Does Saving Cause Borrowing?

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Abstract

We study whether or not nudging individuals to save more has the unintended consequence of 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. Using Machine Learning methods for causal inference, we build a score to sort individuals according to their predicted treatment effect. We then focus on the individuals in the top quartile of the distribution of predicted treatment effects who have a credit card and were paying interest at baseline. Relative to their control, this group increased their savings by 5.7% on average or 61.84 USD per month. At the same time, we can rule out increases in credit card interest larger than 1.25 USD with 95% statistical confidence. We thus estimate that for every additional dollar of savings, individuals incur less than 2 cents in additional borrowing cost. This is a direct test test of the predictions of rational co-holding models, and is an important result to evaluate policy proposals to increase savings via nudges or more forceful measures.

Keywords: savings nudges, credit card borrowing, heterogeneous treatment effects, causal forest.

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1 Introduction

The 2019 American Household Credit Card Debt Study estimates the total revolving credit card debt owed by an average US household to be 7,104 USD, which amounts to a total of 466 billion USD. Such large high-interest debt holdings over longer periods of time are very hard to rationalize in standard economic models. For example, Laibson et al. (2003) argue that such debt holdings constitute "a debt 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. Kaplan and Violante (2014) provide an explanation for the amount of credit that we see in the US: credit card borrowing is a rational response to illiquid savings in retirement accounts or other assets. To date, however, limited evidence exist on whether or not individuals respond with borrowing when they are nudged or forced to save. Clearly, however, this question is of central importance for policy-makers and researchers alike to evaluate whether savings nudges or forced savings should be implemented.

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% (Telyukova, 2013). This simultaneous holding of savings and consumer credit is known as the “credit card debt or co-holding puzzle.” 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) provides an explanation for this behavior by arguing that households need cash for transaction purposes, and they optimally choose to finance their cash holdings with credit card debt. Instead Haliassos and Reiter (2005)

argue that individuals want to constrain their impatient selves or spouses by keeping them indebted while simultaneously building their savings. A key distinctive prediction between rational co-holding models and behavioral models is that in the former case, increases in savings would cause increases in debt (since households optimally finance their liquidity needs using credit card debt). In contrast, behavioral co-holding predicts that increases in savings should not be reflected in borrowing as the two are distinct mental accounts. In this paper, we test whether indeed additional savings causes additional borrowing to distinguish between these two theories for co-holding credit card debt and savings.

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 for individuals that were already paying credit card interest. This question is important to understand the origins of the credit card debt puzzle and to evaluate policy proposals designed to increase savings. 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 by one of the largest banks in Mexico, Banorte. The bank ran a randomized experiment with 3,054,438 customers out of which 374,893 customers were randomly selected to be in a control group. Clients in the treatment group received ATM and SMS messages that suggested them to save and had been proven impactful in previous experiments ran by the same bank. The intervention lasted 7 weeks from September 13 to October 27, 2019.

To focus the analysis on individuals that indeed responded to the savings nudge, we use machine learning techniques to predict individual treatment effects and study the behavior of individuals with the largest predicted treatment effects. Specifically, we estimate a causal forest model as discussed in Athey and Imbens (2015), Hitsch and Misra (2018),

and Athey et al. (2019). The algorithm calculates heterogeneous treatment effects for different sub-populations and then predicts for each individual an estimated average treatment effect using a rich set of pre-treatment covariates. In turn, we focus on the subsample of customers that are in the top quartile of the predicted treatment effect distribution and 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 a "reverse endogeneity" problem that would arise if we were to select individuals based on their observed treatment effect. Selecting individuals for having the largest observed treatment effect would be problematic: after all, something else could have happened to this subpopulation that drove their responses in saving and may impact borrowing too. 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 groups and cross-validating the results in another test subsample). This procedure eliminates the possibility that some pre-treatment covariates, by chance, predict a large treatment effect (and also affect borrowing). In turn, we are confident that the the sub-populations with the largest predicted treatment effects have indeed a large response in savings, and we can thus look at borrowing as another outcome variable for the subgroup of individuals with the largest predicted treatment scores for savings.

More specifically, we estimate a causal forest with 2,000 causal trees. To estimate each causal tree, the algorithm splits the sample in to two parts: a trainning and a test sample. The training sample is further split in two subsamples: a splitting sample, and

an estimation sample. The splitting sample is used to identify splitting rules where the estimated treatment effect differs the most. Then, it uses the rules obtained from the splitting sample to calculate the treatment effects in the estimation sample with an Augmented Inverse Probability Weighted Estimator (AIPW) for orthogonalization – the AIPW estimator ensures that characteristics of each sub-population are balanced between treatment and control groups. Both the splitting rule and treatment effect estimates go through a cross validation procedure in the test sample. The algorithm gives a consistent estimate of heterogeneous treatment effects when there is unconfoundedness. The multiple sampling method rules out that by chance people with some characteristics just ended up having higher savings during that period (because they would not be in all 2,000 random samples and would therefore not be consistently showing large effects but only sometimes).

We thus estimate the responses in saving and borrowing for the top quartile of predicted treatment effect individuals that have a credit card to then also look at their borrowing. For this population, the increase in savings estimate is 6.01% on a baseline savings of 31,681 MXN in their control group (1,489 USD), i.e., an increase of 1,904 MXN (89 USD).[1] On average, this group of individuals 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 cost 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 11/1,904 increase in borrowing or a 0.006% increase in borrowing in response to a 1% increase in savings. For the group of individuals that also paid credit card interest at baseline, we have an increase in savings of 5.67% on a baseline value of 23,080 MXN, i.e.,

[1] Over our sample period, 1 MXN was corresponding 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.

1,316 MXN (62 USD). In turn, we can rule out a 6.64% increase in credit card borrowing with 95% confidence. This equals an increase of 26.68 MXN in borrowing cost. To conclude, for every 1 MXN in savings we can thus rule out a 27/1,409 or larger than 1.9 cents increase in credit card borrowing. We find however that individuals that were carrying substantial levels of credit card debt respond to the savings nudge by increasing their liquid savings.

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. We propose mental accounting and rules of thumb as a potential explanation, following Haliassos and Reiter (2005). The idea is the following: individuals have a spending account, i.e., their credit card, as well as an account for savings. They separate these two accounts mentally to cope with their overspending and self control problems. The reason is that individuals can maintain a rule to not touch their savings but have trouble to restrict their credit card borrowing. On their credit cards, they will spend up to some personal limit. Once they get close to that personal limit, they feel constrained and can restrict their overspending more successfully. If individuals would take their savings and repay their credit card debt, they 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 optimally decide to hold the two positions simultaneously.

To provide further evidence for this psychological mechanism behind the co-holding puzzle, we show that those individuals that 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, i.e., the co-holding indi-

viduals are also most susceptible to the savings nudge without increasing their credit card borrowing in response.

To evaluate rational and behavioral theories behind the credit card debt puzzle, and to understand whether or not we should induce households to save more, we nudge individuals to save more and study whether they respond with an increase in credit card borrowing. In summary, the answer is No. Our findings are consistent with individuals choosing to hold credit card debt and savings simultaneously to help them cope with limited self-control.

