The Impossibility of Saving by Spending

Job Market Paper *

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Abstract

I study the effect of enrollment in a round-up savings program on consumer spending behavior and financial outcomes. I find that upon enrollment in a round-up savings program, households increase their total spending. This effect mostly stems from discretionary spending and is driven by both spending frequency and average purchase amount. This increase in spending, with income fixed, leads to a gradual increase in the propensity of liquidity shortfalls. I use a difference-in-differences estimator to measure causal effects of round-up savings on consumer spending. I find that consumers increase their spending by around $300 per month upon enrollment in round-up savings over a 2-month post-enrollment period. Compared to a saving amount of approximately $4.50 per week after enrollment, these results suggest a short-run detrimental effect of round-up savings on household finances.

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1 Introduction

Several reasons might prevent households from saving enough to cover an unexpected expense (e.g. financial constraints, behavioral factors such as self-control issues).[1] Nudging or commitment devices are methods which can support households in their saving endeavour while circumventing some of the constraints.[2] Round-up saving as a partial commitment device commits individuals to save with spending transactions. Perfect commitment devices are difficult to come by in practice, however, imperfect or partial commitment devices are common.[3] Round-up saving works by rounding up a transaction amount to the next dollar. That is, a coffee for $2.50 is rounded up to $3.00 and the difference of $0.50 gets transferred to the connected savings account. This helps households save small amounts while they spend which can aggregate to useful emergency savings. Conversely, it can tempt households to spend more in order to increase their savings. Given the general assumption that savings are made up of the difference between disposable income and consumption, an increase in consumption, while holding income fixed, makes an increase in savings paradoxical and can lead households into financial distress.

In this paper, I estimate the effects on household spending of enrollment in a round-up saving program and its consequences on financial liquidity. I exploit account aggregator data over the period from 2010 to 2015 to show that households increase spending after enrollment into a round-up saving program which over time increases their propensity of liquidity shortfalls. Liquidity shortfall is defined as having a bounced check or overdraft on their account(s). The increase in the propensity of liquidity shortfall is a direct consequence of decreased self-control when it comes to spending. The initial purpose of round-up saving as a partial commitment device is to help with committing to saving and preventing self-control issues with respect to saving (Laibson, 1994; Shefrin & Thaler, 2004). Through the direct link of saving and spending, self-control in the direction of saving is taken care of, but self-control in the direction of spending is decreased under the banner of increased savings.

Round-up programs are interesting and widely used in practice, yet understudied in the academic domain. A reason for the lack of detailed studies about round-up programs is the scarcity of

[1] See, for instance, Thaler & Shefrin (1981), Laibson (1994), Laibson (1997), Laibson et al. (1998), Baumeister (2002), Shefrin & Thaler (2004), Benhabib & Bisin (2005), Lusardi & Mitchell (2007)

[2] See, for instance, Thaler & Sunstein (2009), Karlan et al. (2016)

[3] See Laibson et al. (1998)

suitable data. A number of well-established U.S. financial institutions started adding a round-up saving program into their business model several years ago. More recently, FinTech companies have also started incorporating rounding-up into their business models resulting in in a large amount of households who round up. Despite the widespread adoption, not much is known about the effects of using round-up programs. In both cases, banks and FinTech companies, the matter of privacy and data access is what prevents a thorough analysis of round-up programs. This paper overcomes this limitation by using data provided by an account aggregator service, also used in, for example, Baugh et al. (2018). The advantage of this indirect view (i.e. not directly through the round-up program provider) on the data in question is that other financial activity can be analyzed as well, and it is possible to draw wider-spanning conclusion on the individuals' spending habits and patterns.

Round-up saving as a partial commitment device is part of a broader and more established literature on commitment devices. Commitment devices have been the topic of a broad selection of literature and their impact is not yet fully understood. DellaVigna & Malmendier (2006) studied gym contracts as commitment devices and find that, since there are no direct financial penalties connected to non-compliance, this commitment device is less effective than hard commitment devices. Gargano & Rossi (2021) find in a recent paper that soft, self-designed commitment devices, such as setting a savings goal, increases individuals' saving rate. Mullainathan & Shafir (2009) take a more general approach and focus especially on low-income households stating that poor self-control can lead to a state of cognitive dissonance where one's actions and underlying intentions don't line up. Commitment devices can help in such a situation to commit to the initial underlying intentions. This paper adds further evidence to the domain of soft commitment devices and investigates their effects.

To my knowledge, this is the first paper in the finance domain to explore round-up saving programs. Generally, only few papers have addressed round-up programs across all fields of research. Kelting et al. (2019) look at rounding-up decisions in connection to donating the difference and find that there are greater acceptance rates and donation likelihoods for round-up requests versus flat requests. These results demonstrate the effectiveness of rounding-up methods in the specific application of donations.

The paper also states that round-up methods can reduce the perceived pain of donating. In a more general sense, the related concepts of pain of paying and mental accounting of savings (Prelec

& Loewenstein, 1998) are one possible theoretical consideration in the case of round-up saving programs as well. The original idea behind round-up saving is that enrolled households spend as they did before enrollment and aggregate savings autonomously and passively in the background. Zellermayer (1996)'s work on pain of paying gives ground for deviations from the original idea. The paper finds that every transaction that happens through an exchange of goods or services and money carries a certain pain of paying. The pain of paying varies depending on different attributes of the transaction. If households mentally see the round-up amount as an increase in the price of the goods and services bought, it might increase their pain of paying and prevent them from spending as they did before enrollment. However, if households mentally see the round-up amount as saved money, it might decrease their pain of paying of the associated transaction through a halo effect simply from the action of saving. This, in turn, would increase their spending compared to the pre-enrollment state.

I investigate several hypotheses about the effects of round-up saving total spending, mandatory and optional spending, spending frequency, and average spending amount. Finally, I analyze whether enrollment in a round-up saving program has any effects on bounced checks or overdraft on a household's account.

In the analysis of my first hypothesis, I find that spending increases, mostly driven by increases in optional spending. The magnitude of the positive association between enrollment and total spending is more than $80 per week. This increase is mainly driven by optional spending. The results I find go against my expected effects of the round-up program. A household should not see an increase in total spending. One could expect an increase in the spending frequency and decrease in the average amount spent to optimally use of the round-up savings program. I analyze these subquestions in hypotheses 2 and 3. From the results under hypothesis 1 alone, it is not clear whether an increase in the spending frequency, the average amount spent, or both are behind the effect.

Round-up saving only works through a preceding transaction and the only way of increasing savings purely through rounding-up is to either increase spending frequency or increase transactions with very small cent amounts (i.e., between $0.01 and $0.10) to maximize round-up amounts.

The former is what the second hypothesis studies. That is, whether the spending frequency increases, as a result of the households perceiving to save more. My results show an increase in the spending frequency upon enrollment meaning there's a positive relationship between enrollment and the extensive margin on spending.

The second driver behind an increase in total spending might be an increase in the average transaction amount. I also find a positive effect of enrollment on the average transaction amount. With the goal of "saving more" in mind, it seems counter-intuitive to observe an increase in the average transaction amount. Per the design of round-up saving programs, the amount saved depends on the within-dollar or cent amount of the transaction. If a transaction amount is $5.01, $0.99 go towards saving, whereas with a transaction amount of $5.99 only $0.01 goes towards saving. The difference between $5.99 and $50.99 is irrelevant to the amount saved through round-up saving programs. The results of hypotheses 2 and 3 taken together then suggest that the increase in total spending is driven by both spending frequency and average amount spent.

The last and fourth hypothesis examines at the propensity of liquidity shortfall as defined by bounced checks and overdraft fees. The analysis shows a gradual increase in the propensity of liquidity shortfall after enrollment. This might be connected to the increase in spending, spending frequency, and average spending amount described above. An increase in the amount spent while controlling for income can increase the financial strain on households in the form of bounced checks and account overdrafts.

Additionally, I run a difference-in-differences analysis for my setup with multiple time periods. The analysis finds an average treatment effect on the treated in an effort to find a causal effect of enrollment in a round-up saving program. From this, I find an increase in household spending by approximately $300 per month upon enrollment in a round-up saving program. This goes hand-in-hand with the baseline results.

The results taken together suggest a causal increase in spending upon enrollment in a round-up saving program. With an average weekly amount saved of $4.50, there seems to be a short-run detrimental effect on household financials from enrollment.

Given the results of my analysis of round-up programs, it is not advisable to incorporate them into policy in the isolated form under analysis in this study. Round-up programs could be especially harmful for lower income individuals who might have a hard time saving out of constrained inflows and might fall into liquidity shortfall after enrollment. Incorporating other features, not included in the design of the specific round-up program studied here, could help flatten out the initial increase in spending. That is, for instance, notifications informing the enrollee about their current higher-than-average spending. FinTech companies which offer round-up programs have the option to control notifications when providing an app with their services. Delivering well-timed, short, and precise notifications to users could be used to counteract the initial increase in spending with enrollment.

Given that households know that they only save when they spend when using their debit card, they might shift their spending activity from credit cards to their debit card. I use the same methods as in the baseline analysis with the outcome variables credit card spending, extensive margin of credit card spending and intensive margin of credit card spending. I find that credit cards are a sticky method of payment with no discernible effect of enrollment on any of the outcome variables.

