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Abstract

Recipients of the Supplemental Nutrition Assistance Program (SNAP) run out of most benefits before halfway through a benefit deposit cycle. I study the introduction of a mobile software application, Fresh EBT, that enables beneficiaries to check their available balance and previous spending history conveniently. Using an event study, I show that the introduction of the application on average has small but statistically significant impacts on the ability of recipients to extend the time frame over which they have benefits available within a cycle. On a very general measure of spending over time, this impact corresponds to a 4% increase. Average days spent with less than \$5 within a deposit cycle decreases from eleven to just over ten. While the application assists beneficiaries in financial management, they continue with minimal benefits for several days within a cycle. These effects are higher for recipients who are new to SNAP, who are highest in the distribution of SNAP benefits, and who have the largest tendency pre-adoption to spend down quickly. The results are consistent with the impact of salience on consumer choice and offer evidence that such software tools may help support beneficiaries in financial management.

1 Introduction

Figure 1 charts the proportion of Supplemental Nutrition Assistance Program (SNAP) beneficiaries who have $5 or less remaining on their balance at various points within a benefit deposit cycle. By halfway through the cycle, forty-percent of SNAP beneficiaries have less than five dollars remaining. The anonymized data come from a mobile application that displays transaction history to SNAP recipients, Fresh EBT. Other data confirms the quick spend down of SNAP benefits (Castner & Henke, 2011); a majority of SNAP recipients spend several days without benefits available to them.

One way to view the spend down of SNAP benefits is through the lens of the Permanent Income Hypothesis from Economics. While beneficiaries may spend down SNAP benefits quickly, in this view real consumption - either through the gradual depletion of a food stock at home or through supplemental sources of income - remains relatively smooth throughout time. In other words, the sharp decline in availability of *SNAP benefits* may not be of concern given availability of *resources for food* generally.

Another view on the rate of spend down emphasizes time-inconsistency in decision making. Beneficiaries may desire more smoothing of spending, but time-inconsistency and the demands of the present end up creating asymmetry in spend throughout a cycle. Such a view is well supported by recent work looking at "payday" responses. Stephens (M. Stephens, 2003; M. J. Stephens, 2006) finds a strong response of instantaneous consumption to receipt of income among social security recipients in the United States and paycheck recipients in the United Kingdom. Similar evidence emerges in the analysis of personal financial management software: payday effects arise in the absence of clear liquidity constraints (Olafsson & Pagel, 2017).

Evidence for the "First of the Month Effect" also emerges in SNAP. On average, from the first week to the fourth week, prices fall by three percent while quantities purchased fall by thirty-two percent (J. Hastings & Washington, 2010). Shapiro finds evidence that this decrease in spending translates to decreases in consumption: reported caloric intake drops 10-15% over the deposit cycle, and beneficiaries report a greater willingness to sacrifice money in the future for money today (Shapiro, 2005). A final piece of evidence comes from the medical literature. There, administrative data on inpatient admissions show a twenty-seven percent increase in the risk of admission for hypoglycemia for low-income populations, but not for high-income populations (Seligman, Bolger, Guzman, López, & Bibbins-Domingo, 2014).

The dynamics of consumption are explored theoretically and empirically in several settings. A prominent story focuses on time inconsistency and the implications of present bias (Laibson, 1997). While acknowledging that present bias may explain a significant portion of the SNAP spend down curve, I focus here on a different element of planning consumption over time: consumer attention.

Previous empirical work in the setting of cell phone contracts has shown that consumers can be inattentive to past "spending" of cell phone minutes (Grubb & Osborne, 2015). This limitation of memory, combined with a three-part tariff contract design, creates large and unexpected bills at the end of the month. Despite repeated experience with cell phone bill cycles, consumers in that work show limited evidence of learning or ability to forecast usage well. This strand of literature is consistent with studies on the impact of salience - or how differential attention and availability of good attributes can influence consumer choice (Bordalo, Gennaioli, & Shleifer, 2013; Chetty, Looney, & Kroft, 2009).

In this paper, I ask whether a reduction in the cost of attention impacts spending behavior for SNAP recipients. I study the adoption of a mobile application, Fresh EBT, that enables SNAP beneficiaries to view their balance and previous spending history instantly on their phone. Fresh EBT increases the salience of benefit balance when recipients contemplate spending down that balance with a transaction.