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 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. The measure of credit card borrowing in this paper are 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 can 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 and can ensure that individuals would have the ability to borrow as we observe credit limits.

Previous literature on the credit card debt puzzle began with Gross and Souleles (2002), who document the phenomenon and note that transaction demand for liquidity may contribute to it. Maki (2002) study 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. Bertaut et al. (2009) study whether households may hold liquidity and credit card debt simultaneously as a means of self-(or spouse) control. If one spouse in the household is the earner, and the other is the compulsive shopper, it is argued that the earner will choose not to pay off credit card debt in full in order to leave less of the credit line open for the shopper to spend.

Laibson et al. (2012) examine a related puzzle: 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 not consume them. As mentioned, 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. However, strictly speaking, these two explanations cannot apply to the credit card debt puzzle. The

key difference is that retirement assets involve a significant penalty for early withdrawal, i.e., they are not liquid in contrast to savings accounts. That said, analyzing whether liquid savings results in borrowing should provide us with a lower bound for the borrowing response to illiquid savings.

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 occur 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 relaxation of liquidity constraints. Soman and Cheema (2002) present experimental and survey evidence that consumers interpret available credit lines as indications of future earnings potential when deciding consumption expenditures.

3 Background on the Mexican credit card market

As of June 2017 in Mexico, there were 17.9 million general-purpose credit card accounts in good standing holding a positive balance, in a population of 124 million. The credit card market has expanded rapidly as in 2009 only 13 million cards were in circulation. In spite of these trends, credit card penetration in Mexico has remained small 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 card holder 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.[2] 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 percentage points above the federal short-term interest rate, which was 7.17%.

The credit card market in Mexico is fairly concentrated, 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 sixth 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.[3]

4 Experimental Design and Data Description

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 customers were randomly selected to be in a control group. Clients in the control group received no message. Clients in the treatment group were randomly assigned to receive 1 of 7 messages that have been proven to be effective in previous experiments nudging individuals to save. Half of the treated customers were cross-randomized to re-

[2] INEGI, Encuesta Nacional de Inclusion Financiera, 2018.

[3] Refer to Banco de Mexico, multiple reports.

ceive the messages on a weekly basis, while the other have were assigned a bi-weekly frequency.[4] The intervention lasted 7 weeks from September 13 to October 27, 2019.

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

The treatment messages were the following:

> **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.[5]"
>
> **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 in $XXX and reach your dreams. Commit to it. You can do it by saving only 10% of your income."

[4] Users in the treatment group were further cross randomized across two additional dimensions: First, half of them would stop receiving the messages for two weeks, after 2 months of receiving, and then resume. Second, half of the consumers in the treatment group would receive the same message through 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.

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

Message 6: "The holidays are coming. Commit to saving $XXX on your Banorte Account and see your wealth grow!"

Message 8: "Be preparaed for an emergency! Commit to leaving 10% more in your account. Don't withraw all your money on payday."

Table 1 shows descriptive statistics for all individuals, i.e., all 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.[6] In turn, their checking account balance is approximately 19,384 MXN. About 30% of credit card holders pay credit card interest.

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

The experiment was stratified along a number of dimensions: Income quartiles, age quartiles, median of tenure with the bank, quartiles of baseline savings, quartiles of credit card balances, dummy for clients for whom Banorte is the main bank, dummy for clients for whom 70% or more of the debit account charges are through card payments (people that do not use much cash), and quartiles of credit card balances as a percentage of income.

[6] Over our sample period, 1 MXN was corresponding 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.

Table 2 shows that there is covariate balance across a number of variables of interest.

More specifically, Table 2 shows the same descriptive statistics 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. We argue this age difference is not an economically meaningful difference.

In terms of the credit card debt puzzle, Table 3 shows by deciles of savings over income the fraction of individuals that pay credit card interest and their balances on checking accounts, credit cards, and interest payments. We here restrict to only individuals who have a credit card. We can see that 20% to 30% of individuals that have a credit card pay credit card interest even when they are in the higher deciles of checking account balances. This is the population that we are concerned about: 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). Note that 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 population as individuals holding more than 50% of their income in their checking account and paying credit card interest. 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 individuals who pay credit card interest but are not in the puzzle group. 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. Both populations appear to hold debt persistently as there is a high correlation between rolling over debt in any given month and doing so in the previous month. While credit cards in the first place and co-holding are not as common in our overall population relative to the US, the size of our experiment will provide sufficient statistical power to analyze this subpopulation.

5 Methodology

For every customer we observe balances in their checking accounts at the end of each day. We calculate the average of daily balances over the 7 week treatment period as our main dependent variable. We analyze the effects of the experiment using two approaches. First, we evaluate the effect of the savings nudges on daily balances for the entire population. For this, we use standard ordinary least squares (OLS) specifications comparing treatment to control outcomes, as 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), Hitsch and Misra (2018), and Athey et al. (2019).

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. Thus, the interaction coefficients identifies the incremental effect of the treatment on individuals above 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, at the risk of overfitting or capturing heterogeneous treatment effects by chance. Causal forest allow us to identify heterogeneity in treatment effects without concern about invalidating inference due to multiple hypothesis testing problems or overfitting. This method is tailored for efficiently predicting causal effects of a treatment for a rich set of different sub-population through three distinctive features that will be discussed below: sample splitting, orthogonalization, and an optimization method designed to capture treatment effect heterogeneity.

Causal forests are based on causal trees, which in turn are a modification of the widely known regression trees. Regression trees predict an individual outcome Y_i using the mean Y of observatins 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 leaves, all observations share values (or belong to the same value interval) of certain X's. A tree starts with a trainning 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 sample, i.e. 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 last set of leaves, the three provides out-of-sample predictions by figuring out in which terminal leaf a certain observation falls in, 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 ensamble 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 the n predictions, obtainined 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 unlike Y, we do not observe $Y_1 - Y_0$ for any 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. And thus define a new criterion for sample splitting specifically designed to identify treatment effect heterogeneity. They further show that to reduce over fitting 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 used to calculate treatment effects within each leaf. In addition, Athey et al. (2019) argue for the importance of orthogonalization, by which

Thus, causal forests are different than off-the-shelve Machine Learning methods in three ways: 1) they estimate treatment effects with a repeated split sample method (referred to by Athey and Imbens (2016) as “honest estimation"), 2) they use a splitting rule for the trees that aims to directly find sub-populations with different treatment effects, instead of predicting levels of the outcome of interest in treatment and control groups separately,

and 3) they use orthogonalization methods to ensure covariate balance across multiple subpopulations.

First, in addition to dividing data in training and validation 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 subpopulation 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]

[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.

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 methods 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), aggregates the 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 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 random subset of variables are selected as candidates to split on. [8]

[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.

- For each of these variables, the 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.
- 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, i.e. we estimate 2,000 trees.
7. Treatment effects are predicted for each observation on a test dataset (potentially the full dataset) as follows:
   - Each test observation is pushed down each tree to determine what leafs it falls in. Given this information, a list with neighborhoring 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.
   - Treatment effects are calculated using orthogonalized outcomes and treatment status of the neighbor observations.
8. In addition to personalized treatment effects, causal forests can be used to estimate average treatment effects across all observations in a dataset, or subsamples of it.

