.g., Telyukova (2013). In this model, the agent has an optimal plan for consumption and savings; if she needs to save more because of transaction purposes in the future, her optimal present consumption is not affected, and she will simply borrow more to maintain the same level of optimal present consumption.

Instead, in a second toy model, we propose mental accounting and rules of thumb as a potential explanation, following Haliassos and Reiter (2005). The theoretical idea is the following: an individual has a spending account (that is, her credit card) as well as an account for savings. On her credit card, she will spend up to some personal limit. Once she gets close to that personal limit, she feels constrained and can restrict her overspending more successfully. If this individual would take her savings and repay her credit card debt, she would feel unconstrained and rack up more credit card debt. Individuals thus prefer to hold liquid savings while simultaneously holding consumer debt instead of paying off their credit card debt. They separate these two accounts mentally to cope with their overspending and self-control problems. In the model, when the agent is nudged to save more, this money is placed in a different mental account. She then effectively allocates fewer resources between the present and future and adjusts her present consumption downwards instead of borrowing more.

The first toy model thus predicts that savings nudges should increase borrowing whereas that is not true in the second toy model. In our setting, we find that individuals do not respond with borrowing when nudged to save. We thus interpret this as evidence against transaction-convenience explanations of the credit card debt puzzle and in favor of preference-based explanations for it.

Additionally, we have two more pieces of evidence in favor of a preference-based explanation of the credit card debt puzzle:

First, in Figure 5, we plot the fraction of the co-holding puzzle population, defined as the fraction of individuals paying credit card debt interest and holding more than 50% of their income in their checking accounts, for each quartile of the savings score distribution. We can see that most co-holding individuals are in the highest quartile of the savings score distribution (approximately 40%). By focusing the analysis on the top quartile of the predicted treatment effects, we are capturing a relevant fraction of the puzzle population. This also speaks to the idea that co-holding is a psychological mechanism to exercise self-control, as it also makes individuals more susceptible to savings nudges.

Second, as mentioned, Message 4 "[...] you have the safest money box [...] reach your goals" carries a large average treatment effect and alludes to the safeness of the savings and reaching general goals. This message and its effect are in line with the behavioral hypothesis of mental accounting and constraining oneself to save more.

8 Conclusion

We estimate whether or not nudging individuals to save more has the unintended consequence of generating additional borrowing in high-interest unsecured consumer credit. We analyze the effects of a large-scale experiment in which 3.1 million bank customers were nudged to save more via bi-weekly SMS and ATM messages over 7 weeks. We uncover strong heterogeneities in the magnitude of the treatment effects. Compared to the control group, the subset of customers in the top quartile of the predicted treatment effect distribution increased their savings considerably. However, this increase in savings was not accompanied by an increase in rolled over high-interest unsecured consumer debt. We thus conclude that saving does not cause borrowing.

Our results are important to evaluate policy proposals to increase savings via nudges or more forceful measures. A vast number of policies are currently in place aimed at increasing savings (Benartzi et al., 2017). When policymakers or researchers evaluate these interventions, they often focus on the immediate savings outcome and do not consider other margins of adjustment (Beshears and Kosowsky, 2020).

Our results can also help us to understand the mechanism behind the so-called credit card debt puzzle, that is, when individuals hold credit card debt and savings simultaneously. We find that the individuals who paid credit card interest at baseline also responded to the savings nudges with significant increases in their liquid savings. But these increases in savings were not accompanied by increases in credit card debt or credit card debt repayment. A null increase in savings is inconsistent with the predictions of rational explanations of the credit card debt puzzle based on transaction purposes. We argue that this result is consistent with the idea that individuals hold savings and credit card debt simultaneously to deal with self-control problems via mental accounting, that is, they can maintain a rule of not touching their savings (that are parked in a separate mental account) but are simultaneously indebted due to overspending.

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Figures and Tables

Table 1: 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

This table presents summary statistics for all individuals in the experiment, and for the subset of individuals who have a credit card. For each individual, we consider information from the 6 months previous to the intervention. Monthly income, balances, and interest payments are in Mexican Pesos (MXN). 1 MXN = 0.047 USD.

Table 2: Covariate Balance

Variable	Control	Treatment	Difference
Age (Years)	44.73	44.72	−0.01
			(0.01)
Monthly Income ($)	13,506.49	13,498.98	−7.51
			(19.71)
Tenure (months)	81.75	81.66	−0.08
			(0.1)
Checking Acct. Balance ($)	19,322.25	19,392.22	69.98
			(76.91)
Credit Card Balance ($)	3,858.71	3,882.64	23.94
			(25.76)
Credit Card Limit ($)	17,203.11	17,164.27	−38.84
			(101.91)

This table presents a covariate balance test in which we estimate Equation 1 with different dependent variables (as specified in Column 1). Columns 2 and 3 present the average value of each dependent variable for Treatment and Control groups. Column 4 shows the coefficient of regressing the corresponding outcome on the treatment indicator with strata fixed effects. The p-value of an F-test from regressing the treatment indicator on all of the covariates with strata fixed effects is 0.1519. Monthly income and balances are in Mexican Pesos (MXN). 1 MXN = 0.047 USD.

Table 3: 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

This table presents statistics about credit card borrowing and checking account balances for individuals who have a credit card and pay interest, holding different levels of checking account balances over income. Individuals are split into deciles of checking account balances over income. For observations in each decile group, we first present the average of checking account balances over income as well as the fraction of individuals with a non-zero credit card balance and the fraction of individuals paying credit card interest. We then focus on individuals who are paying credit card interest. For them, we present average checking account balances, average credit card balances, and average monthly interest charges. Monthly balances and interest charges are in Mexican Pesos (MXN). 1 MXN = 0.047 USD.