In addition to providing an empirical example of the relationship between attention and consumption choices over time, I offer evidence for additional policy approaches to the challenges of scarcity. Recent work has documented the causal impact of scarcity of resources on cognitive bandwidth (Mani, Mullainathan, Shafir, & Zhao, 2013). That is, poverty itself creates large demands on cognitive bandwidth. One implication of that view is that policy makers should avoid "cognitive taxes" (Schilbach, Schofield, & Mullainathan, 2016). Reducing the costs of attention - by information technology such as the one I study here - may be one route to mitigating the challenges of managing scarcity. I study one application of this approach through SNAP - the second largest means-tested benefits program enrolling 44.2 million, or one out of seven, Americans.

Fresh EBT gathers anonymized historical transaction data for recipients who download and sign into the application on their phones. This feature enables me to use an event study to estimate the impact of joining the application on the time horizon over which benefits are spent. By three periods after recipients have had access to the application, their tendency to smooth consumption over time shows an increase of 4-5%. I estimate these impacts first visually with a non-parametric model, and then fit three parametric models to examine the average difference pre and post adoption, the differences controlling for pre-period trends, and differences in trend among these outcomes pre and post adoption. The results are concentrated on recipients new to SNAP, recipients who receive the highest benefit amounts, and recipients who showed the largest tendency to spend down quickly pre adoption.

I interpret these findings through the lens of salience and scarcity. Fresh EBT provides recipients with a convenient way to access their SNAP balances, increasing the salience of balance information during the time in which the costs of a lower balance are weighed against the benefits of increased spending. Scarcity provides one frame in which to view the heterogeneity in impacts. Characteristics which indicate that a recipient may have high financial management costs also correspond with larger benefits from adoption of the application.

Section 2 begins with an overview of SNAP, charting its objectives and scope. Section

3 lays out the empirical framework used to estimate the impact of joining the application. Section 4 explains the structure of the data and documents basic facts about spending within deposit cycles on SNAP. Section 5 reports the results of an event study to measure the impacts on spending over time. Section 6 interprets the results within the frame of salience and scarcity. Section 7 concludes.

2 Empirical Context

SNAP provides monthly support to low-income Americans in the form of vouchers for eligible food items. SNAP is funded and managed by the Food and Nutrition Service (FNS) of the U.S. Department of Agriculture. The Service's goals are "to increase food security and reduce hunger by providing children and low-income people access to food, a healthful diet and nutrition education in a way that supports American agriculture and inspires public confidence." (*Supplemental Nutrition Assistance Program (SNAP)*, 2017).

FNS funds and oversees SNAP, which is administered by state governments. Each state is partially responsible for administrative costs of the program and has control over certain aspects of program design and eligibility, such as whether car ownership is included in an asset test. In 2016, there were 44.2 million SNAP beneficiaries who received $66.5 billion in benefits. SNAP was the second largest means-tested program in the United States - just below Medicaid in terms of spending and above the Earned Income Tax Credit. (*Supplemental Nutrition Assistance Program (SNAP)*, 2017)

Eligibility for SNAP is governed by two primary criteria. The first is a monthly income test. The gross income of eligible households must be 130% or less of the poverty line; the net income must be 100% or less of the poverty line. Some households may exceed these limits depending upon allowable deductions and receipt of other government assistance such as TANF. Table 1 documents the income limits based on household size for households of size one to eight. For example, a single individual is allowed a net monthly income of $990; a household of four is allowed $2,025 in monthly income.

The second main eligibility requirement is a resources test. The criteria varies by state, but in general households may not have more than $2,250 in countable resources or $3,250 if the household includes someone over the age of 60. Homes are not counted for the resources test (*Supplemental Nutrition Assistance Program (SNAP)*, 2017). Depending upon the state, SNAP recipients must recertify for eligibility every 6-12 months. In 2011, take up of SNAP was estimated at 79% (Hoynes & Schanzenbach, 2016).

Conditional on eligibility for SNAP, households receive monthly benefits in an amount that is proportional to their net income. The program is designed to provide households with thirty percent of targeted monthly income available for food consumption. Benefits are calculated according to the following formula:

$$Benefit = Maximum\,Allotment - 0.3 * Net\,Income$$

The maximum allotment for each household size is shown in Table 2, along with the average monthly allotment given to households in 2016. For that year, the average SNAP beneficiary for a household size of four received $471.