This is done with an AIPW estimator, that ensures balance across all covariates in the group.

In turn, we can look at the frequency distribution of those 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 on credit card outcomes.

6 Results

6.1 Results for Savings

This section identifies the subpopulation with the largest increases in savings as a result of the intervention. We thus estimate treatment effects, with especial interest on heterogenous treatment effects.

We first estimate the treatment effect of the intervention of checking account balances over experimental strata. To do so, we estimate average treatment effects running the following specification:

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

where α_s represents fixed effects for randomization blocks, β identifies the treatment effect of the intervention as the difference in outcomes between 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 and then choose how much to respond.

Table 5 shows the average treatment effects across all treatments, by treatment message and by treatment frequency. Column 1 shows that on average there is a 0.6% increase in savings, from a basis of 21,867 MXN. Column 2 shows that if we break out the effect by treatment message, we can see that only Message 2 has a positive and small treatment effect. Column 3 shows that only the treatment with weekly messages has a positive treatment effect. However, all treatment messages and frequencies have similar coefficients, and they are not statistically different from each other.

When looking at the strata design, we can see that there are strong heterogeneities across users with different observable characteristics. Figure 1 shows that the impact on savings was concentrated on clients in the top quartile of the pre-treatment distribution of average daily balances. Figure 2 shows that within this group of clients all income levels displayed a considerable average increase in savings (676 MXN to 1,805 MXN). In addition, Figure 3 shows that customers at different ages displayed increases in savings between 862 MXN and 2,746 MXN. Customers under the age of 50 displayed a larger response than customers older than 50 years.

Figure 4 shows that customers with less number of transactions in their debt cards (TDD transactions) displayed a greater response than high-transactional customers. Figure 5 shows that customers who visited ATMs less often at baseline displayed a slightly larger response.

Figure 6 show the estimates broken up by the range of individual's credit card balances. We can see that individuals with more negative credit card balances display a larger response. This is the puzzle population we are concerned about, individuals who have

liquid wealth but also credit card debt. Finally, Figure 7 breaks the effects down by tenure with the bank and we find that customers who have been banking for longer with Banorte display a slightly larger response.

We then characterize heterogeneities in treatment effects using machine learning methods for causal inference. Using the dataset with 3.1 million clients in treatment and control. 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. This 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 the higher importance, i.e. those who saw the largest number of splits in the first estimation. For this second causal forest estimation, Figure 8 shows the 27 variables with the highest variable importance, and Figure 9 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.

Before turning to the analysis of identifying subpopulations with the largest treatment effects, we ask whether the causal forest succeeded in estimating treatment heterogeneity. As seen if Figure 9 the predictions of the causal forest exhibit variation, however this is not enough to conclude that individual predictions are a better estimand of the overall average treatment effect of the intervention. We test for whether heterogeneity in individual predictions is associated with heterogeneity in treatment effects using the “calibration test" described in Athey and Wager (2019), motivated by Chernozhukov et al. (2018). This tests seeks to fit conditional average treatment effects as a linear function of the causal estimates

of the causal forest. This test 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 6 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.

We thus 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 according to each individual’s score value into quartiles. For each quartile we estimate the group average treatment effects using a doubly robust estimator. Figures 10 and 11 show how the treatment effects on savings is larger for individuals with larger scores. The top 5% of individuals in the sample have a treatment effect of 5.33% or 1,162.5 pesos.

Table 7 compares the baseline characteristics of individuals in the top and bottom quartiles of the distribution of predicted treatment effects. Compared to individuals in the bottom quartile of the distribution of predicted treatment effects, individuals with the highest predicted response are about one year older, have higher income, larger tenure with the bank, larger checking account balances, as well as larger credit card balances and credit card limits.

In Figure 12 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 in the top quartile of predicted treatment effects, we are capturing a relavant fraction of the puzzle population. This also speaks to the idea that co-holding is a psychological mechanism to exercise self control, which also makes individuals more susceptible to savings nudges.

6.2 Results for Credit Card Borrowing

For the rest of the analysis, we focus on individuals in the top quartile of the predicted treatment effect distribution. After all, we are primarily interested in whether an increase in savings is accompanied by an increase in borrowing and thus focus on the sample of the population that displayed an increase in savings.

We are only using the predicted treatment effects rather than the actual treatment effects as a score to sort individuals. Otherwise we would provide an analysis that suffers from a type of "reverse endogeneity" problem i.e., we would pick a group of individuals that displayed large savings in response to the treatment but something else might be going on with this group of individuals. In contrast, when we look at a group of individuals using the predicted treatment effect based on observables then there is a predicted treatment effect in both treatment and control groups. Again, that predicted treatment effect is based on pretreatment characteristics. In turn, once we split people based on the predicted treatment effect we calculate the actual treatment effect, comparing outcomes of treatment

versus control group during the treatment period.

That said, we are performing a cut by pretreatment variables that may not correspond to the experimental strata. Therefore, there may not be covariate balance in certain subsets of the predicted treatment effect distribution. Therefore, instead of calculating average treatment effects with a simple regression, we use a method that controls for covariate imbalance – it is called inverse adjusted probabilty weighting (AIPW) as in Glynn and Quinn (2010).

The AIPW method is based on calculating a propensity to be in the treatment group given the observable characteristics. Under perfect covariate balance, the propensity is constant across all observable characteristics. But that is not necessarily the case across all partitions of the sample. AIPW effectively controls for these imabalances.

Let us now turn to our results for borrowing, i.e., 1 + the logged value of card balances, or 1 plus the interest paid on credit cards. As said, for the rest of the analysis, we focus on individuals in the top quartile of the predicted treatment effect score distribution. After all, we are interested in the effect on borrowing for the population that was predicted to respond to the savings nudge with additional savings.

Our baseline results are displayed in Table 8. In Column (1), we can see the savings results for the top quartile of predicted treatment effect individuals that have a credit card. Here, the increase in savings estimate is 6.01% on a baseline savings of 31,681 MXN, i.e., 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 with a standard error of 3.34% as can be seen in Column (3). 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 cost respectively. In other words, we can rule out a 0.06% increase in borrowing or 0.01% increase in borrowing cost 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 months whereas for Banorte credit cards we use the average daily balances.

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 percentage points on a baseline probability of 42%. Thus, for every 1 MXN in savings, the increase in the likelihood to borrow is only 0.68/1,904 or 0.00036 percentage points.

Finally, in Column (5) we report results for credit card payments, i.e., whe individuals repay their outstanding credit card balances or rolled over credit card debt. Here, we also document a very small and tightly estimated treatment effect.