The results I find can have two underlying economic channels. First, the spend-and-save channel and second, the round-up channel. In the spend-and-save channel, the spending transaction receives a positive halo effect from saving. This decreases the pain of paying as defined by Zellermayer (1996) and can result in an increase in spending, since every spending transaction now also helps with saving more. In the round-up channel, the increase in spending is motivated by the rounding-up itself in a "gamification" sense. Households might see the saving endeavour as a "game" in which they try to arrive at savings amounts that are more than just a few cents. I am able to test the second channel with data on a saving program that does not have a round-up feature. Instead, every qualifying transaction results in a $1 transfer into the savings account. I find similar results to the round-up saving program. This leads me to revert to the first, the spend-and-save channel as main channel for the findings.

In the next section of this paper, I will talk about the data and the institutional setting. That will be followed by methodology and baseline results. In the fourth section, I run a difference-in-differences analysis. Section 5 discusses economic channels driving the found effects, while section 6 includes robustness analyses. In the last section I will conclude.

2 Data and Institutional Setting

I study financial outcomes around the round-up savings program of a U.S. financial institution. Once enrolled in the round-up savings program, every time a customer uses their debit card for a transaction, the transaction amount is rounded up to the nearest dollar. If a customer pays for a coffee worth \$2.50, the transaction will show up on the checking account together with a pending round-up transaction of \$0.50. This process is continued throughout the day and at the end of the day, the cumulative round-up amount is posted and transferred to the customer's savings account at the same financial institution.

Transactions belonging to this savings program show up in the data provided by an online account aggregator. Subscribers can pool their different financial accounts (e.g. checking, savings, credit card, brokerage, retirement, mortgage, and student loan) in one place and receive spending reports, balance sheets, etc. Data are limited to checking account, savings account, and credit card transactions. This makes the baseline dataset a transaction-level panel with information on the amount, date, and description of each transaction that a household makes. The full dataset is de-identified to protect the identity of the households. Households are given a unique user ID, which makes it possible to follow a household's transactions over time. More information on the dataset can be found in Baugh et al. (2018) and Baugh & Correia (2022). The analyses in this paper are based on a random 10% subsample of the full data set available.

In the context of account aggregator data, self-selection bias is a valid concern. This issue has been explored thoroughly by Baker & Yannelis (2017), Baker (2018), and Gelman et al. (2020) who find that in the case of their account aggregator data, there's a higher concentration of younger and male individuals using the service than there is in the U.S. consumer population. This might influence the external validity of the results. However, it should be noted that round-up saving is used heavily by FinTech companies whose average user base is generally younger and male as well (e.g. D'Acunto et al. (2020), Gargano & Rossi (2021)).

Self-selection into a round-up program is another issue worth considering. Generally, self-selection into a round-up program with a financial institution would result in a different sub-population than self-selection into an online account aggregator. There are two possible scenarios of how individuals get to be enrolled in the round-up program. First, they might find out about it themselves and feel motivated to enroll. Second, they might be advised or nudged to enroll after opening a checking and saving account or after opening a saving account when the checking account is already there. Enrollment can be done in person, via phone or online. Unfortunately, there is no possible way to investigate enrollment circumstances for my sample. Anecdotal evidence exclusively implied the second scenario, however. This fact might function as an attenuating force on validity concerns. [4]

The summary statistics in Table 1 show findings on the household-month level for all round-up and non-round-up users together, only round-up users and only non-round-up users, respectively. Table 1 reports that there are 25,575 households through the time frame of July 2010 to May 2015 for the full sample of round-up and non-round-up users. The round-up household subsample consists of 578 households, which is found after using several filters on the group of round-up households. Interestingly, round-up households seem to have smaller incomes than non-round-up households. It can also be the case that mostly single households enroll in round-up savings programs. The higher total income for non-round-up only households can stem from a two-person household being signed up under the same credentials in the account aggregator.

A comparison of credit card payments and borrowing shows a sizable difference between the two. For the round-up only sample, there are average credit card payments of $715 and credit card borrowing of $336. This can be explained by a scenario in which a household does not connect all the credit cards they have and borrow with, however, they connected their main checking account which they use to pay down all their credit cards.

[Table 1 - Summary Statistics]

Figure 1 shows a frequency distribution of daily round-up amount transfers from the checking to the savings account for all round-up users in the 10% sample. Most daily transfers to savings range between 0 and 1 dollar. Once the bin that includes the $1 barrier is reached, there is a steep drop and steady decrease in the frequency of transactions with such amounts.

[Figure 1 - Roundup Amounts Distribution]

Figure 2 reports a frequency count of enrollment dates for the 578 enrolled households I study starting nine weeks into the sample. Per definition, enrollments in the first nine weeks were left out in order to get sufficient input about pre-enrollment spending behavior. The figure shows a higher

[4] On a visit to a branch of the financial institution discussed above, I asked about the enrollment process. The information in this paragraph was reported. Additionally, I was able to talk to and read online posts from individuals who are enrolled in the program.

enrollment activity for the early years from 2010 to the end of 2012 compared to the years 2013 to 2015.

[Figure 2 - Enrollment Frequency by Week]

3 Methodology and Baseline Results

The overarching research question I aim to answer through this analysis is whether the widely used round-up savings program has any effects on household financial behavior. The results are then related to achieved savings through the program. For this, I will first directly test four hypotheses relating to the following subquestions:

1. Does enrollment in a round-up savings program affect (total, discretionary, and non-discretionary) spending?
2. Does enrollment in a round-up savings program affect spending frequency (i.e. extensive margin of spending)?
3. Do individuals spend more money whenever they make a transaction (i.e. intensive margin of spending)?
4. Does enrollment in a round-up savings program increase liquidity shortfall?

As a robustness check, I will also show that spending does not seem to shift away from credit cards to debit cards in order to take advantage of the round-up savings program. This assumes that the round-up program discussed in this project depends on spending through debit cards and thus transactions showing up on a household's checking account. Spending transactions through credit cards do not qualify for the round-up program.

[Table 2 - Difference in Means]

As can be seen in Table 2, the differences in means for all seven variables are significantly different from zero with a statistically significant increase in the pre-means versus the post-means.

The pre-period encompasses weeks 8 to 1 before enrollment and the post-period encompasses weeks 1 to 8 after enrollment in the round-up program.

H1: Enrollment in a round-up savings program has no effect on (total, discretionary, and non-discretionary) spending.

In the first part of the analysis, I want to test for an effect on spending - total spending, discretionary and non-discretionary spending - after enrollment in the round-up savings program. There are different possible effects from enrollment in such a program. That is, an decrease in spending, an increase in spending, or no effect.

Every transaction that happens through an exchange of goods or services and money carries a certain pain of paying (Zellermayer (1996)). This pain of paying varies depending on different attributes of the transaction. Typically, in round-up savings programs, two types of transactions show up in an enrollee's checking account, the spending transaction itself and the round-up transaction. Theoretically, there are three ways an individual might see and react to this setup. One the one hand, if pain of paying is sufficiently high for a transaction, the round-up amount increases the transaction amount and thus, the pain of paying even more and make an individual more sensitive to their spending. In the moment of the transaction, the round-up amount is seen as an additional charge decreasing one's current purchasing power instead of as money saved and increasing future purchasing power. This in turn decreases spending subsequent to enrollment in a round-up savings program in order to avoid increased cumulative pain of paying. This assumes that individuals are sensitive to the total transaction size including the round-up portion.

On the other hand, the effect of enrolling in a round-up program on spending can be positive. One can assume that individuals participate in such a program because they perceive saving as a good and responsible act. Previous to enrollment, they could have struggled with saving (enough) by themselves and want to take advantage of a commitment device which would make saving easier. The joint nature of saving and spending would then have an added halo effect through the saving portion. The individual perceives the spending transaction more as a saving transaction at that point, which helps her achieve the previously difficult to reach goal of saving. This motivates her to increase her spending transactions in order to solidify her new and "healthier" habits.

The third option would be no effect on total spending, as advertised by banks and FinTechs, with the program running in the background in an autonomous and passive way. Round-up programs advertise this as an advantage, that they can automatically run in the background without any adjustments by the customer when it comes to their spending habits. Additionally, with saved amounts only ranging from $0.01 to $1.00, it is assumed by most providers that individuals won't take enough notice to trigger a change in their behavior. This reaction is what is expected from a household that is trying to optimize their enrollment outcomes. Given budget constraints, households are not expected to increase their total spending after enrollment. However, from an optimization point-of-view, it would be expected to see an increase in spending frequency paired with a decrease in average amount spent to take full advantage of the round-up savings program. I analyze the extensive and intensive margin in hypotheses 2 and 3 for this reason.

My analysis finds support for a positive effect of enrollment on spending. An increase in spending can take place through two channels. First, pairing spending with saving gives spending transactions the positive halo effect of saving. Zellermayer (1996) introduced the concept of pain of paying which states that transactions, depending on certain attributes, carry a degree of pain. Thus, pairing a saving transaction with a spending transaction might decrease or neutralize the pain of paying and decrease the inhibition for further spending transactions. This would cause more spending to take place.