Table 4: Individuals Paying Credit Card Interest With Checking Account Balances Over or Below 50% of Their Income

Variable	No-Puzzle (Less than 50%)	Puzzle (50% or more)	Difference
Age (Years)	42.72	48.03	5.32
			(0.08)
Monthly Income ($)	19,602.03	21,339.81	1737.78
			(112.84)
Tenure (months)	100.89	134.53	33.64
			(0.44)
Checking Acct. Balance ($)	29,243.58	65,127.67	35884.1
			(423.32)
Credit Card Balance ($)	19,855.37	44,921.26	25065.89
			(205.6)
Credit Card Limit ($)	96,785.91	163,643.28	66857.37
			(823.46)
$P(Interest_t > 0 \mid Interest_{t-1} > 0)$	0.82	0.86	0.03
			(0.0014)

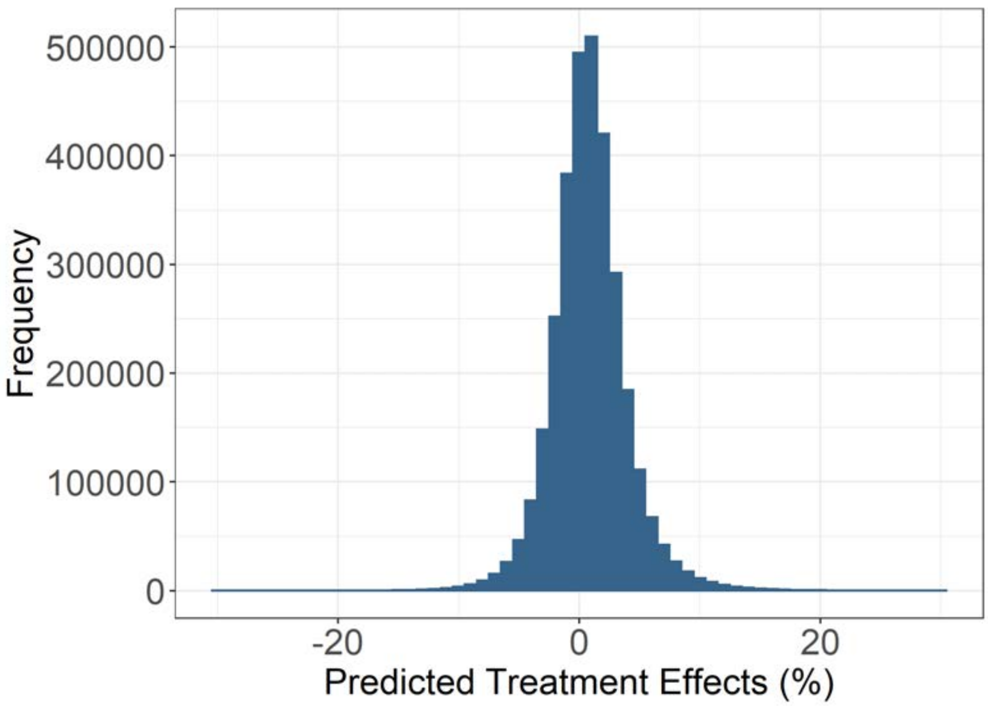
This table presents simple means of each variable for individuals that fall or not into our credit card debt puzzle definition. We say that an individual falls into the credit card debt puzzle definition if she is paying credit card interest while holding average daily balances in her checking account that are higher than 50% of her income. Monthly income and balances are in Mexican Pesos (MXN). 1 MXN = 0.047 USD.

Table 5: Overall Treatment Effects of the Intervention

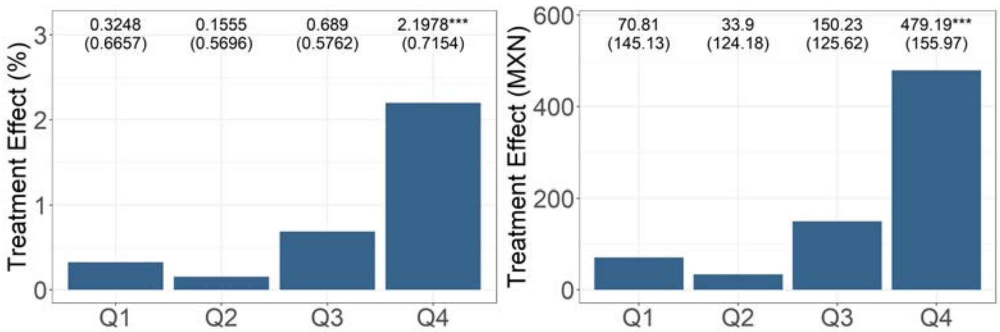
	All Individuals			Individuals with a Credit Card	
	(1)	(2)	(3)	(4)	(5)
	Log of Checking Acct. Balance +1	Log of Checking Acct. Balance +1	Log of Checking Acct. Balance +1	Log of Checking Acct. Balance +1	Log of Credit Card Interest +1
Any treatment	0.006*			0.014**	-0.005
	(0.004)			(0.007)	(0.004)
Msg1		0.007			
		(0.005)			
Msg2		0.008*			
		(0.005)			
Msg3		0.006			
		(0.005)			
Msg4		0.006			
		(0.005)			
Msg5		0.002			
		(0.005)			
Msg6		0.007			
		(0.005)			
Msg7		0.006			
		(0.005)			
Bi-weekly			0.006		
			(0.004)		
Weekly			0.007*		
			(0.004)		
Observations	3054503	3054503	3054503	362223	362223
Mean of Dep. Var in Control Group	17393.63	17393.63	17393.63	24331.63	213.84