In turn, in Table 9 we also see the results for individuals that pay credit card interest at baseline. For this group, we have an increase in savings of 5.67% on a baseline of 23,194 MXN, i.e., 1,315 MXN. In turn, we can rule out an increase of 133.97 MXN in credit card

borrowing or 26.68 MXN in borrowing cost. 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 10 shows the increases in savings and borrowing for five quintiles of the treatment effect score for the group of individuals that have a credit card. To be clear, the figure conditions on the top quartile of predicted treatment effect for savings and then further splits the sample into quintiles. Additionally, the table shows the respective increase in borrowing costs and the likelihood to borrow. As we can see, for all predicted treatment effect quintiles, the increases in borrowing are very small. Table 11 shows the same for individuals with a credit card that pay interest at baseline.

Figure 13 shows in a graph the treatment effect on interest charges for consumers with credit cards and separately for those consumers who pay interest at baseline. We can see that the negative effect is concentrated in the first quintile of predicted savings effect but all quintiles' estimates are insignificant and small.

Finally, we now want to know whether individuals increased their saving without increasing their borrowing by decreasing their spending or increasing their income. Table 12 shows the treatment effects on deposits, ATM withdrawals, and spending for the top quartile of predicted savings 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 card spending. This is true for all individuals with a credit card and also the subset of those paying credit card interest. We thus conclude that a decrease in spending, in particular, discretionary spending that may be financed by cash, was responsible for the increase in savings.

6.3 Second Experiment

As another piece of supporting evidence, we also report the borrowing results of a second experiment using savings nudges. In this experiment, Banorte clients were incentivized to save in mutual funds in early 2019 using SMS and ATM messages. The most effective message resulted in a 22.8% increase (9,773 MXN) in the average mutual fund balances relative to the control group. This resulted in an increase in net acquisition of 5,502 MXN per treated customer. In this experiment, we also observe a lot of heterogeneity in responses, customers that have higher incomes reacted more strongly and so did younger customers.

The nudges were sent to 16,186 individuals with 8,068 customers in the control group every two weeks during January and February 2019. The 112 experimental strata were chosen in the same way as for our main experiment. The statistical balance checks show successful covariate balance between the treatment and control groups.

In Table 13, we can see the results for clients' mutual fund balances and certificates of deposit balances. We see a clear increase in savings in these vehicles of approximately 12% to 16% relative to an initial balance of 468,010 to 275,797 MXN which translates into increases of 65,161 to 44,128 MXN.

Here, we just look at the whole experimental population's results for borrowing. The table displays the increase in credit card balances, interest paid, and the likelihood of paying credit card interest. For credit card interest, we can rule out a 10.05% increase with 95% confidence on a baseline amount of 16,168 MXN which thus translates into a 1,697 MXN increase in borrowing costs. For each MXN in savings, we can thus rule out a larger than 1,697/65,161 = 0.026 to 0.038 cents increase in borrowing costs. Similarly

small effects can be ruled out for the increase in credit card balances and the likelihood of paying credit card interest.

7 Conclusion

We estimate whether or not nudging individuals to save more has the unintended consequence of 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 customers with similar characteristics, the subset of customers in the top quartile of the treatment effect distribution who have a credit card increased their savings considerably. However, this increase in savings was not accompanied by an increase in rolled over high-interest unsecured consumer debt. This is an important result to evaluate policy proposals to increase savings via nudges or more forceful measures.

Our results help us to understand the mechanism behind the so-called credit card debt puzzle, i.e., when individuals hold credit card debt and savings simultaneously. In particular, we can comfortably rule out that savings nudges increase high-interest unsecured borrowing for the subsample of puzzle population as well as the overall sample. We thus find evidence for the idea that individuals hold savings and credit card debt simultaneously because they deal with their self control problems via mental accounting, i.e., they can maintain a rule to not touch their savings but are simultaneously indebted due to overspending. Consistent with this strategy, increasing savings does not seem to increase their

borrowing.

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Figures and Tables

Table 1: Descriptive Statistics

All Individuals	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	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

Income, balances, and interest payments are in Mexican Pesos (MXN). 1 MXN = 0.047 USD. For each individual, we consider information from the 6 months previous to the intervention.

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)

Income and balances, are in Mexican Pesos (MXN). 1 MXN $=$ 0.047 USD. We test for covariate balance estimating Equation 1 with different dependent variables. Columns 1 and 2 present the average value of each dependent variable for Treatment and Control groups, adjusting to reflect only differences within strata, and to reflect the average in the experimental pool. The adjusted average for the Control group is defined as the α such that $\bar{y} = \alpha + \beta\bar{x}$, where β is the coefficient of the treatment indicator estimated within strata using Equation 1. The adjusted average for the Treatment group is defined as $\alpha + \beta$. Column 3 shows the coefficient of the treatment indicator estimated within strata i.e. β. The p-value of an F-test from regressing the treatment indicator on all of the covariates with strata fixed effects is 0.1519.

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		*Clients Paying Credit Card Interest*			
Decile	Checking Account Balance over Income (Average)	Fraction Of Clients with non-zero Credit Card Balance	Fraction Of Clients Paying Credit Card Interest	Checking Account Balances (Average)	Credit Card Balances (Average)	Credit Card Interest (Average)
All	1.81	0.61	0.31	43,475.83	16,340.12	346.58
1	0.01	0.62	0.42	340.20	29,917.08	1,018.99
2	0.05	0.56	0.37	1,086.67	24,165.70	854.02
3	0.08	0.59	0.37	2,054.23	26,525.30	956.52
4	0.13	0.61	0.36	3,204.63	27,805.94	1,001.48
5	0.20	0.64	0.35	5,293.93	31,556.76	1,107.03
6	0.33	0.64	0.32	8,467.78	35,507.68	1,215.31
7	0.58	0.63	0.28	15,266.06	38,101.32	1,280.91
8	1.16	0.62	0.24	29,971.89	42,637.44	1,366.57
9	2.81	0.59	0.21	66,548.62	43,713.88	1,381.63
10	12.73	0.58	0.18	295,446.99	45,925.31	1,463.94

Balances and interest payments 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)

Income and balances, are in Mexican Pesos (MXN). 1 MXN = 0.047 USD. The probability of incurring credit card interest, conditional on incurring credit card interest on the previous period is calculated with monthly information corresponding to the 6 months previous to the intervention, and with standard errors clustered at the user level.