A second channel is the feature of rounding-up itself. In a "gamification" sense, individuals might be inclined to increase their spending to increase their rounded up savings from mere cent amounts to higher amounts. Gamification usually entails challenges, competitions, and rewards. There is no direct challenge or competition which the financial institution sets up with their round-up savings program. However, the reward from using the program is to have future savings. Thus, individuals would enter into a competition with the program or themselves even to increase their savings from mere cent amounts to higher dollar amounts.

I test this hypothesis by comparing households' spending before and after enrollment using an OLS fixed effects regression as well as an event study regression with fixed effects. In the OLS fixed effects regression, I control for weekly income or for monthly income. Spending is split up into discretionary and non-discretionary spending. The former category includes spending in restaurants, retail, entertainment, travel, other, check, cash, and outgoing investing. The latter includes spending in groceries, mortgage, gas, loan repayment, car payment, insurance, healthcare, utilities, interest expenses, and fees.

The simple empirical specification is:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta Enrollment_{i,t} + X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ is total spending, discretionary spending or non-discretionary spending for user i at time t. $Enrollment_{i,t}$ is an indicator variable equal to "0" if the user is not enrolled in the round-up savings program at time t and "1" once she enrolls. The coefficients α_i and α_t denote household and week fixed effects, respectively. The standard errors are clustered at the household-level. $X_{i,t}$ includes controls for weekly income or monthly income.

[Table 3 - H1 Regression Results]

The coefficient of interest, β, identifies the change in weekly spending when users enroll in the round-up savings program, controlling for household-specific characteristics and time-effects. For total spending, there is an average increase in weekly total spending of about \$87 when controlling for weekly income, for discretionary spending of about \$69 when controlling for weekly income and for non-discretionary spending of about \$18 when controlling for weekly income. Compared to their pre-enrollment means of \$633, \$514, and \$119, respectively, there is a 14% increase in weekly total spending, a 13% increase in weekly discretionary spending, and a 15% increase in weekly non-discretionary spending. These results go against my expectations of a household who is constrained by its income but is trying to optimally use the round-up savings program.

I also examine the dynamics of changes in consumption upon enrollment, through the following specification:

$$Y_{i,t} = \alpha_i + \alpha_t + \sum_{s=-8}^{8} \beta_s Enrollment_{i,t,s} + \epsilon_{it}, \tag{2}$$

where $Y_{i,t}$ is total spending, discretionary spending or non-discretionary spending for user i at time t. $Enrollment_{i,t}$ is an indicator variable equal to "1" if the user is enrolled in the round-up savings program in the s-th week in the calendar week t and "0" otherwise. The coefficients α_i and

α_t denote household and week fixed effects, respectively. The standard errors are clustered at the household-level.

[Table 4]

In Table 4, the period of reference is period -1, the period immediately preceding enrollment. The coefficients for period 0, the enrollment period, up to period 8 after enrollment, are almost all positive and some are significant for the three dependent variables - total spending, discretionary spending, and non-discretionary spending. The coefficients with their 95 % confidence intervals are graphed in Figure 3, Figure 4, and Figure 5 below.

The figures show a jump upon enrollment for total spending, discretionary, and non-discretionary spending relative to the pre-enrollment period. A possible explanation for this is a "new toy" effect. That is, households spend a lot more upon enrollment in the program, but their spending decreases from the initially very high level over the following weeks as the novelty of the round-up savings program fades and becomes less salient. In the weeks following enrollment, there are still elevated levels for all three dependent variables for most of the weeks, with non-discretionary spending showing the most consistent results. Gargano & Rossi (2021) find a similar effect in their analysis of the effectiveness of goal setting on saving through a savings app.

[Figure 3, Figure 4, Figure 5]

H2: Average spending frequency increases after enrollment in a round-up savings program.

Under hypotheses two and three, I disentangle whether the effects found under hypothesis 1 are mainly driven by an increase in spending frequency or an increase in the average amount spent, or by both. First, I analyze spending frequency (extensive margin) around enrollment.

I test this hypothesis by comparing households' extensive margin of spending before and after enrollment using a similar analysis as under hypothesis 1 where the dependent variable $Extensive\_Margin_{it}$ is an indicator variable equal to "0" if the user i had total spending of 0 in a specific week t and "1" if a user had total spending of greater than 0 in a specific week t. In another definition of this variable, I sum up the positive spending instances per week and call the variable Ext. Margin_{sum}.

[Table 5 - H2 Regression Results]

The coefficient of interest, β, identifies the change in weekly spending frequency when users enroll in the round-up savings program, controlling for household-specific characteristics and time-effects. Table 5 shows the results using slightly different methods of definition for the extensive margin. The variable Ext. Margin_{sum} uses the sum of spending instances per week, while the variable Ext. Margin_{maxf} is an indicator variable for spending greater than zero in a specific week. Column (3) of Table 5 shows an average increase in the number of weekly transactions by 0.26 transactions when controlling for monthly income. Compared to its pre-enrollment mean of 3.77, there is a 7% increase in the number of weekly transactions.

Column (6) of Table 5 indicates a 1% increase on average in the probability of a spending transaction after enrollment. All effects are statistically significant at the 1% level. [5]

I also examine the dynamics of changes in spending frequency upon enrollment, through the a similar specification as in equation (2) under hypothesis 1.

[Table 6]

In Table 6, the period of reference is period -1, the period before enrollment. The coefficients for periods 0, the enrollment period, up to period 8 after enrollment, are all positive for both variables and significant for almost all of the weeks. The coefficients with their 95 % confidence intervals are graphed in Figure 6 and Figure 7 below, separately for the two definitions of extensive margin presented here.

Both figures show a clear jump upon enrollment relative to the pre-enrollment period and elevated levels throughout the observation period of 8 weeks post-enrollment. These results in isolation would go hand-in-hand with expectations of an individual or household who increases spending frequency in order to benefit maximally from the round-up savings program. The only important factor in a round-up savings program is the cent amount, and not the total amount spent. Since it is difficult to fully control the cent amount with taxes not being included in displayed price tags in the US, an increase in the spending frequency provides a control mechanism for the amount saved through the program. My results show that households increase their spending frequency

[5] The pre-mean for the total spending frequency is 0.98.

once enrolled in the program which answers one part of my inquiry into the increase in spending I found under hypothesis 1. The second part is an analysis of the average amount spent.

[Figure 6, Figure 7]

H3: Average transaction amount decreases after enrollment in a round-up savings program.

The third hypothesis looks at the average amount spent (i.e. intensive margin of spending). As stated, the expectation from a household with a budget constraint is no effect on total spending from an increase in the extensive margin of spending and a decrease in the intensive margin on spending. Since the only important feature in a round-up savings program is the cent amount, effects described in the previous sentences take advantage of the round-up savings program design to increase the amount saved while staying within the budget constraint. As shown under hypotheses 1 and 2, I find an increase in total spending driven by spending frequency. Another possible reason for seeing an increase in spending besides an increase in spending frequency is an increase in the average amount spent.

I test hypothesis 3 by comparing households' intensive margin of spending before and after enrollment using a similar set-up as in equation (1) where the dependent variable $Intensive\_Margin_{it}$ denotes weekly spending by user i at time t, conditional on the previously defined variable $Extensive\_Margin_{it}$ being 1.

[Table 7 - H3 Regression Results]

The coefficient of interest, β, identifies the change in weekly spending amount conditional on spending when users enroll in the round-up savings program, controlling for household-specific characteristics and time-effects. Table 7 shows the results for total spending. Column (2) indicates a $84 increase in average total spending after enrollment in the round-up program. The effect is statistically significant at the 1% level. The amount represent around a 13% increase in average total spending compared to the pre-enrollment mean.

Similar to equation (2) under hypothesis 1, I examine the dynamics of changes in the average amount spent upon enrollment where $Intensive\_Margin_{it}$ denotes weekly spending by user i at time t, conditional on the previously defined variable $Extensive\_Margin_{it}$ being 1.

[Table 8]

Table 8 reports positive coefficients from the enrollment period on for total spending for all coefficients but the one in week 7 after enrollment.

Figure 8 shows a similar "new toy effect" with a jump in total spending upon enrollment of about $164 and a subsequent increase in the first week after enrollment. The level then decreases again and fluctuates throughout the rest of the event window.

[Figure 8]

Taking the findings from hypotheses 1, 2, and 3 together, I conclude that there is a positive association between enrollment and spending which is mainly driven on the expense-category side by discretionary spending and on the expense-component side the spending frequency as well as the average amount spent.

Most of these findings do not align with my hypotheses of a budget-constrained household trying to optimally use the round-up savings program. Under those assumptions, no increase in total spending would have been found and also no increase in the average amount spent. However, I find an increase in both, total spending and the average amount spent, additional to an increase in the spending frequency. The scenario above also differs from the original expectation of round-up savings programs providers. That is, consumers save automatically and passively in the background with savings amounts so small that no change in day-to-day financial behavior will occur.