This table presents the results of estimating Equation (1) with different outcomes and with different treatment definitions. Observations are at the user level. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Distribution of Predicted Treatment Effects

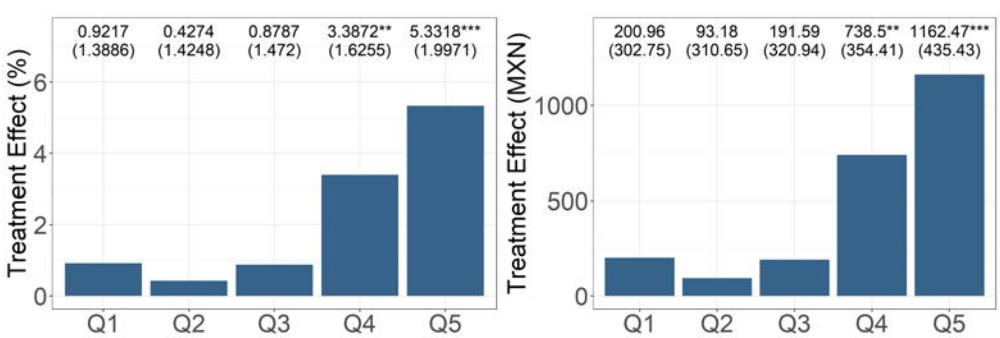


This graph shows the distribution of predicted treatment effects. We estimate a causal forest that predicts for each individual in treatment and control groups an individual treatment effect. We first estimate the causal forest using 161 pre-treatment variables and then restrict to the 52 most important ones in the second estimation (results shown here). The 52 variables are: ADB Checking t-1, Payroll Deposits (amount) t-2, ADB Checking t-2, ATM Withdrawal (Amount) t-2, ADB Checking t-3, Payroll Deposits (amount) t-5, Tenure in Job (months), Debit Card Spending t-5, Payroll Deposits (amount) t-3, ATM Withdrawal (Amount) t-4, Direct Profit to the Bank, Tenure with Bank (months), ATM Withdrawal (Amount) t-3, Debit Card Spending t-3, ATM Withdrawal (Amount) t-6, ADB Checking t-2, ATM Withdrawal (Amount), Payroll Deposits (amount), ADB Checking t-1, Debit Card Spending t-2, ATM Withdrawal (Amount) t-1, ADB Checking t-3, Payroll Deposits (amount) t-4, Percentage of CC Limit used t-5, Mthly Income, Payroll Deposits (amount) t-1, Tenure with CC (months), Percentage of CC Limit used t-3, CC Spending, Percentage of CC Limit used t-6, ATM Withdrawal (Amount) t-5, Percentage of CC Limit used t-4, Percentage of CC Limit used, Payroll Deposits (amount) t-6, Debit Card Spending t-6, CC Spending in Others, CC Spending in Services, CC Spending in Food, Debit Card Spending t-4, Total Balance of internal and external Credits, Percentage of CC Limit used t-2, Percentage of CC Limit used t-1, Debit Card Spending, Debit Card Spending t-1, CC Spending in Personal Items, Non-Banorte CC Balance t-2, Debit and CC Spending in Luxury Items, Non-Banorte CC Balance t-4, CC Spending in Transportation, Non-Banorte CC Balance, Non-Banorte CC Balance t-6, and CC Spending in Entertainment. ADB refers to average daily balances, all variables are monthly.



(a) average treatment effect (% Change) (b) average treatment effect (MXN)

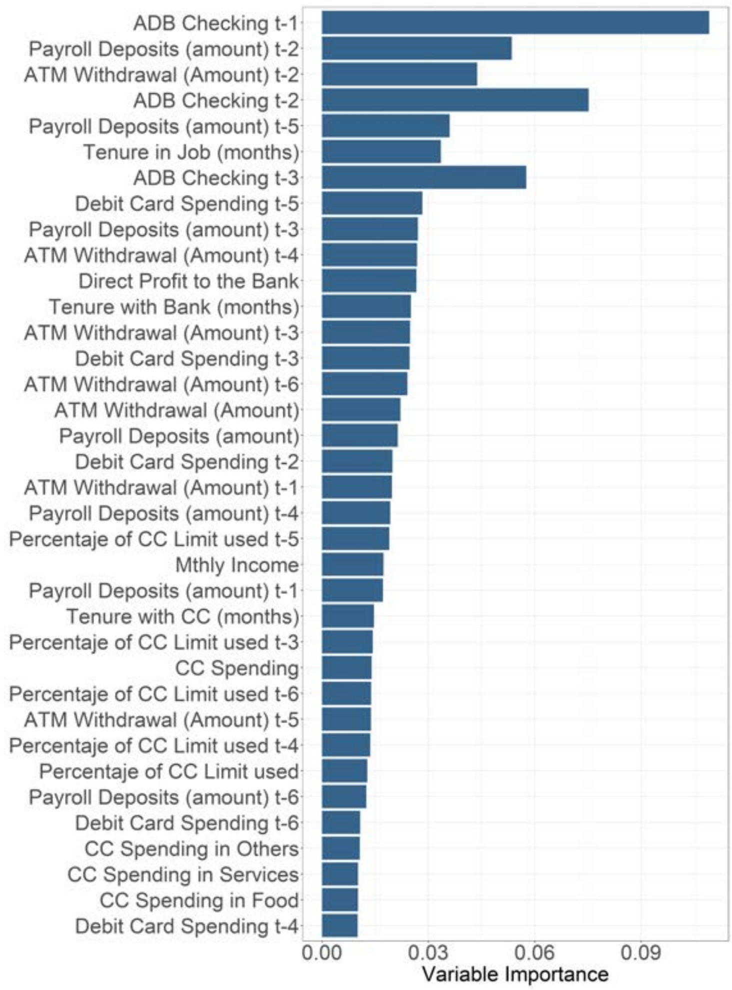
Figure 2: Treatment effects on checking account balances, as a function of predicted individual treatment effects by the causal forest. Individuals are split in to quartiles of treatment effects on savings, based on the score generated by the causal forest.