Table 5: Overall Treatment Effect of the Intervention

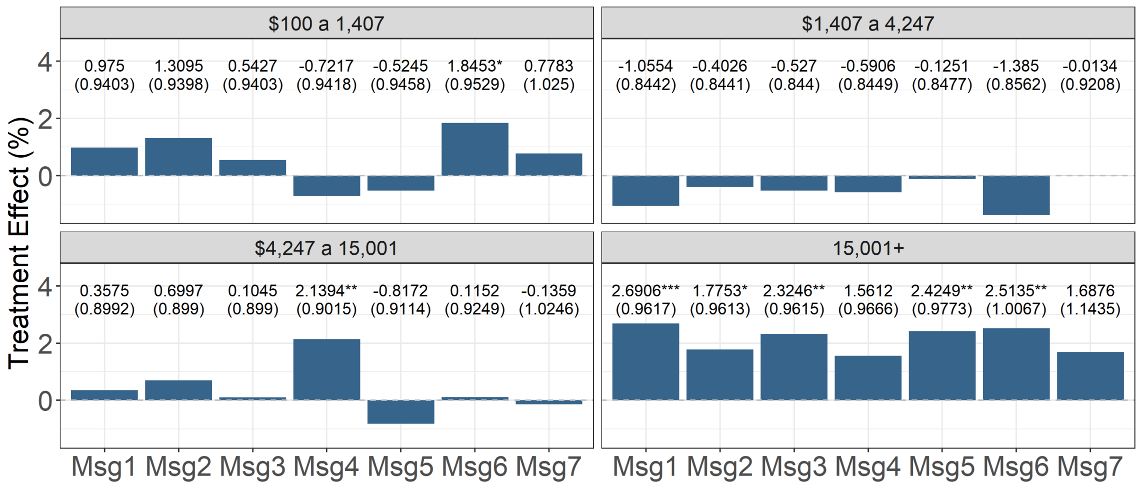
	(1) Log of Checking Acct. Balance +1	(2) Log of Checking Acct. Balance +1	(3) Log of Checking Acct. Balance +1
trat=1	0.006*		
	(0.086)		
Msg1		0.007	
		(0.121)	
Msg2		0.008*	
		(0.062)	
Msg3		0.006	
		(0.194)	
Msg4		0.006	
		(0.226)	
Msg5		0.002	
		(0.633)	
Msg6		0.007	
		(0.109)	
Msg7		0.006	
		(0.216)	
Bi-weekly			0.006
			(0.140)
Weekly			0.007*
			(0.077)
Observations	3054503	3054503	3054503
Mean of Checking Acct. Balance in Control Group	21866.61	21866.61	21866.61

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Treatment Effects by Pre-treatment Checking Account Balances and Treatment Message

(a) Treatment Effect (% Change)



(b) Treatment Effect (MXN)

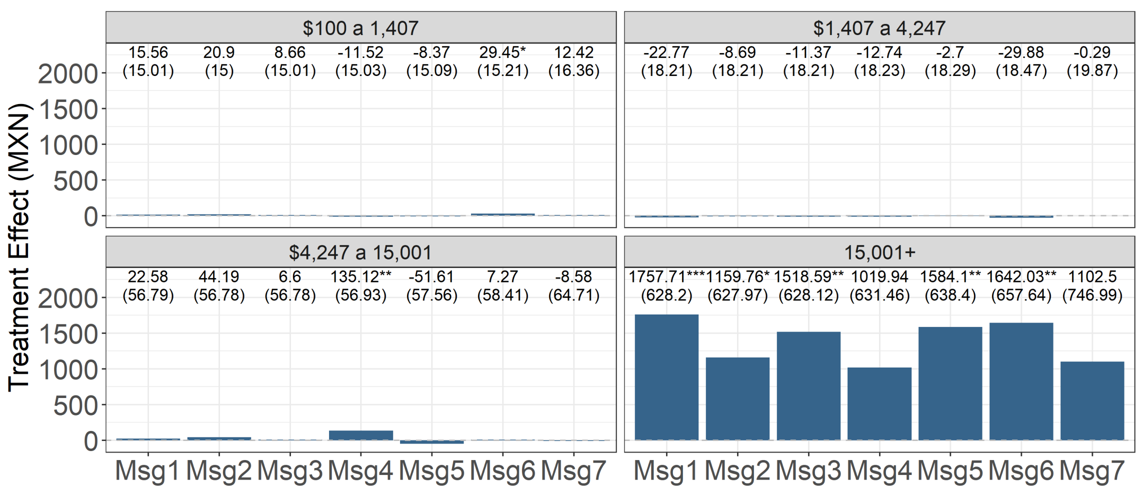
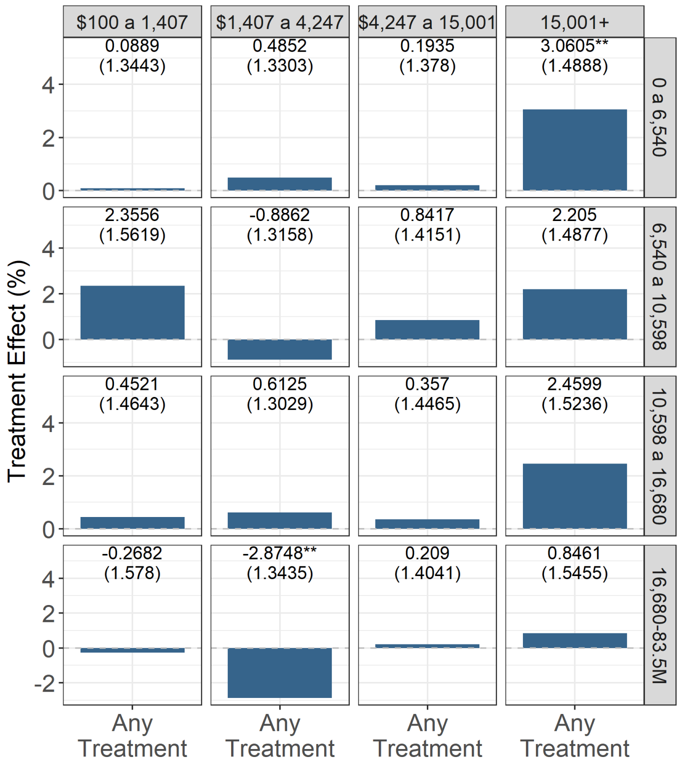


Figure 2: Treatment Effects by Pre-treatment Checking Account Balances and Income

(a) Treatment Effect (% Change)



(b) Treatment Effect (MXN)

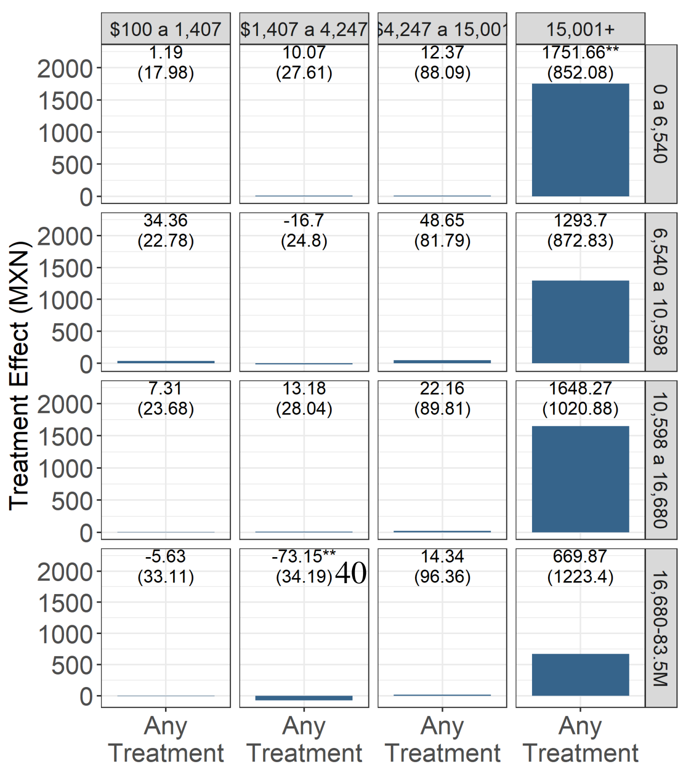


Figure 3: Treatment Effects by Age (Top Quartile of Pre-treatment Checking Account Balances)