My findings so far, and especially the findings pertaining to the average amount spent, hint towards the save-and-spend channel as a possible driver behind the observed effect. When spending and saving transactions are paired, the positive effect of saving is transferred onto the spending transaction, lowering the pain of paying and thus making transactions more likely to take place. In a round-up savings program, increasing the average amount spent, is not the optimal strategy given a budget constraint. Spending $\$1,000$ instead of $10 does not have an influence on the round-up amount. In both cases, the round-up amount is $1. Thus, seeing an increase in the average amount spent, together with an increase in the spending frequency, makes it plausible that a halo effect of saving on spending after pairing the two processes is the driver behind my findings. The halo effect decreases the pain of paying of transactions and lowers the threshold for making a transaction. It effectively adds another layer to the decision process by partially justifying the necessity of the transaction.

H4: Liquidity shortfall increases after enrollment on average.

The last hypothesis investigates whether enrollment in the round-up savings program affects liquidity shortfall through the channel of increased spending. Liquidity shortfall is defined as an indicator variable and is 1 when a household experiences a bounced check or an overdraft.

As seen in the analyses for hypotheses 1 to 3, there seems to be an increase in spending amount and frequency upon enrollment. Given fixed effects and controlling for income, households appear to spend more without experiencing an increase in inflows. This could bring some households into the situation of liquidity shortfall over time measured via overdraft fees or bounced check fees. My baseline results for this last hypothesis are similar to equation (1) under hypothesis 1, but using the dependent variable $Liqu\_SF_{it}$ which is an indicator variable equal to "1" if user i has a bounced check or overdraft at time t.

[Table 9 - H4 Regression Results]

The coefficient of interest, β, identifies the probability of liquidity shortfall when users enroll in the round-up savings program, controlling for household-specific characteristics and time-effects. Table 9 shows that there is a statistically significant 1.4% increase in the probability of liquidity shortfall on average upon enrollment into the round-up savings program controlling for weekly income. [6]

Subsequently, I examine the in an event study setup similar to equation (2) under hypothesis 1.

[Table 10]

Table 10 reports a significant increase in liquidity shortfall for periods 3,4,5,7 and 8 after enrollment. This increasing trend is displayed in Figure 9 as well. There is no immediate reaction upon enrollment, however, with time, liquidity constraints increase in the form of bounced checks and account overdrafts.

[6] Pre-enrollment liquidity shortfall mean is 0.046.

[Figure 9]

Taking results from hypotheses 1 to 4 together, my analyses show a positive association between enrollment in the round-up savings program and spending amount driven by the average amount spent and spending frequency. Enrolled households then on average see an increase in liquidity shortfall through bounced checks and overdrafts approximately 3 weeks into enrollment.

In the next section, I run a difference-in-differences design by Callaway & Sant'Anna (2021) to establish causality claims between enrollment in a round-up savings program and spending behavior.

4 Causality

The general setup of the round-up saving program makes it difficult - yet not impossible - to establish a causal effect of the round-up savings program on spending. These difficulties include many unique enrollment/event dates through the event window and selection bias into the round-up savings program.

For my baseline results, I used data on the weekly level with 140 unique enrollment weeks over the sample window from 2010 to 2015. As my group sizes aren't big enough for the purpose of the difference-in-differences analysis, I aggregate the data to the monthly level. This leaves me with 41 unique enrollment months over the full sample time period from 2010 to 2015. Furthermore, to ensure big enough treated groups per unique enrollment month, I restrict the event window to the end of 2013. As can be seen in Figure 2, most enrollments take place in 2010, 2011, and 2012. This results in 29 unique enrollment groups.

Once the data is filtered and aggregated to the monthly level with monthly total spending as the main variable of interest, I apply the difference-in-differences estimator by Callaway & Sant'Anna (2021). [7]

My final sample for the analysis is made up of 324 treated (i.e. enrolled) households and 4060 untreated households. The reduced sample size compared to the baseline results sample size stems from the data availability filter I had to apply to the data for the diff-in-diff analysis. Within the difference-in-differences analysis, propensity score matching is used to match treated and untreated households. I set the matching variables to income and credit card spending.

[7] For more information see https://bcallaway11.github.io/did/articles/did-basics.html

Table 11 and Figure 10 show the results of this analysis. In Figure 10, the red dots and lines give point estimates and simultaneous 95% confidence bands for pre-treatment periods while the blue dots and lines give point estimates and simultaneous 95% confidence bands for the treatment effect. Given the parallel trends assumption, the pre-treatment estimates should be equal to 0. That is, the pre-treatment trends of both treatment and control group should be the same. These estimates are all close to 0 in my analysis.

Table 11 shows all coefficients from enrollment on forward as positive. The average treatment effect on the treated is given as $297.44. This confirms results found in the baseline analysis which showed an increase in spending amount upon enrollment as well.

Selection bias is oftentimes a concern with FinTech data (Baker & Yannelis, 2017; Baker, 2018; Gelman et al., 2020). There are some ways to alleviate selection concerns in my analysis. For one, as stated in the data section, anecdotal evidence suggests that individuals in the program might have become enrolled in different ways. Some individuals might have enrolled out of pure self-motivation while others might have enrolled after a suggestion from an employee of the institution. These different ways of enrollment, self-selection vs. targeting potentially over- and understate my effects at the same time. Additionally, the staggered design of my analysis over several years makes it less likely that the same event influenced households to sign up for either the round-up savings program and/or the account aggregator.

5 Economic Channels

The analysis so far has shown that spending increases for both, discretionary and non-discretionary spending, upon enrollment, and on average stays at an elevated level for most of the 8 weeks of the event window. Total spending is made up of discretionary and non-discretionary spending and is driven mostly by discretionary spending. The analyses show a "new toy effect" in discretionary and total spending upon enrollment which attenuates somewhat in the weeks following. From the regression results, there is an increase in total spending of about $87 per week. Table 12, which shows summary statistics for the weekly rounding-up amounts per event day, reports an average round-up savings amount of about $4.50 dollars per week with a max ranging from $38.81 in event week 5 to $20.20 in event week 6. Thus, the saved amount does not seem to justify the disproportional increase in spending. Lastly, there is an increase in liquidity shortfalls slowly starting in the third week after enrollment and showing an upward trend for the remainder of the event period.

There are two possible channels to explain these results. The first channel is the spend-and-save channel, the second channel is the round-up channel. First, in the spend-and-save channel, when pairing spending with saving, the spending transaction receives a positive halo effect of saving. This is under the assumption that saving is perceived as a positive act by most people in contrast to some spending transactions. Some spending transactions are connected to a pain of paying. Zellermayer (1996) introduced the concept of pain of paying which states that transactions, depending on certain attributes, carry a degree of pain. The addition of a saving feature to spending transactions might then decrease or neutralize the pain of paying and decrease the inhibition for future spending transactions. More spending would take place, since these transactions can be justified to help with saving.

In the round-up channel, individuals increase spending because of a "gamification" factor. Gamification in finance usually entails challenges, competitions, and rewards. There is no direct challenge or competition which the financial institution sets up with their round-up savings program. However, the reward from using the program is to have future savings. So, individuals would enter into competition with the program or themselves to increase their savings from mere cent amounts to higher dollar amounts. This would see them increase their spending upon enrollment in a round-up savings program.

To test the second channel, I use information about a similar saving program which was introduced by another U.S. financial institution. This program does not use the round-up mechanism, but transfers $1 to one's savings account for every qualifying transaction. If the round-up channel was the only driver of the increase in spending observed, there would not be an increase in spending in the flat savings program, since the program does not round up. Results for this analysis can be found in Table 13, which are similar to the analyses done for hypotheses 1 to 4, and I used similar filters to arrive at the sample. Table 13 shows a statistically significant increase in total spending of $370 per week on average. For discretionary spending in column (5), this increase is $324 and for non-discretionary spending it is $44. All results are statistically significant at the 1% level.

Both results taken together hint at the spend-and-save channel as the main driver behind the increase in spending. Generally, the round-up savings program can be split up into two possible features, the round-up feature and the spend-and-save feature. After analyzing a similar savings program without the round-up feature and finding a similar effect, I conclude that the round-up feature might not be the main driver behind the positive effect on total spending. The second channel, the spend-and-save channel appears to be the main driver instead. The addition of saving to spending decreases the pain of paying and thus lowers the threshold to spending transactions which would explain the observed increase in total spending.

6 Robustness

An alternative explanation for the increase in checking account spending via debit card transactions could be a substitution effect between credit and debit card spending.

A household might be inclined to shift their spending from the credit card to the debit card to benefit more from the savings program after enrollment. I expect to see more spending being shifted from the credit card account to the checking account (via debit card). Also, this hypothesis more broadly explores a change in the choice of spending device. Many similar savings programs only work through spending on debit cards. That is, every outgoing transaction made through a debit card will be rounded up to the nearest dollar. Thus, daily spending via credit cards does not contribute to the aggregate round-up amount.

I test this hypothesis by comparing households' credit card spending before and after enrollment using a similar setup as utilized in equation (1) where the dependent variable $Y_{i,t}$ is either total credit card spending, extensive margin of credit card spending or intensive margin of credit card spending. $cc\_Spending_{it}$ denotes credit card spending for user i at time t, $Extensive\_Margin_{it}$ is an indicator variable equal to "0" if the user i had total spending of 0 in a specific week t and "1" if a user had total spending of greater than 0 in a specific week t (in another definition of this variable, I sum up the positive spending instances per week as done under H1), and $Intensive\_Margin\_cc_{it}$ denotes weekly spending by user i at time t, conditional on $Extensive\_Margin\_cc_{it}$ being "1".