(a) Treatment Effect (% Change) (b) Treatment Effect (MXN)

Figure 3: Treatment effectd on checking account balances, as a function of predicted individual treatment effects by the causal forest for individuals in the top quartile of the predicted treatment effect distribution. Individuals in the top quartile of the predicted treatment effect distribution are split in to quintiles of predicted treatment effects, based on the score generated by the causal forest.

Figure 4: Variable Importance: Causal Forest



This graph shows the variable importance of the 27 most important variables used in the estimation of the causal forest. Variable importance indicates how often the given variable was used to select splits in the multiple trees of the causal forest. We first estimate the causal forest using 161 pre-treatment variables and then restrict to the 52 most important ones in the second estimation (of which the 27 most important ones are shown here). The 52 variables are listed in the caption of Figure 1. ADB refers to average daily balances, all variables are monthly.

Table 6: Treatment Effects on Saving and 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 of 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 of 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						

This table shows average treatment effects on a selection of variables related to saving and borrowing behavior. Column 1 shows the treatment effect on ln(Checking Account Balances +1). Columns 2 and 3 show the treatment effect on ln(Credit Card Balances) considering only credit cards held at Banorte and all credit cards reported to the credit bureau respectively. Columns 4 and 5 show the treatment effect on ln(Credit Card Interest +1) and a binary variable indicating if an individual is paying interest on her credit card, respectively. Column 6 shows the treatment effect on ln(Credit Card payments). In all cases we consider individuals in the top quartile of the predicted treatment effect distribution stemming from the causal forest. Panel A considers all individuals who have a credit card. Panel B considers only individuals who have a credit card and incurred interest at baseline (in the 6 months previous to the intervention). Average treatment effects are calculated with the AIPW method. The increase in savings, expressed in MXN, is calculated by multiplying the ATE and the Mean of Checking Account Balances in the Control Group. Upper confidence intervals, expressed in MXN, are calculated as (point estimate + 1.96*Standard Error)*Mean of Dep. Var in Control Group. [1]The upper confidence interval for the probability of incurring credit card interest during the treatment period is expressed in percentage points and not in MXN (point estimate + 1.96*Standard Error). Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Treatment Effects On Deposits, ATM Withdrawals, and Spending

	(1)	(2)	(3)
Dep.Var.	Ln Deposits	Ln ATM Withrawals	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

This table considers all individuals with credit cards in the top quartile of the distribution of the predicted treatment effect distribution stemming from the causal forest. Deposits, withdrawals, credit card spending, and debit card spending are all monthly. Spending with Credit or Debit Card is defined as the sum of debit or credit card store or online purchases. Interest payments are in Mexican Pesos (MXN). 1 MXN = 0.047 USD. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Treatment Effects on Saving and Credit Card Borrowing for Individuals with Banorte as their Main Bank

	(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					

This table shows average treatment effects on a selection of variables related to saving and borrowing behavior. Column 1 shows the treatment effect on ln(Checking Account Balances +1). Columns 2 and 3 show the treatment effect on ln(Credit Card Balances) considering only credit cards held at Banorte and all credit cards reported to the credit bureau respectively. Columns 4 and 5 show the treatment effect on ln(Credit Card Interest +1) and a binary variable indicating if an individual is paying interest on her credit card respectively. Column 6 shows the treatment effect on ln(Credit Card payments). In all cases we consider individuals in the top quartile of the predicted savings effect distribution stemming from the causal forest and for whom Banorte is their main bank. We say that Banorte is the main bank for individuals who receive their payroll at Banorte and who do not have credits with other banks according to credit bureau records. Panel A considers all individuals who have a credit card. Panel B considers only individuals who have a credit card and incurred interest at baseline (in the 6 months previous to the intervention). Average treatment effects are calculated with the AIPW method. The increase in savings, expressed in MXN, is calculated by multiplying the ATE and the Mean of Checking Account Balances in the Control Group. Upper confidence intervals, expressed in MXN, are calculated as (point estimate + 1.96*Standard Error)*Mean of Dep. Var in Control Group. [1]The upper confidence interval for the probability of incurring credit card interests during the treatment period is expressed in percentage points and not in MXN (point estimate + 1.96*Standard Error). Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 9: 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?