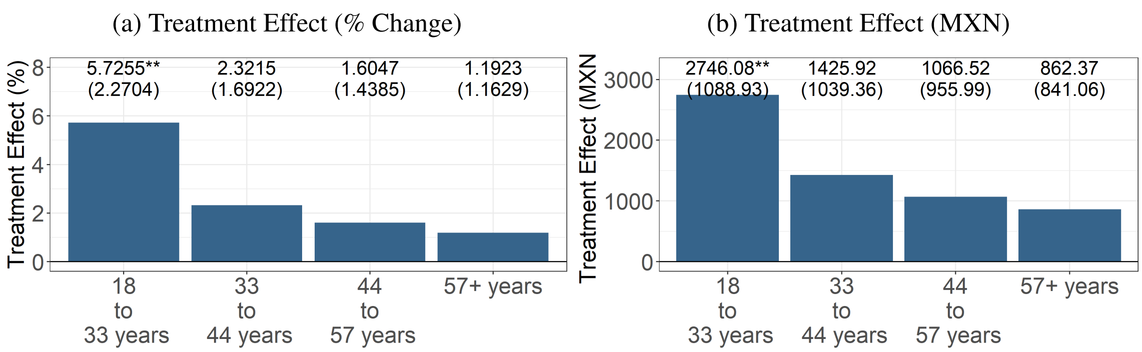


Figure 4: Treatment Effects by Pre-treatment Debit Card Use (Top Quartile of Pre-treatment Checking Account Balances)

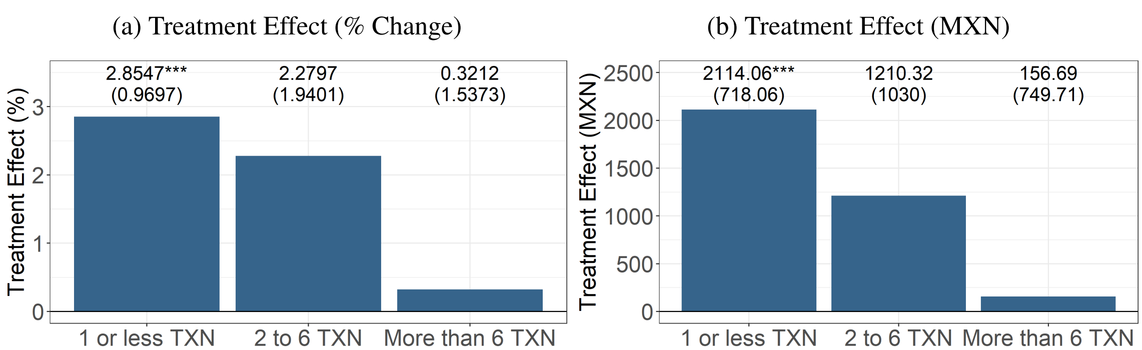


Figure 5: Treatment Effects by Pre-treatment ATM Activity (Top Quartile of Pre-treatment Checking Account Balances)

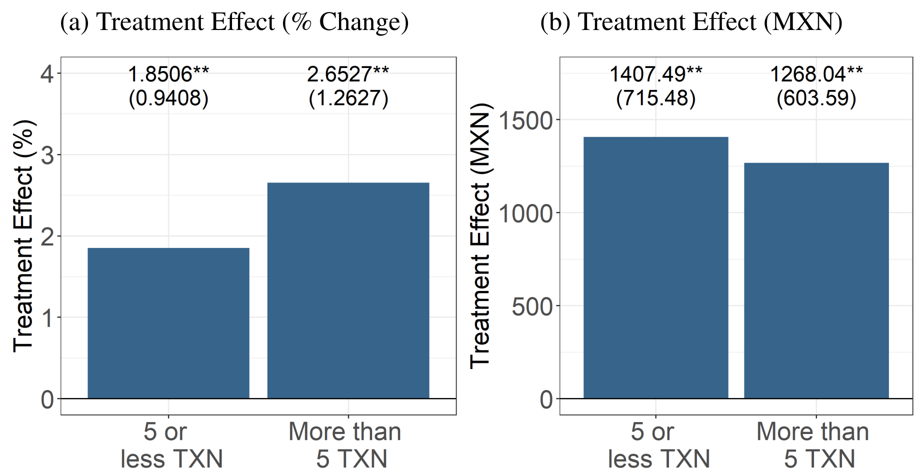


Figure 6: Treatment Effects by Pre-treatment Credit Card Balances (Top Quartile of Pre-treatment Checking Account Balances)

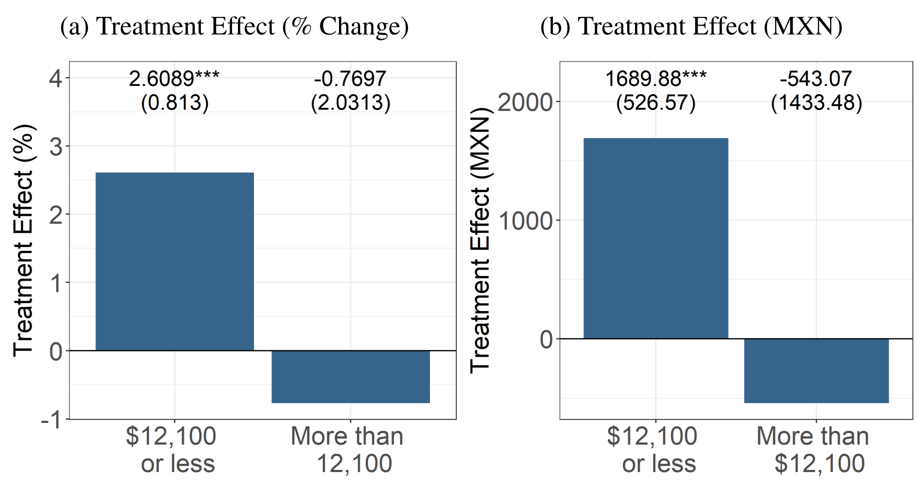


Table 6: Calibration Test for Evaluation Of The Quality Of The Causal Forest

	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.