[Table 14 & Table 15 - Regression Results]

The coefficients of interest, β, identifies the change in weekly credit card spending, weekly credit card spending frequency, or weekly spending amount conditional on spending when users enroll in the round-up savings program, controlling for household-specific characteristics and time-effects. Table 14 shows results for the total credit card spending amount in columns 1 to 3 and results for the extensive margin - sum definition over each week - in columns 4 to 6. The results upon enrollment are not significant. Table 15 shows results for the indicator definition of extensive margin and the intensive margin. Again, the results are not significant. The results for the intensive margin and total credit card spending are negative and range from $5 to $19.

The analysis of credit card spending highlights the stickiness of credit cards as a means of payment. There are no discernible effects of enrollment on credit card variables to be found.

7 Conclusion

I study the effect of enrollment in round-up savings programs on household spending variables and liquidity shortfall using data from an account aggregator. The results indicate a positive effect of enrollment on total spending, which mainly comes from discretionary spending. The effect on total spending is driven by an increase in spending frequency and average amount spent. Furthermore, I find a gradual increase in the propensity of liquidity shortfall.

I am also able to identify a causal effect of enrollment in the round-up savings program on total spending. The average treatment effect on the treated is about $300 on a monthly level. This confirms the results found in the baseline analysis on a weekly level.

Possible channels to explain this are the round-up and the spend-and-save channel. Through an additional analysis using data on a flat saving program from another U.S. financial institution, I am able to show that the spend-and-save channel dominates. The positive halo that is attached to spending transactions after spending and saving are combined, can work almost as a justification for additional spending transactions for households, since it increases their savings.

Taking all the findings together, enrollment in the round-up savings program increases spending through an increase in spending frequency and an increase in the average amount spent. In the course of the eight weeks post enrollment, liquidity shortfall increases. That is, instances of bounced checks and overdrafts increase. This could be connected to an increase in spending without experiencing an increase in income. Relating this to the amount saved of approximately $4.50 per week, a clear disproportion must be noted.

This first analysis of round-up programs suggests that an exact setup as in the program I study might on average not be too beneficial if spending is not controlled and inflows are constrained. FinTech companies might have different means at hand to attenuate the initial negative impact on financial health due to how they set up their applications and notifications for the users.

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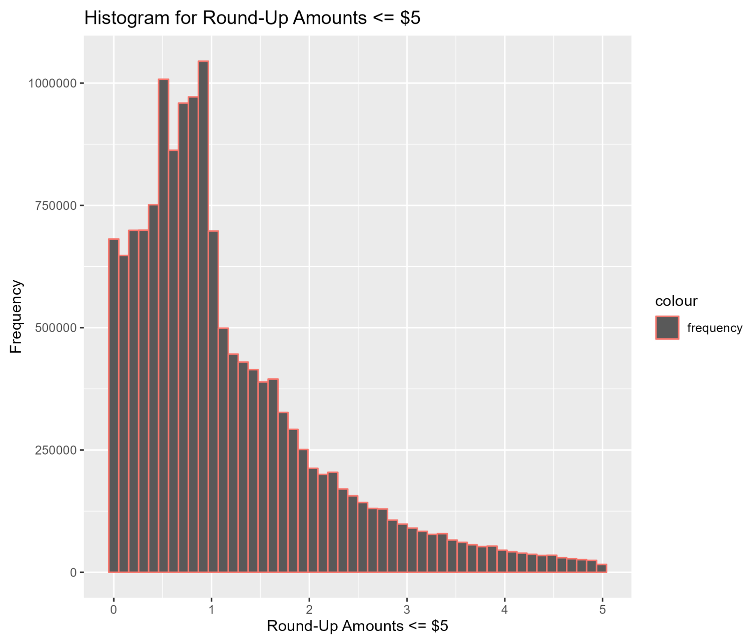
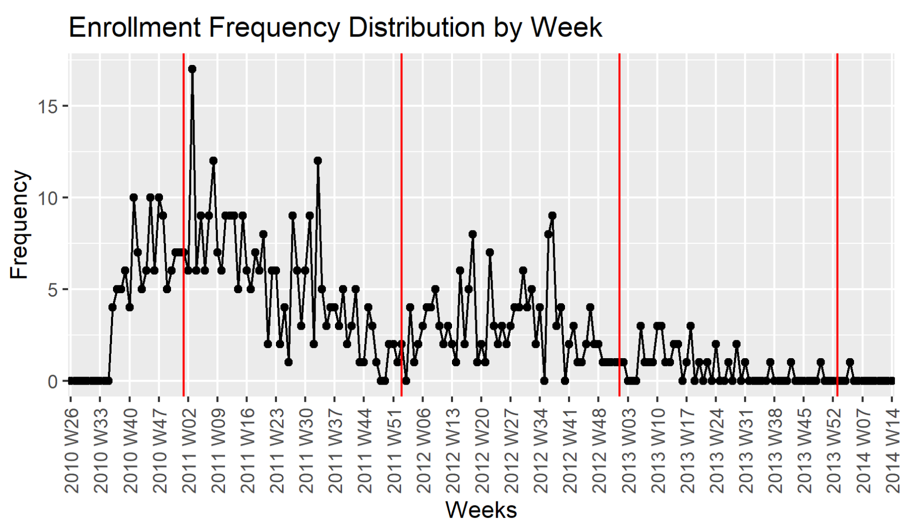
8 Figures and Tables

Figure 1: Histogram for Round-Up Amounts $\leq$ \$5



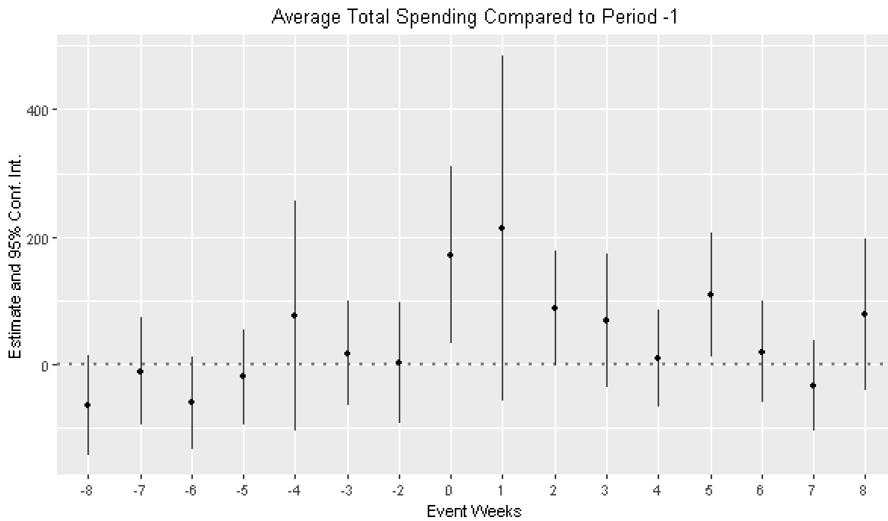
Note: This figure shows the daily frequency distribution of round-up saving amounts less than or equal to \$5 for the full, non-filtered sample of households who are enrolled in the round-up program.

Figure 2: Enrollment Week Frequency



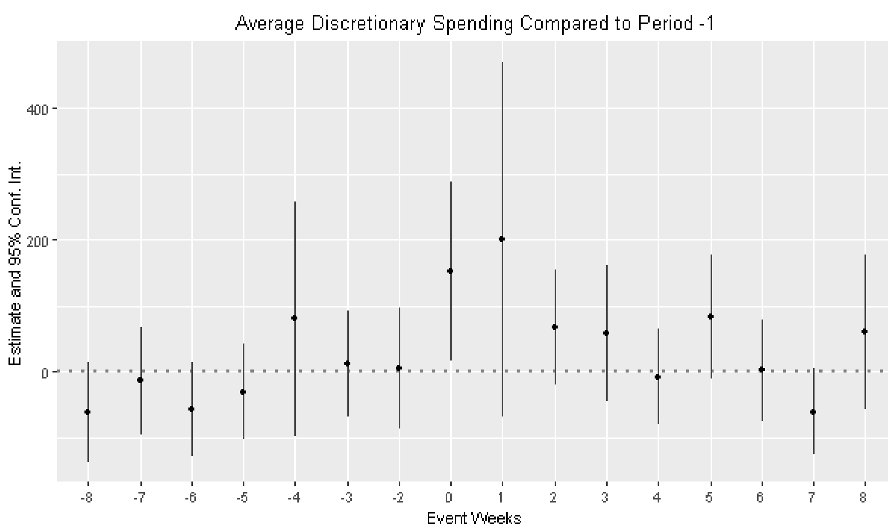
Note: This figure shows the daily frequency counts per week for the event window of week 26 in 2010 to week 11 in 2015 for the sample of 528 enrolled households. Red vertical lines indicate the first week of each year from 2011 to 2015. The first weeks are zero by definition. This figure represents the filtered subsample of enrolled households used for the analysis.