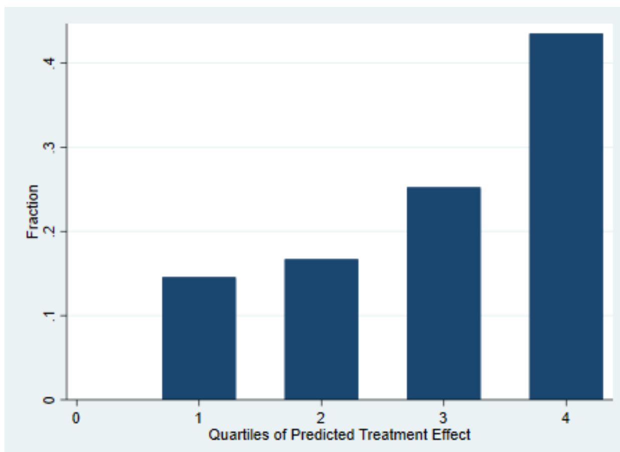
This table presents heterogeneous treatment effects by experimental strata. Treatment effects are estimated in each column with the following OLS regression: $y_i = \alpha_s + Treatment_i + Group_{ij} + Treatment * Group_{ij}$ where $alpha_s$ represents strata fixed effects and $Group_{ij}$ is a dummy variable that takes the value of 1 when individual i belongs to Group j. In each column the groups are defined over a different variable which in turn defines the experimental strata. In all cases we consider all 3.1 million observations at the user level. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 10: 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

		Top Quartile of Individuals Observed Average Treatment Effects				Top Quartile of Individuals 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

This table shows average treatment effects on a selection of variables related to saving and borrowing behavior, for clients in groups with the highest ex-post observed average treatment effects or for clients with the highest individual treatment effects predicted by the causal forest. For columns 1 to 4, we split the sample into 6,104 mutually exclusive groups defined by the interaction of all experimental strata. For each group we calculate average treatment effects. We then assign to each observation in the group the average treatment effect of its group. We then split the sample into quartiles based on the average treatment effect assigned to each observation. The top quartile corresponds to the 25% of observations, which belong to strata blocks with the highest observed average treatment effect. For them, we calculate treatment effects on checking account balances, credit card interest, and credit card balances regressing the corresponding outcome variable on a treatment indicator and strata-block fixed effects. We do the same in columns 5 to 8 but for the top quartile of individuals with the highest individual treatment effects as predicted by the causal forest. Robust standard errors in parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure 5: Distribution of the Puzzle Group by Quartiles of Predicted Treatment Effects



This graph presents the distribution of individuals in the puzzle group, across quartiles of predicted treatment effects. The puzzle group is defined as the set of individuals who carry checking account balances of at least 50% of their income, and also pay credit card interest. Predicted treatment effects are calculated with the causal forest.

A Appendix

A.1 Causal Forests and The Generalized Random Forest Algorithm

This appendix elaborates on the details of the algorithm for causal forests, which are different from off-the-shelf machine learning methods in three ways:

First, in addition to dividing data in training and test samples, causal forests divide the training data further in two sub-samples: a splitting sample and an estimation sample. The splitting sample is used to grow trees (2,000 in our case) and the estimation sample is used to estimate the treatment effects. This honesty is crucial for causal forests to attain consistent estimation of treatment effects, and similar strategies are implemented in other recently developed methods for causal inference with machine learning (Chernozhukov et al., 2018).

Second, causal forests use a splitting rule that tackles treatment effect heterogeneity directly. This is, each tree splits into two children nodes where heterogeneity in treatment effects is maximized. Thus, causal forests are tailored to find sub-populations with different treatment effects.

Finally, causal forests calculate treatment effects ensuring that the treatment indicator is orthogonal to all covariates for all observations. The algorithm computes estimates of propensity scores and outcomes for treatment and control group by training separate regression forests. Then the algorithm performs sample splits to identify heterogeneous treatment effects on residual treatments and outcomes. To calculate the average treatment effect on a sub-population of interest, the algorithm plugs the individual predictions of the causal forest into an Augmented Inverse Probability Weighting Estimate (AIPW) that combines models of outcome regressions with models of treatment propensity to estimate causal effects.[7]

We use the generalized random forest package in R, to estimate our causal forests. This package allows for estimation of causal forests, but also allows for estimation of other forest-based methods for causal inference. To do so efficiently, this package involves an approximate gradient based loss criterion (instead of the exact loss criterion described above to build intuition), aggregates the

[7]This estimator is locally efficient and is known as a “doubly robust estimator" since it is consistent whenever the model of treatment propensity *or* the model of expected outcomes are correctly specified.

results of the n trees with one single weighted estimation of treatment effect, instead of averaging n estimations of treatment effects. The mechanics of the algorithm is as follows:

1. The first step is to compute estimates of propensity scores for the treatment and marginal outcomes conditional on covariates, by training separate regression forests and performing predictions (fitted values) for each observation. These predictions are used to calculate residuals, which will be referred to as orthogonalized outcomes and orthogonalized treatment status.

2. For each tree, a random subsample with 50% of the database is drawn (training sample).

3. The trainning sample is further split into a splitting subsample and an estimation subsample (50-50 by default).

4. A single initial root node is created for the splitting sample, and child nodes are split recursively to form a tree. Each node is split using the following algorithm:

   (a) A random subset of variables are selected as candidates to split on. [8]

   (b) For each of these variables, we look at all of its possible values and consider splitting into two child nodes based on a measure of goodness of split, determined to maximize the heterogeneity in treatment effect estimates across nodes.

   (c) All observations with values for the split variable that are less than or equal to the split value are placed in a new left child, and all examples with values greater than the split value are placed in a right child node.

5. The estimation sample is used to populate the leaf nodes of the tree. Each observation is 'pushed down' the tree, and assigned to the leaf in which it falls.

6. Steps 2 to 5 are repeated 2,000 times, that is we estimate 2,000 trees.

[8] By default $min\{sqrt(p) + 20, p\}$ variables are sampled, where p is the total number of variables in the dataset. In our analysis, $p = 161$ the first time we run the algorithm, and $p = 52$ the second time we run the algorithm, and we use 32 or 27 candidate variables in each split.