Figure 7: Treatment Effects by Tenure with the Bank (Top Quartile of Pre-treatment Checking Account Balances)

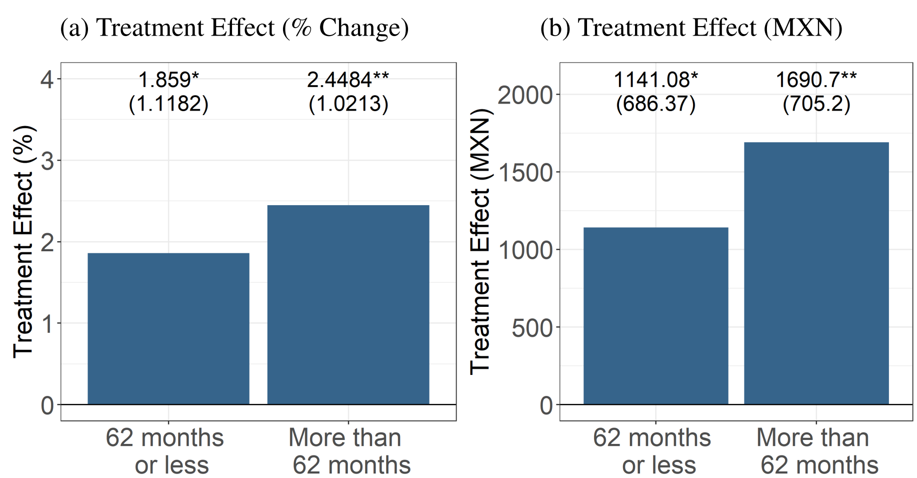
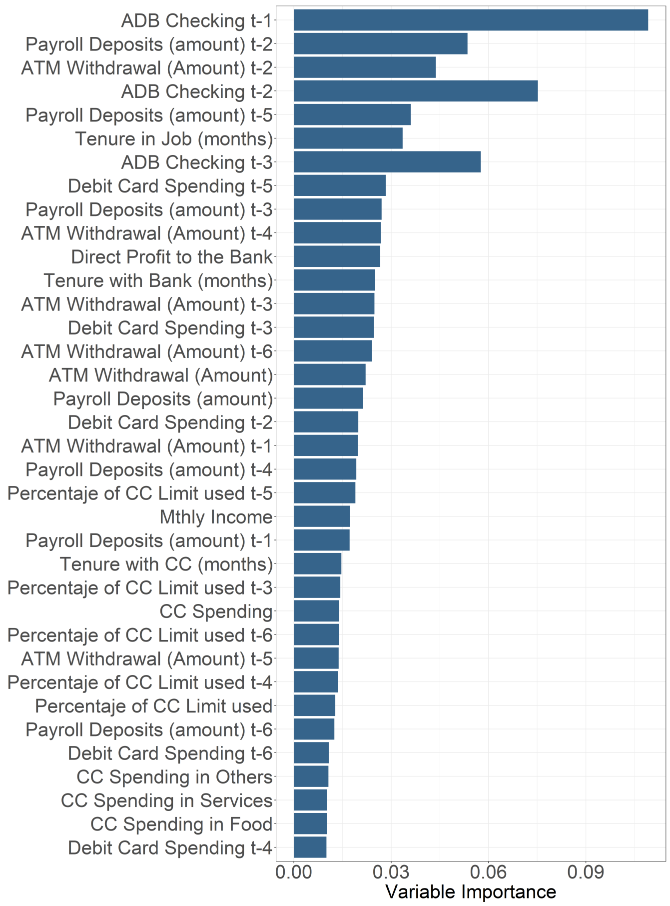
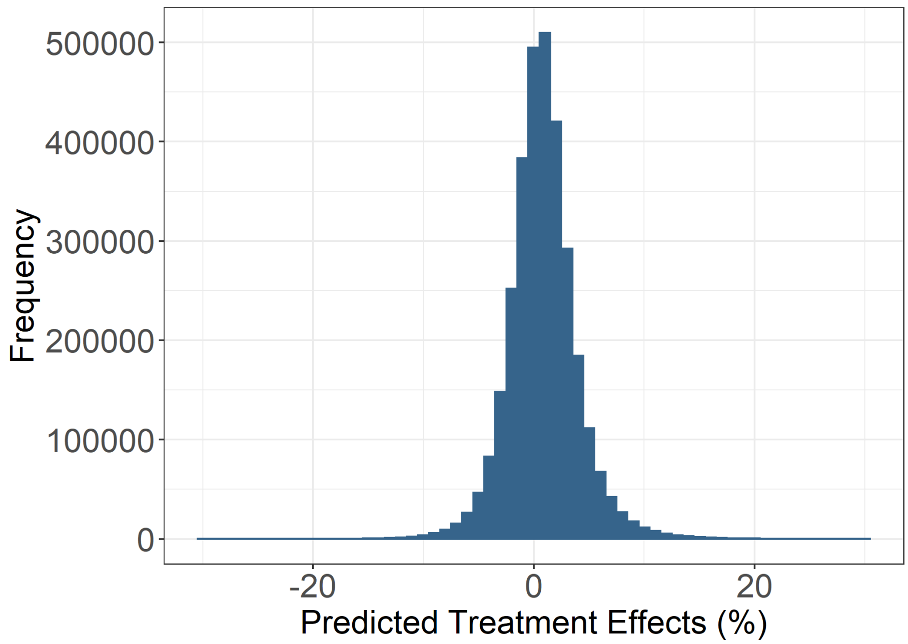


Figure 8: Variable Importance: Causal Forest

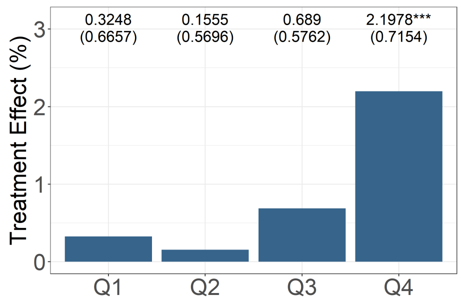


This graph shows the variable importance of the 27 most important variables used in the estimation of the causal forest. Variable importance indicates how often was the given variable used to select splits in the multiple trees of the causal forest. We first estimate the causal forest using 161 pre-treatment 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 9. ADB refers to average daily balances, all variables are monthly.

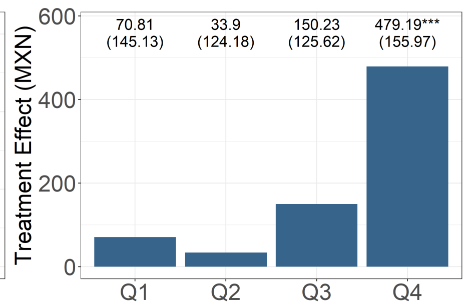
Figure 9: Distribution of Predicted Treatment Effects.



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)



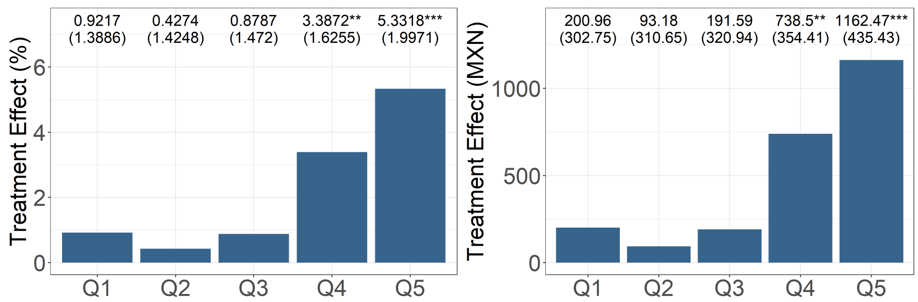
(b) Average Treatment Effect (MXN)

Figure 10: Treatment effect on checking account balances, as a function predicted treatment effects for each individual. Individuals are split in to Quartiles of treatment effects on savings, based on the score generated by the causal forest.