Figure 3: Total Spending around Enrollment - Event Study



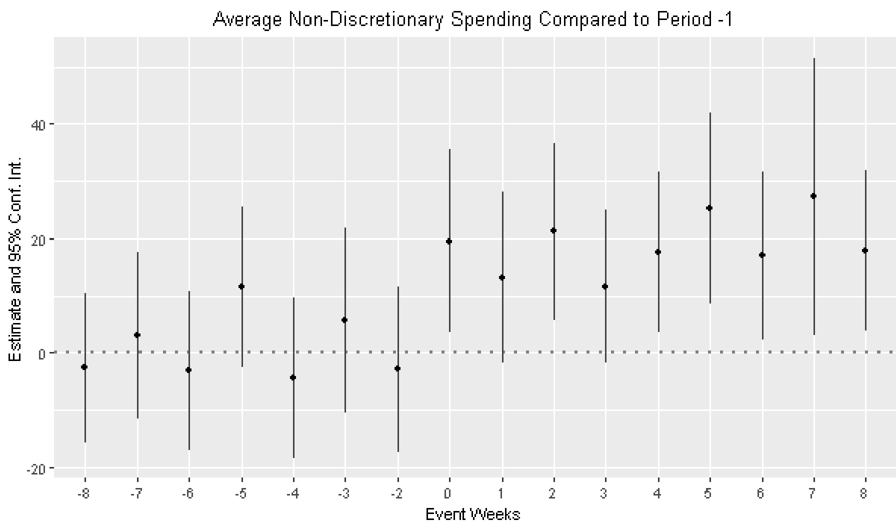
Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 1 for the dependent variable total spending. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 4: Discretionary Spending around Enrollment - Event Study



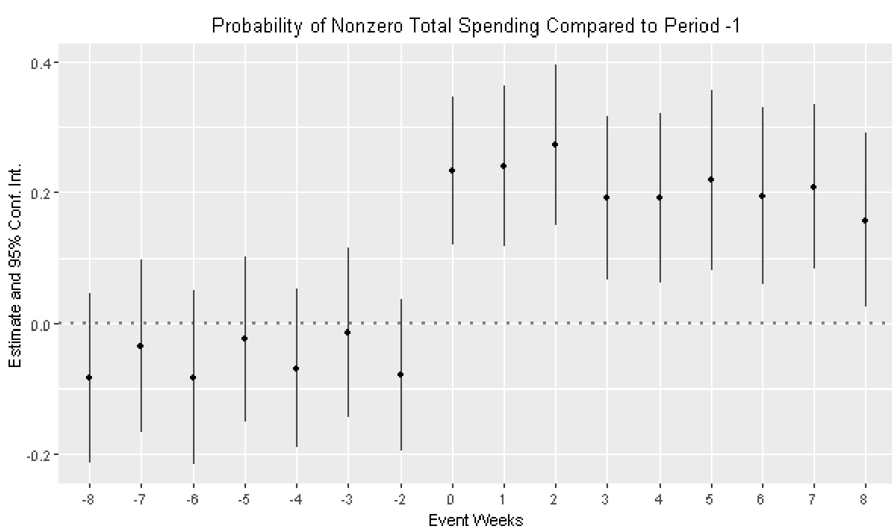
Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 1 for the dependent variable discretionary spending. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 5: Non-Discretionary Spending around Enrollment - Event Study



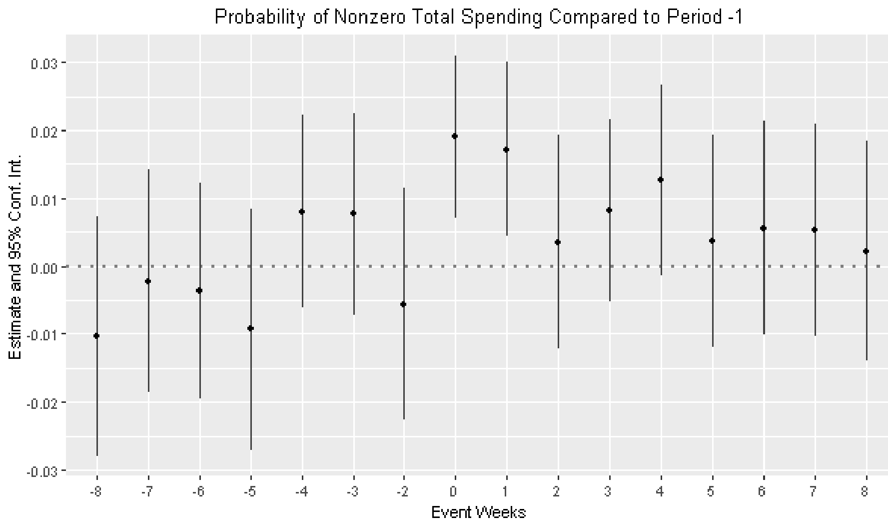
Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 1 for the dependent variable non-discretionary spending. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 6: Average Extensive Margin of Total Spending around Enrollment (Sum) - Event Study



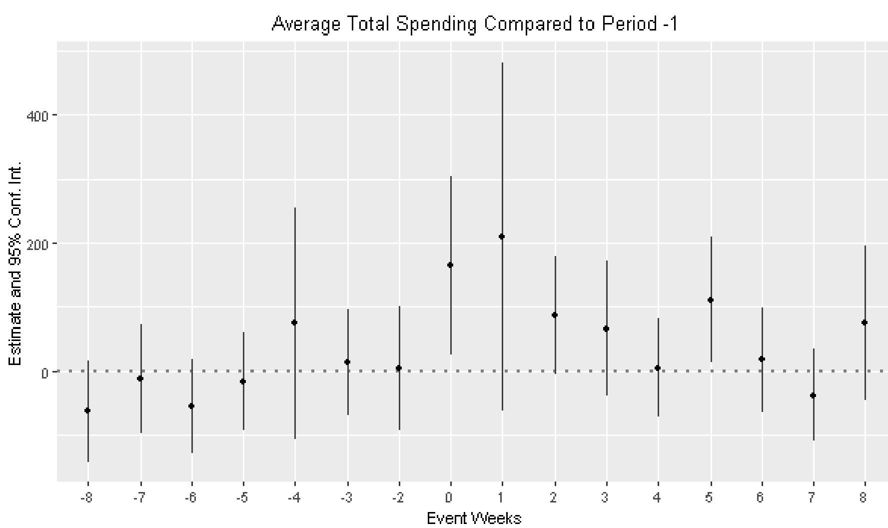
Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 2 for the dependent variable extensive margin. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 7: Average Extensive Margin of Total Spending around Enrollment (Max) - Event Study



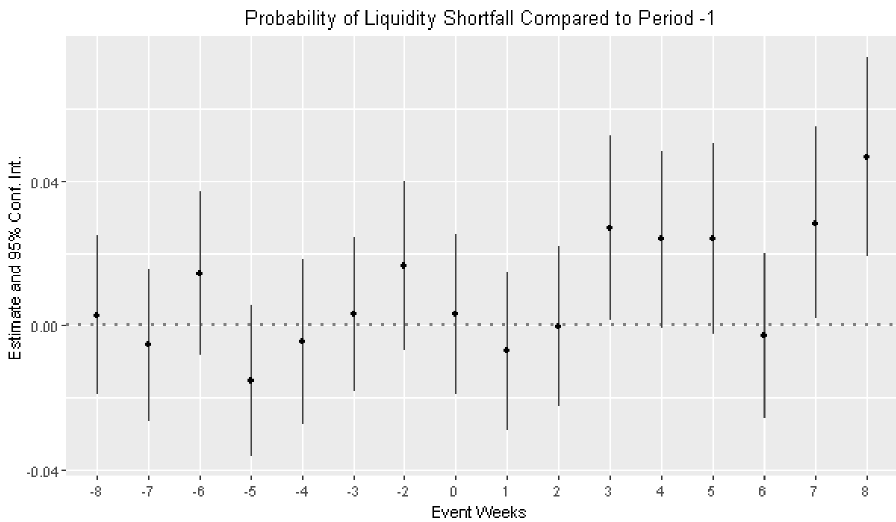
Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 2 for the dependent variable extensive margin. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 8: Average Intensive Margin of Total Spending around Enrollment - Event Study



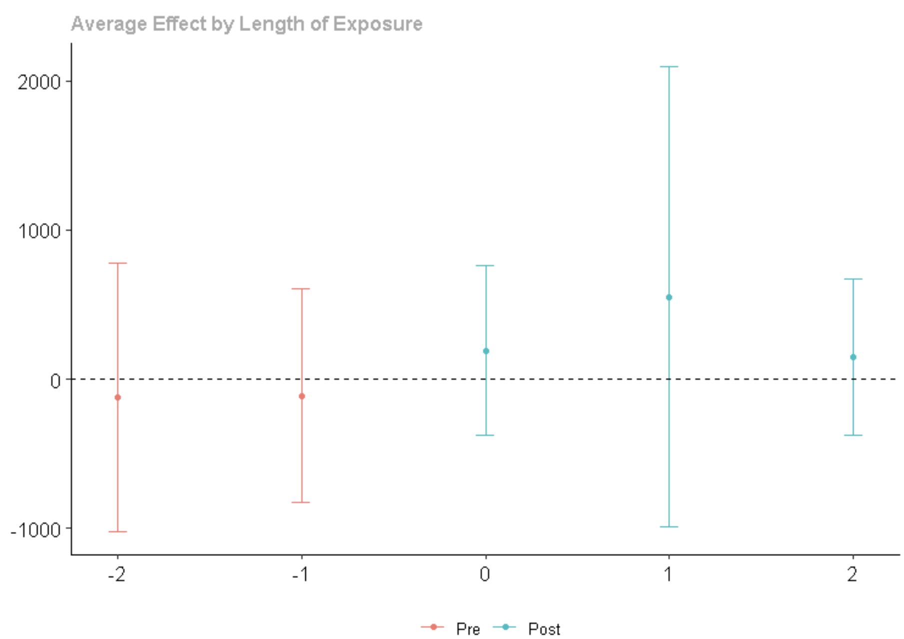
Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 3 for the dependent variable intensive margin. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 9: Average Liquidity Shortfall around Enrollment - Event Study



Note: This figure displays coefficient estimates and 95 % confidence intervals of the β_s coefficients from the event study regression specified under hypothesis 4 for the dependent variable liquidity shortfall. The standard errors are clustered at the household level. The omitted time period is week -1, the week prior to enrollment

Figure 10: Difference-in-Differences Plot



Note: This figure displays coefficient estimates and 95 % confidence intervals for the difference-in-differences estimate using methodology and code by Callaway & Sant'Anna (2021). This analysis is on the monthly level.