7. Treatment effects are predicted for each observation on a test dataset (potentially the full dataset) as follows:

   (a) Each test observation is pushed down each tree to determine what leaf it falls in. Given this information, a list with neighboring observation in each tree leaf is created (the neighbors come from the estimation sample of each tree). Each neighbor observation is weighted by how many times it fell in the same leaf as the test observation.

   (b) Treatment effects are calculated using orthogonalized outcomes and treatment status of the neighbor observations.

8. In addition to personalized treatment effects, the package allows for estimation of average treatment effects across all observations in a dataset, or arbitrary subsamples of it. This is done with an AIPW estimator, that ensures balance across all covariates in the group, using the treatment propensities estimated in step 1.

A.1.1 Calibration Test

We formally test for whether heterogeneity in individual predictions is associated with heterogeneity in treatment effects using the “calibration test" described in Athey and Wager (2019). This test seeks to fit conditional average treatment effects as a linear function of the causal estimates of the causal forest and computes the best linear fit of the treatment effects using the forest prediction as well as the mean forest prediction as the sole two regressors. A coefficient of 1 for ‘mean.forest.prediction’ suggests that the mean forest prediction is correct, The p-value of the ‘differential.forest.prediction’ coefficient acts as an omnibus test for the presence of heterogeneity: If the coefficient is significantly greater than 0, then we can reject the null of no heterogeneity. Table A1 shows the results of the calibration test. We find that the coefficient measuring the ability of the forest to predict heterogeneities in treatment effects is positive and significant. We conclude that the individual level treatment effect predictions are a valid linear predictor for heterogenous treatment effects: larger predicted treatment effects (score value) indeed result in larger treatment effects.

Table A1: Calibration Test for Evaluation Of The Quality Of The Causal Forest

	estimate	std.error	t-statistic	p.value
mean.forest.prediction	1.0286	0.3732	2.7564	0.0029
differential.forest.prediction	0.3470	0.1280	2.7132	0.0033

This test computes the best linear fit of the target estimand using the forest prediction as well as the mean forest prediction as the sole two regressors. A coefficient of 1 for 'mean.forest.prediction' suggests that the mean forest prediction is correct. The p-value of the 'differential.forest.prediction' coefficient also acts as an omnibus test for the presence of heterogeneity: If the coefficient is significantly greater than 0, then we can reject the null of no heterogeneity.

A.1.2 Comparison Between Top and Bottom Quartiles of the Distribution of Predicted Treatment Effects

Table A2: 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 ($)	12,924.95	14,655.87	1730.93
			(23.45)
Tenure (months)	73.95	87.14	13.19
			(0.12)
Checking Acct. Balance ($)	15,791.01	21,340.95	5549.94
			(84.40)
Credit Card Balance ($)	2,688.76	6,391.2	3702.43
			(29.36)
Credit Card Limit ($)	10,402.82	28,641.07	18238.25
			(117.17)

This table presents simple means for individuals in the top and bottom 25% of the distribution of predicted topment effects on the log of checking account balances. We test the significance of the differences with a t-test. Income and balances, are in Mexican Pesos (MXN). 1 MXN = 0.047 USD.

A.2 Heterogeneous Treatment Effects: Additional Tables and Figures

Table A3: Treatment Effects by Quintiles of Predicted Treatment Effects for Individuals with Credit Cards in the Top Quartile of the Predicted Treatment Effect Distribution

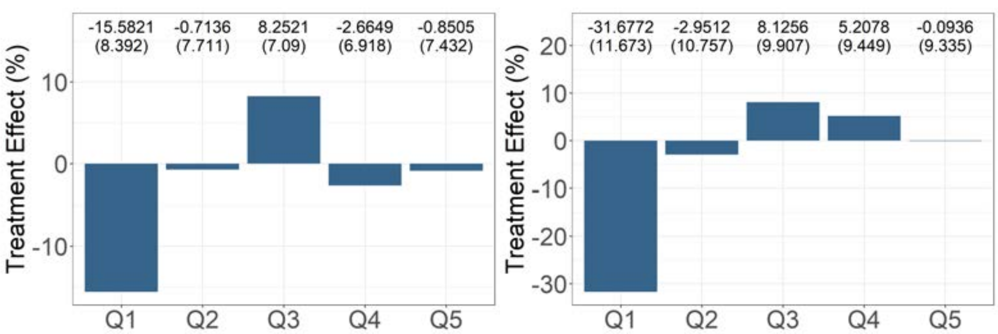
	Q1	Q2	Q3	Q4	Q5
Panel A: Treatment Effect on Checking Account Balances					
ATE Ln Checking Account Balance	0.09***	0.09***	0.05*	0.02	0.06*
	(0.0379)	(0.039)	(0.0357)	(0.0346)	(0.0478)
Mean Checking Account Balance in Control Group (MXN)	30112	28471	32456	36392	30001
Panel B: Treatment Effect on Credit Card Balances					
ATE Ln Credit Card Debt Balance	-0.0179	-0.00834	-0.1053***	0.0072	0.0032
	(0.0159)	(0.0081)	(0.0350)	(0.0081)	(0.0036)
Mean Checking Account Balance in Control Group (MXN)	50169.96	38223.04	43398.37	34334.49	55121.73
Panel C: Treatment Effect on Credit Card Interest					
ATE Ln Credit Card interest)	-0.16	-0.01	0.08	-0.03	-0.01
	(0.0839)	(0.0771)	(0.0709)	(0.0692)	(0.0743)
Mean Credit Card Interest in Control Group (MXN)	200.6	214.5	222.7	233.2	272.9
Panel D: Treatment Effect on Probability of Incurring Credit Card Interest					
ATE Probability of Incurring Credit Card Interest	-0.0213	0.0032	0.0081	-0.0099	-0.0008
	(0.0139)	(0.0127)	(0.0115)	(0.0109)	(0.0115)
Fraction Incurring Credit Card Interest in Control Group	0.3826	0.3970	0.3963	0.4060	0.4882