Table 7: 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)

Income and balances, are in Mexican Pesos (MXN). 1 MXN = 0.047 USD. This Table presetopnts simple means for individuals in the top and bottom 25% of the distribution of predicted topment effects on the log of checking account balances.

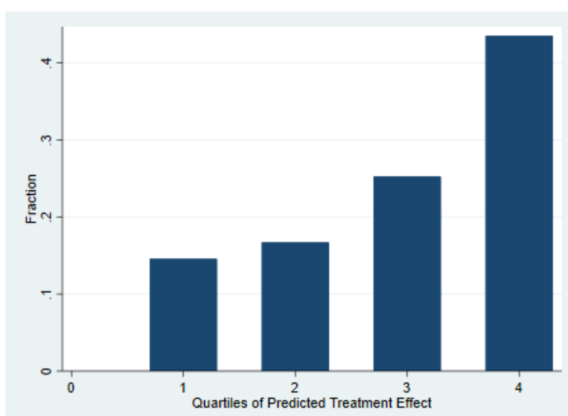


(a) Treatment Effect (% Change)

(b) Treatment Effect (MXN)

Figure 11: Treatment effect on checking account balances, as a function of individual treatment effects. 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 12: Distribution of the Puzzle Group, by Quartiles of Predicted Treatment Effect.



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.

Table 8: The Treatment Effect on Savings and on Credit Card Borrowing: All Clients with Credit Cards

	(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
ATE	0.0601***	-0.0155	-0.0077	-0.0171	-0.0037	-0.0159
	(0.0177)	(0.0116)	(0.0062)	(0.0334)	(0.0054)	(0.015)
Mean Dep. Var in Control Group (MXN)	31681.46	17097.99	43136.75	230.39	0.42	9500.24
Increase in Savings (MXN)	1904.37					
Upper Confidence Interval (MXN)[1]		123.54	195.5	11.12	0.0068	127.79
Upper Confidence Interval (MXN)[1] / Increase in Savings (MXN)		0.06	0.1	0.01	0.0000036	0.07
Note:	*p<0.1; **p<0.05; ***p<0.01					

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 shows 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 ln(Credit Card payments). In all cases we consider individuals in the top quartile of the predicted savings effect. Average Treatment Effects are calculated with the Augmented Inverse Probability Weighted method. Treatment propensities come from estimating Causal Forests on the corresponding dependent variables. The increase in savings expressed in MXN, 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*Estandar 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).

Table 9: The Treatment Effect on Savings and on Credit Card Borrowing: Clients who Paid Credit Card Interests at Baseline

	(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
ATE	0.0567**	-0.0102	-0.0091	-0.0242	-0.004	-0.0133
	(0.0251)	(0.0082)	(0.0072)	(0.0453)	(0.007)	(0.0202)
Mean Dep. Var in Control Group (MXN)	23194.21	23080.11	51491.24	413.31	0.71	8012.99
Increase in Savings (MXN)	1315.58					
Upper Confidence Interval (MXN)[1]		133.97	262.18	26.68	0.0097	210.99
Upper Confidence Interval (MXN)[1] / Increase in Savings (MXN)		0.1	0.2	0.02	0.0000074	0.16

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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 shows 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 ln(Credit Card payments). In all cases we consider individuals in the top quartile of the predicted savings effect who had a credit card and who incurred interest charges at baseline. Average Treatment Effects are calculated with the Augmented Inverse Probability Weighted method. Treatment propensities come from estimating Causal Forests on the corresponding dependent variables. The increase in savings expressed in MXN, 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).

Table 10: Treatment Effects by Quintile of Saving Score for Individuals with Credit Cards

	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 savings effects. We further split them into quintiles and report average treatment effects on savings, interest payments and probability of paying interests for individuals in each of the quintiles who have at least one credit card.

Table 11: Treatment Effects by Quintile of Saving Score for Individuals with Credit Cards who Paid Credit Card Interest at Baseline

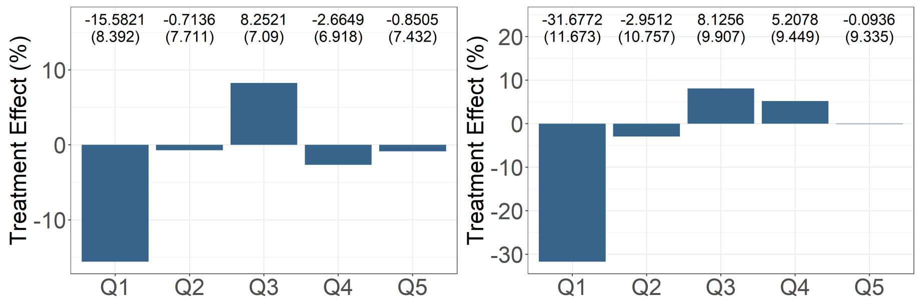
	Q1	Q2	Q3	Q4	Q5
Panel A: Treatment Effect on Checking Account Balances					
ATE Ln Checking Account Balance	0.1**	0.14***	0.02	-0.01	0.06
	(0.052)	(0.0568)	(0.051)	(0.0493)	(0.0658)
Mean Checking Account Balance in Control Group (MXN)	22934	22375	25050	26323	19473
Panel B: Treatment Effect on Credit Card 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 savings effects. We further split them into quintiles and report average treatment effects on savings, interest payments and probability of paying interests for individuals in each of the quintiles who have at least one credit card and paid credit card interest at baseline.

Table 12: Treatment Effects On Deposits, ATM Withdrawals and Spending

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

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 savings effects. Deposits, withdrawals, and spending are all monthly. Spending is defined as the sum of debit card and credit card store purchases.



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

Figure 13: Treatment effect on credit card interest charges for individuals in the top quartile of the predicted savings effect who do or do not pay interest at baseline split in to quintiles of predicted treatment effects on savings, based on the score generated by the causal forest.

Table 13: The Treatment Effect on Borrowing and Savings: Experiment 2

	Mutual Funds Balance	Certificates of Deposit Balance	Credit Card Balance	Credit Card Interest	Pays Credit Card Interest?
Treatment	0.121**	0.157*	0.075	0.049*	0.010**
	(0.057)	(0.085)	(0.066)	(0.028)	(0.004)
Mean in control group (LN or dummy)	10.62	3.37	2.86	0.57	0.09
Mean in control group (MXN or dummy)	468,010.94	275,797.86	22,116.47	93.11	0.09
N	16,186	16,186	16,186	16,186	16,186
R2	0.072	0.142	0.206	0.089	0.094

In this experiment, Banorte clients were sent messages that encouraged them to invest into mutual funds and certificates of deposits. The nudges were sent to 16,186 individuals with 8,068 customers in the control group every two weeks during January and February 2019. The 112 experimental strata were chosen in the same way as for our main experiment. The statistical balance checks showed covariate balance between the treatment and control groups.