SNAP benefits may be used only for the purchase of eligible food items and is accepted by most grocers and convenience stores. Ineligible items include alcohol, vitamins and supplements, hot foods, and nonfood items. It's estimated that 84% of SNAP households also spend cash on food (Hoynes & Schanzenbach, 2016).

States issue SNAP benefits on a monthly basis via an electronic benefit transfer (EBT) card. The issuance schedule varies by state. Benefits typically arrive at the same day or date of the month for an individual SNAP recipient. States also tend to spread issuance of benefits across the month, so that, for example, individuals whose identification numbers end in 1 may receive benefits on one day of the month, while individuals whose benefits end in 9 receive them on another day of the month.

A common challenge for SNAP recipients is monitoring their benefit balance. State governments contract with a handful of private companies to process benefits. These companies manage the EBT cards and may provide recipients with an online portal in which to view their benefit balance. Recipients can find those interfaces user-unfriendly and they may misplace login information.

The data from this study come from a mobile application, Fresh EBT, that allows SNAP recipients to easily check their benefit balance. In lieu of recipients having to login to a website, Fresh EBT shows users their balance and spending history conveniently on their mobile phone. All data is collected and analyzed anonymously; the company does not have access to individual EBT card numbers, for example. Table 3 shows the information a user of Fresh EBT may see upon login: their current balance along with previous transactions, including transaction amounts, transaction dates, and locations. Fresh EBT also allows users to create a shopping list, find nearby stores that accept SNAP benefits, and connect to resources to help stretch a limited budget. In practice, the ability to check a SNAP balance is the most-used feature.

Figure 3 documents the dates of adoption among users in the study sample over the course of the initial year of Fresh EBT - June 2016 through June 2017. Note that this is an unrepresentative subsample of adopters given the need to observe multiple deposit cycles before and after adoption. Figure 2 shows the balance checking behavior over the course of the time period I observe. Within a typical deposit cycle, the average user logs in 8.9 times; the 25th percentile is 4 times and the 75th percentile is 12 times.

SNAP benefit spending patterns before and after adoption of Fresh EBT provide an empirical context in which to study the impacts of reducing the cost of attention on consumer behavior. Much like Grubb's study of bill shock alerts, Fresh EBT provides consumers, on a regular basis, the ability to place their current spending within the context of available amounts and past spending.

3 Empirical Framework

3.1 An Event Study

To estimate the impact of balance availability I use an event study framework. The data are a balanced panel of benefit recipients observed during SNAP benefit deposit cycles. When recipients download and sign into Fresh EBT, their previous transaction history is retrieved for display on their phones. Fresh EBT captures this historical transaction data along with ongoing transaction data to form a complete picture of how recipients are spending SNAP benefits for a window before and after adoption.

The panel I use includes three "deposit cycles" before and after the adoption of the application. Each deposit cycle is defined by the receipt of a SNAP benefit deposit. For example, a recipient may receive a deposit on June 10th, 2016 and then again on July 10th, 2016. These deposits would form two separate deposit cycles. The first from June 10th - July 10th, and the next from July 10th until the following deposit.

Since adoption occurs during a deposit cycle, I drop the period of adoption from the panel. That is, the panel only includes three deposit cycles leading up to adoption and the first three deposit cycles after full adoption. Removing the period of adoption from the panel allows a cleaner interpretation of the estimates given pre-existing trends in many of the outcomes (explored below) and mixed timing of adoption across recipients within a deposit cycle.

The event study assumes that the timing of adoption is uncorrelated with spending outcomes and shocks that affect both adoption and spending. This assumption would be violated, for instance, if recipients learn about the application at the same time as they begin to receive other financial assistance. There are two reasons to suspect the assumption holds. The first is that the panel includes the first year of the application's rollout - a time in which it is likely information about the application spreads fairly stochastically. The second is that adoption rates are fairly smooth across time. Figure

3 shows the join dates across time in the sample. Due to the construction of the sample - requiring the availability of three deposit cycles pre and post adoption, there are some months with greater mass than others. However, across days within months, adoption is widely spread.