Interest payments are in Mexican Pesos (MXN). 1 MXN = 0.047 USD. This table considers individuals in the top quartile of the distribution of the predicted treatment effect stemming from the causal forest who have a credit card. We further split them into quintiles and report the average treatment effects on savings, interest payments, and probability of paying interests for individuals. Average treatment effects are calculated with the AIPW method. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table A4: Treatment Effects by Quintile of Predicted Treatment Effects for Individuals with Credit Cards who Paid Credit Card Interest at Baseline

	Q1	Q2	Q3	Q4	Q5
Panel A: Treatment Effect on Checking Account Balances					
ATE Ln Checking Account Balance	0.1**	0.14***	0.02	-0.01	0.06
	(0.052)	(0.0568)	(0.051)	(0.0493)	(0.0658)
Mean Checking Account Balance in Control Group (MXN)	22934	22375	25050	26323	19473
Panel B: Treatment Effect on Credit Card Balances					
ATE Ln Credit Card Debt Balance	-0.0116	-0.0142	0.0003	-0.0606***	-0.0161
	(0.0105)	(0.0114)	(0.0084)	(0.0268)	(0.0122)
Mean Checking Account Balance in Control Group (MXN)	63517.78	48032.82	41684.96	52989.8	63553.46
Panel C: Treatment Effect on Credit Card Interest					
ATE Ln Credit Card interest	-0.32	-0.03	0.08	0.05	0.00
	(0.1167)	(0.1076)	(0.0991)	(0.0945)	(0.0934)
Mean Credit Card Interest in Control Group (MXN)	387.8	396.4	411.1	418.7	440.0
Panel D: Treatment Effect on Probability of Incurring Credit Card Interest					
ATE Probability of Incurring Credit Card Interest	-0.0388	0.007	0.0066	-0.0013	-0.0025
	(0.0186)	(0.0169)	(0.0155)	(0.0145)	(0.0138)
Fraction Incurring Credit Card Interest in Control Group	0.6845	0.6886	0.6909	0.6977	0.7581

Interest payments are in Mexican Pesos (MXN). 1 MXN = 0.047 USD. This table considers individuals in the top quartile of the distribution of the predicted treatment effect stemming from the causal forest who have a credit card and pay credit card interest at baseline (in the 6 months previous to the intervention). We further split them into quintiles and report average treatment effects on savings, interest payments and probability of paying interests for individuals. Average treatment effects are calculated with the AIPW method. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.



(a) Individuals without Interest Charges (b) Individuals with Interest Charges

Figure A6: Treatment effects on credit card interest charges for individuals in the top quartile of the predicted treatment effect stemming from the causal forest who do or do not pay interest at baseline (in the 6 months previous to the intervention) split into quintiles, based on the score generated by the causal forest.

A.3 Saving and Borrowing by Treatment Message

To explore the relation between borrowing and savings across each of the seven messages included in the experiment, we focus on the 126,458 individuals in the top quartile of predicted treatment effects who had a credit card. For them, we calculate the average treatment effect on saving and borrowing of receiving each specific treatment message.

Table A5: Treatment Effects on Saving and Credit Card Borrowing: Individuals in the Top Quartile of Predicted Treatment Effects who Have a Credit Card

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var	Ln Checking Account Balance	Increase in Savings (MXN)	Ln Credit Card Interest	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	0.0265 (0.0228)	839.56	-0.0055 (0.0336)	13.90	0.017	38802
Msg 2	0.1170*** (0.0228)	3705.46	-0.0183 (0.0336)	10.96	0.003	38775
Msg 3	0.0413* (0.0228)	1306.86	-0.0142 (0.0336)	11.90	0.009	38822
Msg 4	0.0979*** (0.0229)	3102.57	-0.0256 (0.0339)	9.41	0.003	38700
Msg 5	0.0623*** (0.0237)	1974.71	-0.0348 (0.0350)	7.79	0.004	38803
Msg 6	0.0338 (0.0253)	1069.25	-0.0291 (0.0374)	10.20	0.010	38752
Msg 7	0.042 (0.0298)	1330.94	0.008 (0.0440)	21.72	0.016	38590

This table shows average treatment effects on a selection of variables related to saving and borrowing behavior. Column 1 shows the treatment effect on ln(Checking Account Balances +1). Column 2 shows the treatment effect on ln(Credit Card Interest +1). In all cases we consider individuals in the top quartile of the predicted treatment effect distribution stemming from the causal forest who had a credit card. Average treatment effects are calculated with the AIPW method. The increase in savings, expressed in MXN, is calculated by multiplying the ATE and the Mean of Checking Account Balances in the Control Group (31,681.46 MXN). Upper confidence intervals, expressed in MXN, are calculated as (point estimate + 1.96*Standard Error)*Mean of Dep. Var in Control Group. The Mean of Dep. Var in Control Group for credit card interest is 213.39 MXN. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

A.4 Comparison of Sorting Methods for Heterogeneous Treatment Effects

We first estimate the average treatment effect on saving and borrowing outcomes for individuals in the top quartile of pre-treatment checking account balances who have a credit card.