Table 1: Summary Statistics

	FULL SAMPLE		ROUND-UP ONLY		NON-ROUND-UP ONLY	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Total Income	$4,243	$22,845	$ 1,594	$ 2,317	$ 4,250	$ 22,873
Net Savings	$ 12	$ 14,051	$ 21	$ 798	$ 12	$ 14,069
Net Transfer	$ (115)	$ 35,878	$ (34)	$ 3,554	$ (116)	$ 35,922
Borrowing	$ 777	$ 2,513	$ 336	$ 1,223	$ 778	$ 2,515
Other Inflows	$ 2,963	$ 53,549	$ 2,277	$ 8,657	$ 2,964	$ 53,613
Total Inflows	$ 7,880	$ 60,344	$ 4,194	$ 9,588	$ 7,889	$ 60,416
Recurring Expenses	$ 2,580	$ 5,918	$ 1,304	$ 2,577	$ 2,583	$ 5,924
Mortgage Pmt	$ 569	$ 3,001	$ 324	$ 994	$ 569	$ 3,005
Car Pmt	$ 136	$ 419	$ 88	$ 243	$ 136	$ 420
Credit Card Pmt	$ 1,676	$ 4,593	$ 715	$ 1,950	$ 1,678	$ 4,598
Utilities	$ 199	$ 352	$ 177	$ 258	$ 200	$ 353
Banking Fees	$ 110	$ 8,519	$ 35	$ 291	$ 110	$ 8,530
Interest Expense	$ 15	$ 53	$ 12	$ 44	$ 15	$ 53
Other Spending	$ 4,955	$ 30,647	$ 2,590	$ 4,697	$ 4,961	$ 30,684
Total Outflow	$ 7,757	$ 34,823	$ 3,985	$ 6,087	$ 7,766	$ 34,864
Household-Months	1,307,801		3,229		1,304,572	
Households	25,575		578		24,997	

Note: This table provides summary statistics from my sample from 2010 to 2015. The unit of observation is household-month. The first two columns present summary statistics for all households not using the round-up savings program and the filtered treated group of round-up program households. The next two columns present summary statistics for the subset of households which use the round-up program and passed several filters, the last two columns present summary statistics for all households that are not enrolled in a round-up program. Variables are winsorized at the 1% level.

Table 2: Difference in Means

Variable	**Mean Pre** (Weeks -8 to -1)	**Mean Post** (Weeks +1 to +8)	**Difference** (Post - Pre)	**P-value**
Spending				
Total	$633.58	$713.26	$79.68	0.00
Discretionary	$514.41	$576.78	$62.37	0.04
Non-Discretionary	$119.17	$136.48	$17.31	0.00
Extensive Margin				
Ext. Margin_{sum}	3.77	4.03	0.26	0.00
Ext. Margin_{max}	0.9777	0.9868	0.0091	0.01
Intensive Margin				
Int. Margin	$640.74	$718.45	$77.71	0.01
Liquidity Shortfall				
Liqu. SF	0.0458	0.0614	0.0156	0.00

Note: This table provides a difference in means test for the outcome variables used in this paper. The pre-sample covers weeks 8 to 1 before enrollment and the post-sample covers weeks 1 to 8 after enrollment for all outcome variables used in the following analysis.

Table 3: Regression Results for H1 - Spending

Dep. Vars.:	Total Spending			Optional Spending			Necessary Spending		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Enrollment	87.86***	86.80***	87.48***	69.83**	68.69**	69.43**	18.03***	18.12***	18.06***
	(30.14)	(30.39)	(30.21)	(29.21)	(29.46)	(29.29)	(3.18)	(3.18)	(3.18)
Weekly		94.74			102.49			-7.753	
Income		(73.35)			(73.07)			(7.20)	
Monthly			20.34			21.88			-1.55
Income			(16.79)			(16.58)			(1.44)
Fixed-effects									
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	9,826	9,826	9,826	9,826	9,826	9,826	9,826	9,826	9,826
R^2	0.231	0.232	0.232	0.199	0.199	0.199	0.412	0.412	0.412
Within R^2	0.001	0.002	0.001	0.001	0.001	0.001	0.004	0.004	0.004

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in total, discretionary, and non-discretionary spending explained by enrollment in a round-up savings program. The regressions include household and week fixed effects to control for household-specific characteristics and time-effects. It also includes controls for weekly and monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 4: Event Study Results H1 - Spending

Dependent Variables:	Total Spending	Optional Spending	Necessary Spending
Model:	(1)	(2)	(3)
Variables			
t-8	-63.38	-60.72	-2.65
	(40.06)	(38.75)	(6.70)
t-7	-10.60	-13.56	2.96
	(43.01)	(41.85)	(7.41)
t-6	-59.08	-55.86	-3.21
	(36.81)	(35.98)	(7.13)
t-5	-18.98	-30.46	11.49
	(37.96)	(36.98)	(7.17)
t-4	76.34	80.79	-4.45
	(91.17)	(90.71)	(7.18)
t-3	17.60	11.96	5.64
	(41.64)	(40.78)	(8.25)
t-2	2.81	5.74	-2.93
	(48.34)	(47.00)	(7.37)
t	171.52**	152.06**	19.45**
	(70.55)	(69.22)	(8.16)
t+1	214.10	200.92	13.18*
	(137.63)	(136.77)	(7.62)
t+2	87.91*	66.72	21.19***
	(45.83)	(44.48)	(7.88)
t+3	69.53	57.98	11.56*
	(53.02)	(52.30)	(6.83)
t+4	10.33	-7.12	17.45**
	(38.47)	(37.03)	(7.15)
t+5	108.83**	83.62*	25.21***
	(49.20)	(47.48)	(8.51)
t+6	19.64	2.73	16.91**
	(40.53)	(39.17)	(7.49)
t+7	-32.71	-59.96*	27.25**
	(35.79)	(33.08)	(12.40)
t+8	77.98	60.14	17.84**
	(60.34)	(59.49)	(7.20)
Fixed-effects			
Household	Yes	Yes	Yes
Week	Yes	Yes	Yes
Fit statistics			
Observations	9,826	9,826	9,826
R^2	0.233	0.201	0.413
Within R^2	0.004	0.003	0.006

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows event study regression estimates of differences in total, discretionary, and non-discretionary spending explained by enrollment in a round-up savings program. The regressions include household and week fixed effects. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 5: Regression Results for H2 - Extensive Margin

Dependent Variables:	Ext. Margin_{sum}			Ext. Margin_{max}		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Enrollment	0.2613***	0.2596***	0.2607***	0.0106***	0.0104***	0.0105***
	(0.0332)	(0.0331)	(0.0331)	(0.0031)	(0.0031)	(0.0031)
Weekly		0.1549***			0.0086*	
Income		(0.0561)			(0.0046)	
Monthly			0.0352*			0.0022*
Income			(0.0186)			(0.0011)
Fixed-effects						
Household	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	9,826	9,826	9,826	9,826	9,826	9,826
R^2	0.4708	0.4713	0.4713	0.0929	0.0931	0.0931
Within R^2	0.0150	0.0160	0.0159	0.0018	0.0021	0.0021

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in the extensive margin of spending explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. It also includes controls for weekly and monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 6: Event Study Results for H2 - Extensive Margin