3.2 Non-Parametric Estimation

I begin with a non-parametric fixed effects model which flexibly shows the level and trajectory of outcomes over time [1]. Equation 1 specifies the model:

$$y_{id} = \eta_i + \delta_d + \sigma_i + \sum_{r=-3}^{r=-1} \mu_r + \sum_{r=1}^{r=3} \mu_r + \varepsilon_{id} \tag{1}$$

Here y_{id} is an outcome for individual recipient i during deposit cycle d. I start with three sets of fixed effects. The η_i are individual fixed effects. The δ_d are fixed effects for each deposit cycle. The deposit cycles are the units of time and vary across individuals. For example, some deposits begin July 10th, 2016 and end on August 11th, 2016, while others start on July 12th, 2016 and end on August 9th, 2016. Finally, the σ_i are state fixed effects. Results are robust to the exclusion of the state fixed effects; I include them here given that each state can administer and manage SNAP benefits in its own way. The μ_r are indicators for relative event time - i.e., μ_{-2} is the deposit cycle that precedes adoption of Fresh EBT by two cycles. The omitted category is μ_{-1} , the cycle immediately prior to adoption of Fresh EBT.

Equation 1 examines variation within individuals across time, conditioning on the average of outcomes within their state and each deposit cycle. In theory, Equation 1 allows estimation of the effect of adoption. In practice, as part of a robustness check, I observe that the amount of SNAP benefits individuals receive has a time trend, which complicates interpretation. Figure 6 shows the estimates on the μ_r coefficients when deposit amount is included as an outcome. While no period shows a statistically significant

[1]Here I follow the approach taken in (Dobkin, Notowidigdo, & Finkelstein, 2016)

difference, there is a suggestive time trend, and I cannot rule out differences as large as \$20. In light of this complication, I instead estimate Equation 2:

$$y_{id} = \gamma_i + \delta_d + \sigma_i + \sum_{r=-3}^{r=-1} \mu_r + \sum_{r=1}^{r=3} \mu_r + \varepsilon_{id} \tag{2}$$

In Equation 2, the γ_i , fixed effects for deposit amount group, replace η_i, fixed effects for each recipient. This approach solves the problem of potentially shifting deposit amounts, but changes the approach to rely on variation across as opposed to within individuals. Figure 7 shows that both the amount of the deposit and length of the deposit are now precise and near zero across all periods. Table 5 shows that parametrically.

In practice, both approaches show similar results for the analysis below. I use Equation 2 as the preferred specification given the simpler interpretation stemming from the deposit amount fixed effects. Both models allow for an arbitrary variance-covariance matrix at the recipient level.

3.3 Parametric Estimation

Equation 2 allows for clear visualization of the dynamics of spending across relative event time. The results show pre and post trends among some outcomes, suggesting the need for a parametric approach to estimate the magnitude of the impact reliably. For each outcome, I estimate results from three parametric approaches.

The first approach shown in Equation 3 is a simple pre and post comparison:

$$y_{id} = \gamma_i + \delta_d + \sigma_i + \pi * post + \varepsilon_{id} \tag{3}$$

Here π is an estimate of the average difference across outcomes pre and post adoption. It is appropriate for outcomes in which there is no significant pre or post trend. The second approach shown in Equation 4 allows for a pre-trend in the outcome while flexibly showing the impact after adoption at each period:

$$y_{id} = \gamma_i + \delta_d + \sigma_i + \tau r + \sum_{r=1}^{r=3} \mu_r + \varepsilon_{id} \tag{4}$$

The coefficients of interest here are the μ_r . The introduction of r , relative event time, controls for pre-period trends. A final specification, Equation 5, allows me to estimate differences in trends pre and post adoption:

$$y_{id} = \gamma_i + \delta_d + \sigma_i + \tau r + \pi post + \zeta post * r + \varepsilon_{id} \tag{5}$$

Relative event time, r , is included along with an interaction with *post* , an indicator variable that the deposit cycle occurred after adoption of the application. The magnitude and significance of ζ indicates whether there was a break in the trend of the outcome after adoption of the application.