Table A6: Treatment Effects on Saving and Borrowing for Individuals in the Top Quartile of Pre-Treatment Checking Account Balances Who Have a Credit Card

	(1) Ln (Checking Account Balance +1)	(2) Ln (Credit Card Interest +1)
Any Treatment	0.014	-0.012
	(0.009)	(0.008)
N	118,706	118,706
Mean of dependent variable (MXN)	67791.11	184.23

Treatment effects are estimated with equation 1. We consider observations in the top quartile of pre-treatment checking account balances, who have a credit card. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Next, we compare the overlap between observations assigned to quartiles of predicted individual treatment effects calculated with the causal forest, and observations assigned to quartiles of the observed average treatment effects, calculated for each strata block. In Table A7, the rows represent quartiles based on observed average treatment effect for each strata block. The columns represent quartiles of individual treatment effects predicted by the causal forest. A perfect overlap would have all observations across the diagonal. We can see that is not the case: out of the 763,625 observations assigned by the causal forest to the top quartile of predicted treatment effects, only 201,992 are in strata blocks on the top quartile of observed average treatment effects.

Table A7: Distribution of Observations According to the Average Treatment Effect of Strata Blocks and Predicted Treatment Effects at the Individual Level

Rows: Sorting Based on Observed average treatment effects

Columns: Sorting Based on Predicted Individual Treatment Effects

	1	2	3	4	Total
1	186,989	188,445	192,417	198,695	766,546
2	202,611	191,334	185,986	181,425	761,356
3	191,371	197,792	192,344	181,583	763,090
4	182,655	186,055	192,879	201,922	763,511
Total	763,626	763,626	763,626	763,625	3,054,503

This table shows the distribution of observations according to the observed average treatment effect of their strata blocks, and their individual predicted treatment effect, as returned by the causal forest. The rows represent quartiles based on observed average treatment effect for each strata block. For them we split the sample into 6,104 mutually exclusive groups defined by the interaction of all experimental strata. For each group we calculate average treatment effects, and we assign to each observation in the group the average treatment effect of its group. We then split the sample into quartiles based on the average treatment effect assigned to each observation. The columns represent quartiles of individual treatment effects as predicted by the causal forest. For each observation, the causal forest returns a predicted treatment effect, which we split into quartiles. The across rows and columns adds up to the 3,054,503 observations included in the analysis. We can see that there is poor overlap with these two sorting methods. For example, the predictions of the top quartile according to the causal forest are split across strata groups in all four quartiles of observed average treatment effects, and viceversa.

A.5 Two Toy Models Illustrating the Predictions of Rational versus Behavioral Theories of the Co-Holding Puzzle

We now outline two toy models to rationalize the co-holding puzzle. The first is based on Telyukova (2013) and Kaplan and Violante (2014) and rationalizes co-holding with transaction convenience constraints. The second model rationalizes co-holding with behavioral preferences and self-control problems and is based on the theories in Laibson et al. (2007), Haliassos and Reiter (2005), and Bertaut et al. (2009).

Transaction-convenience model:

We assume a simple model with two periods, one consumption good, and log utility. Individuals receive an endowment x_1 in period 1 and consume $c_{1,2}$ in periods 1 and 2. In addition, they must hold a certain amount of cash x for transaction purposes $x_1 - c_1 > x$, and they may borrow b_1 in period 1 for additional consumption. Additionally, we assume that the agent discounts future utility by a factor δ.

$$max\{log(c_1 + b_1) + \delta log(x_1 - c_1 - (1 + r)b_1)\}$$

subject to $x_1 - c_1 > x$ and $b_1 < b$.

Suppose $r = 0$ and $b = \infty$, then the optimal solution for c_1^* is:

$$c_1^* = \frac{1}{\delta + 1} x_1 \text{ and } b_1 = 0 \text{ if } x_1 - c_1^* \geqq x$$

$$\text{and if } x_1 - c_1^* < x \text{ then } c_1^* = \frac{1}{\delta + 1} x_1 \text{ and } b_1 = c_1^* + x - x_1.$$

It is clear that if we increase the amount of cash x held for transaction-convenience reasons, that is, , by encouraging individuals to save, we increase borrowing b_1 in the rational model.

We note that the assumption of r=0 is only for simplicity, but is not required to lead to the result that savings increases borrowing. The intuition carries forward with r>0, and the results are available from the authors upon request.

Self-control model:

We start from the same setting as in the transaction-convenience model but instead of having a transaction-convenience constraint, we assume that when individuals hold a certain amount of cash dedicated for savings, x. Cash x is in a separate mental account that is not considered at the time of consumption decisions. Therefore, x gets subtracted from the original endowment x_1 available for consumption, and does not enter the consumption decision of the agent more than as an exogenous constraint in the available resources. As an alternative interpretation, we can think of an amount of money, x, that one spouses hides from the other, or that the planner-self is successfully able to remove from spender-self decision problem. In addition, we assume that the agent is impatient: that is, discounts future utility by an additional factor β.

$$max\{log(c_1 + b_1) + \beta\delta log(x_1 - x - c_1 - (1 + r)b_1)\}$$

subject to $b_1 < b$. Suppose $r = 0$ and $b = \infty$, then the optimal solution for c_1^* is:

$$c_1^* = \frac{1}{\beta\delta + 1}(x_1 - x) \text{ and } b_1 = 0 \text{ (independent of } x\text{).}$$

In conclusion, if we increase the amount of money that the saver self/spouse hides from the spender self/spouse, x, we decrease c_1 but nothing happens to borrowing b_1.

As before, we note that the assumption of r=0 is only for simplicity, but is not required to lead to the result that savings increases borrowing. The intuition carries forward with r>0, and the results are available from the authors upon request.