Dependent Variables:	Ext. Margin$_{sum}$	Ext. Margin$_{max}$
Model:	(1)	(2)
Variables		
t-8	-0.0844	-0.0104
	(0.0667)	(0.0090)
t-7	-0.0360	-0.0022
	(0.0674)	(0.0083)
t-6	-0.0836	-0.0036
	(0.0679)	(0.0081)
t-5	-0.0246	-0.0093
	(0.0644)	(0.0090)
t-4	-0.0695	0.0080
	(0.0622)	(0.0072)
t-3	-0.0140	0.0076
	(0.0660)	(0.0076)
t-2	-0.0799	-0.0056
	(0.0595)	(0.0087)
t	0.2345***	0.0190***
	(0.0579)	(0.0061)
t+1	0.2406***	0.0172***
	(0.0631)	(0.0065)
t+2	0.2732***	0.0036
	(0.0629)	(0.0080)
t+3	0.1907***	0.0082
	(0.0638)	(0.0068)
t+4	0.1916***	0.0126*
	(0.0660)	(0.0072)
t+5	0.2188***	0.0038
	(0.0704)	(0.0080)
t+6	0.1951***	0.0056
	(0.0687)	(0.0080)
t+7	0.2089***	0.0053
	(0.0646)	(0.0079)
t+8	0.1571**	0.0022
	(0.0679)	(0.0083)
Fixed-effects		
Household	Yes	Yes
Week	Yes	Yes
Fit statistics		
Observations	9,826	9,826
R^2	0.4713	0.0952
Within R^2	0.0159	0.0044

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows event study regression estimates of differences in the extensive margin of spending explained by enrollment in a round-up savings program. The regressions include household and week fixed effects to control for household-specific characteristics and time-effects. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 7: Regression Results for H3 - Intensive Margin

Dependent Variable:	Intensive Margin		
Model:	(1)	(2)	(3)
Variables			
Enrollment	84.58***	83.52***	84.22***
	(30.58)	(30.84)	(30.66)
Weekly		93.24	
Income		(73.93)	
Monthly			19.79
Income			(16.87)
Fixed-effects			
Household	Yes	Yes	Yes
Week	Yes	Yes	Yes
Fit statistics			
Observations	9,662	9,662	9,662
R^2	0.230	0.230	0.230
Within R^2	0.001	0.001	0.001

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in the intensive margin of spending explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. It also includes controls for weekly and monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 8: Event Study Results H3 - Intensive Margin

Dependent Variable:	Intensive Margin
Model:	(1)
Variables	
t-8	-63.02
	(40.63)
t-7	-12.74
	(43.67)
t-6	-54.71
	(37.57)
t-5	-16.90
	(39.14)
t-4	73.62
	(92.51)
t-3	13.60
	(42.12)
t-2	4.17
	(49.40)
t	164.13**
	(70.78)
t+1	209.56
	(138.48)
t+2	87.02*
	(46.84)
t+3	66.08
	(53.75)
t+4	4.136
	(39.02)
t+5	110.38**
	(49.93)
t+6	17.22
	(41.11)
t+7	-37.88
	(36.43)
t+8	75.52
	(61.47)
Fixed-effects	
Household	Yes
Week	Yes
Fit statistics	
Observations	9,662
R^2	0.232
Within R^2	0.003

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows event study regression estimates of differences in the intensive margin of spending explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 9: Regression Results for H4 - Liquidity Shortfall

Dependent Variable:	Liquidity Shortfall		
Model:	(1)	(2)	(3)
Variables			
Enrollment	0.0144***	0.0143***	0.0144***
	(0.0050)	(0.0050)	(0.0050)
Weekly Income		0.0123	
		(0.0113)	
Monthly Income			0.0022
			(0.0022)
Fixed-effects			
Household	Yes	Yes	Yes
Week	Yes	Yes	Yes
Fit statistics			
Observations	9,826	9,826	9,826
R^2	0.1899	0.1900	0.1900
Within R^2	0.0013	0.0014	0.0014

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in liquidity shortfall explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. It also includes controls for weekly and monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 10: Event Study Results H4 - Liquidity Shortfall

Dependent Variable:	Liquidity Shortfall
Model:	(1)
Variables	
t-8	0.0028
	(0.0112)
t-7	-0.0054
	(0.0108)
t-6	0.0145
	(0.0115)
t-5	-0.0154
	(0.0107)
t-4	-0.0046
	(0.0117)
t-3	0.0032
	(0.0109)
t-2	0.0164
	(0.0120)
t	0.0033
	(0.0113)
t+1	-0.0072
	(0.0112)
t+2	-0.0002
	(0.0113)
t+3	0.0271**
	(0.0130)
t+4	0.0239*
	(0.0125)
t+5	0.0241*
	(0.0134)
t+6	-0.0029
	(0.0116)
t+7	0.0284**
	(0.0135)
t+8	0.0467***
	(0.0141)
Fixed-effects	
Household	Yes
Week	Yes
Fit statistics	
Observations	9,826
R^2	0.1939
Within R^2	0.0061

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in liquidity shortfall explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 11: Regression Results Difference-in-Differences

Overall summary of ATT's based on event-study/dynamic aggregation:				
ATT		Std. Error	95% Conf. Int.	
297.44		264.58	-221.13	816.02
Dynamic Effects:				
Event time	Estimate	Std. Error	95% Simult. Conf. Band	
-2	-123.07	420.19	-1025.50	779.35
-1	-110.42	334.02	-827.77	606.94
0	192.75	263.88	-373.96	759.47
1	552.22	716.80	-987.22	2,091.65
2	147.36	243.61	-375.82	670.55

Signif. codes: "" confidence band does not cover 0*
Control Group: Not Yet Treated, Anticipation Periods: 0
Estimation Method: Doubly Robust

Note: This table shows regression estimates of a difference-in-differences regression using Callaway & Sant'Anna (2021). The event window is two months prior to enrollment and two months after enrollment.

Table 12: Summary Statistics for Round-Up Saving

Week	**Mean**	**St. Dev.**	**Min**	**Median**	**Max**
0	$ 3.29	$ 2.94	$ 0.00	$ 2.55	$ 20.68
1	$ 4.65	$ 3.89	$ 0.00	$ 3.68	$ 20.98
2	$ 4.72	$ 3.78	$ 0.00	$ 3.91	$ 31.93
3	$ 4.65	$ 3.81	$ 0.00	$ 3.76	$ 23.75
4	$ 4.59	$ 4.19	$ 0.00	$ 3.42	$ 25.38
5	$ 4.85	$ 4.23	$ 0.00	$ 3.91	$ 38.81
6	$ 4.42	$ 3.59	$ 0.00	$ 3.83	$ 20.20
7	$ 4.79	$ 3.95	$ 0.00	$ 3.98	$ 25.48
8	$ 4.60	$ 3.89	$ 0.00	$ 3.63	$ 22.35

Note: This table provides summary statistics for the amount saved per event week from enrollment in the round-up program on. Enrollment happens in week 0.

Table 13: Regression Results Flat Amount Savings Program

Dependent Variables:	Total Spending			Optional Spending			Necessary Spending		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Enrollment	378.18***	367.51***	369.02***	333.94***	323.719***	325.84***	44.24***	43.79***	43.18***
	(82.50)	(77.23)	(78.28)	(80.26)	(75.08)	(76.14)	(7.88)	(7.91)	(7.97)
Weekly Income		-315.78			-302.23			-13.56	
		(726.24)			(727.65)			(21.42)	
Monthly Income			-52.75			-46.62			-6.12
			(187.14)			(188.33)			(4.41)
Fixed-effects									
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	1,309	1,309	1,309	1,309	1,309	1,309	1,309	1,309	1,309
R^2	0.189	0.189	0.189	0.186	0.18674	0.187	0.359	0.359	0.360
Within R^2	0.005	0.006	0.006	0.004	0.00452	0.004	0.041	0.0411	0.042

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in total, discretionary, and non-discretionary spending explained by enrollment in a flat amount savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. It also controls for weekly or monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 14: Regression Results for Credit Card Spending (1)

Dependent Variable:	Credit Card Spending			Ext. Margin_{sum}		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Enrollment	-5.45	-5.43	-5.41	-0.0206	-0.0205	-0.0205
	(9.69)	(9.71)	(9.70)	(0.0272)	(0.0273)	(0.0273)
Weekly		-1.23			-0.0070	
Income		(17.38)			(0.0318)	
Monthly			-2.01			-0.0090
Income			(4.37)			(0.0074)
Fixed-effects						
Household	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	9,826	9,826	9,826	9,826	9,826	9,826
R^2	0.307	0.307	0.307	0.684	0.684	0.684
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows regression estimates of differences in total, credit card spending and the extensive margin on credit card spending (sum definition) explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. It also controls for weekly or monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.

Table 15: Regression Results for Credit Card Spending (2)

Dependent Variables:	Ext. Margin$_{max}$			Int. Margin		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Eenrollment	0.0057	0.0057	0.0057	-19.37	-19.39	-19.15
	(0.0078)	(0.0078)	(0.0078)	(32.43)	(32.59)	(32.56)
Weekly		-0.0031			0.88	
Income		(0.0103)			(45.80)	
Monthly			-0.0012			-2.81
Income			(0.0026)			(11.67)
Fixed-effects						
Household	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	9,826	9,826	9,826	2,645	2,645	2,645
R^2	0.632	0.632	0.632	0.281	0.281	0.281
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table shows event study regression estimates of differences in the extensive margin on credit card spending (max definition) and the intensive margin on credit card spending explained by enrollment in a round-up savings program. The regressions include individual and week fixed effects to control for household-specific characteristics and time-effects. It also controls for weekly or monthly income. The regression is run at the household-week level. Clustered standard errors by household are reported in parentheses.