4 Data

Data for the event study come from the anonymized history of SNAP spending captured by Fresh EBT. A core functionality of Fresh EBT is to allow users to see historical spending. Upon joining, Fresh EBT is able to capture deidentified historical spending and all spending going forward, provided the recipient continues to use the application For each transaction, Fresh EBT is able to show date, time, amount, and location. It is unable to show item-level information and does not have access to individual EBT account information.

To obtain a balanced panel of SNAP recipients, I restrict the sample to Fresh EBT users for whom Fresh EBT is able to obtain at least three deposit cycles prior to adoption and at least three following adoption[2]. There are 23,393 users who meet that criteria and who joined between the months of June 2016 and July 2017. They provide a total

[2] Note that there is variation across states in the ability of Fresh EBT to capture historical data. States contract with one of a few companies to administer SNAP benefits. Each company has a different interface for obtaining historical data.

of 140,358 deposit cycles for the sample. The users come from twenty-seven different states. A map of states included in the sample is shown in Figure 4. California, Florida, and New York constitute a large majority of the sample. Other populous states such as Texas, Pennsylvania, and Illinois, have users of Fresh EBT but do not provide detailed enough transaction data to be included in the sample [3].

Table 4 shows summary statistics for the three periods prior to adoption, a total of 70,179 deposit cycles. The mean deposit amount is \$371 (interquartile range of \$194-\$511), which is roughly equivalent to the estimated average benefit amount provided to a three-person household in 2016, as shown in Table 2. The average length of a deposit cycle is thirty days (28-31). There is variation in deposit cycle lengths for a variety of reasons. One is related to dates of deposit - in some states, deposits are provided only on weekdays. In a small proportion of the data, there are deposit cycles that are less than a week or more than a month. From discussions with the company that created Fresh EBT, Propel, it seems that this variation is due to random or one-time state decisions to administer deposits more or less frequently than the typical month-to-month cycle, as well as to individual case circumstances.

Table 4 also introduces "AUC" or area under the curve. AUC is a measure of the distribution of spending across time within a deposit cycle. It is meant to capture in a very general way how well recipients are able to smooth spending over time. Figure 5 shows an example of how AUC is calculated. For each set of transactions within a deposit cycle, I plot the percent of the way through the cycle that transaction occurred, along with the percent of the deposit remaining after the transaction. The area under these points, when connected together by lines, constitutes "AUC". The diagonal line shows what spending would look like if it were perfectly smoothed throughout the month. AUC in that scenario would be 0.5. The horizontal line shows perfect savings. Perfect savings corresponds to an AUC of 1. In the sample, average AUC is 0.28 (0.12-0.41).

[3] In these states, it is impossible to determine the nature of a transaction - e.g., whether it is a SNAP purchase, benefit deposit, or transaction from a different benefits program.

I construct two other measures of spend down throughout a deposit cycle. To provide an outcome that is simpler to interpret, I show the average number of days in which recipients have less than five dollars of their deposit for that month (mean of 11, 2-18) and the average number of days in which recipients have less than five percent of their deposit amount (44%, 17%-68%). Finally, Table 4 shows outcomes related to spending behavior. On average, recipients visit six distinct retailers per deposit cycle (3-8) and have thirteen transactions (6-18).

5 Results

5.1 Average Effects

Figure 8 shows the results of Equation 1 for a variety of time-related outcomes. Each sub figure plots the coefficients on the period indicators after absorbing fixed effects for deposit group amount, deposit cycle, and state. The top left plot shows the coefficients for AUC. Prior to adoption, there is no clear trend in AUC across three periods. After adoption, AUC increases, most prominently in periods two and three. The parametric models confirm the results of the plots. Column two of Table 6 shows no significant pre-period trend in AUC (the point estimate is 0.0001 and standard error is 0.001). Post adoption, there is an average increase of 0.005 (column 1, se=0.001), a positive trend (point estimate of 0.005, se=0.001), and by the third deposit cycle, an average impact of 0.01 (se=0.004). That is, a very general measure for the ability of recipients to smooth spending across time shows statistically significant increases post adoption of Fresh EBT. How large are the effects? The pre-period mean of AUC is 0.28. A perfectly-smoothed transaction history would create an AUC of 0.5. By the third deposit cycle, the average impact is thus 3.5% of the baseline mean. Seen another way, it is 4.5% of a decrease in the gap between average smoothing behavior and a uniform spend down.

While general, the changes in AUC are difficult to quantify meaningfully. The second plot in the first column of Figure 8 shows pre and post adoption levels of the number of days within a deposit cycle recipients go with less than \$5 of their initial deposit remaining. The pre period mean is eleven days, or roughly one-third of an average deposit cycle. The plot suggests there is a pre period increasing trend in the outcome, followed by a reversal in trend. The parametric models in Table 7 show a pre period trend of 0.13, followed by a reversal in trend to -0.22. By the third period there is a 0.8 decrease in the number of days with less than \$5, corresponding to a 7% decrease on the pre period mean.

The bottom-right plot in Figure 8 charts the amount left at the end of a deposit cycle across periods. Since balances do not go to zero automatically at the end of a deposit cycle, recipients are able to spend more than their deposit or less than their deposit within a given deposit cycle. On average prior to adoption, recipients spent \$1.32 more than their deposit. The fact that the mean is negative implies that prior to the third period pre adoption, some recipients had saved some balance for the next month. Post adoption, the mean goes from negative to positive. The plot and Table 8 show a slightly decreasing trend beforehand (slope of -0.68) followed by a fairly stable trend (slope of ~0.3) afterwards with a level shift of around \$2. Conditional on the pre-existing downward trend, the difference in savings by the third period is \$6, or roughly 1.5% of the mean deposit amount.

The results for three additional outcomes in Figure 8 are consistent with the above. The number of days with less than five percent of the initial deposit spent, the number of days with less than twenty percent of the initial deposit left, and the number of days between the last transaction and next deposit show small, but significant impacts on the ability of recipients to stretch spending throughout a deposit cycle. For the remainder of the paper, I focus on the initial three outcomes examined above - AUC, days with less than five dollars, and savings - given similar trends in these other measures.

A second class of outcomes to examine is spending behavior that is not related to smoothing over time. Figure 9 plots the results of Equation 1 for these outcomes. In non-parametric and parametric (not shown) estimates of changes post adoption, there are no significant differences in the number of distinct retailers visited, number of transactions, minimum transaction amount, first transaction amount, and last transaction amount.

Results from Figure 8 and Figure 9 suggest that the application has small (~5%) but statistically significant impacts on the ability of Fresh EBT users to extend spending throughout time. The impacts are seen on a general measure of spending over time - AUC - along with the number of days within a deposit cycle with less than five dollars of the initial deposit amount. There are no significant impacts on other measures of spending behavior such as the number of transactions or distribution of transaction amounts.

5.2 Heterogeneous Effects

SNAP enrolls roughly one in seven Americans, or 44.2 million beneficiaries. The financial situation and habits of people in this population vary significantly. As Table 4 shows, there is a wide range of benefit amounts and preexisting tendency to spend down. Moreover, some Fresh EBT users have more experience using SNAP benefits and use the application more or less frequently. I test whether certain populations benefit more than others from Fresh EBT using a variant of Equation 4 which interacts each parameter - other than the fixed effects - with an indicator for membership in the population of interest.

5.2.1 Length on SNAP

Though the panel for the average effects includes three windows prior to and post adoption of Fresh EBT, some users have significantly longer histories on SNAP. Does a longer experience with SNAP, and greater opportunity to form habits around SNAP spending, correlate with the impact of Fresh EBT? The models in Table 9 interact the parameters of Equation 4 with an indicator variable for whether the user has received more than four prior SNAP deposits. Around 55% of users fall into this category. Table 9, Column 1, shows that the impact on AUC nearly vanishes when I focus on users with a longer SNAP history. By period three, users with shorter SNAP histories show an impact of 0.018, nearly twice the average impact of 0.01 and six times the impact for longer users (~0.003). For users with less SNAP experience, the impact of Fresh EBT by the third period is around 7%, while those with longer histories on SNAP show nearly zero impact.

An alternative approach to this question is to conduct the event study separately for users with five or more pre period deposit cycles. Figure 10 confirms that deposit cycle characteristics are consistent across periods in this sub population as in the overall sample. Figure 11 charts outcomes for this subgroup over ten periods, showing no impacts on outcomes related to the timing of spend.

5.2.2 Use of Application

Revealed preference would suggest that SNAP recipients who use the application more frequently than others may benefit more. Table 10 tests this hypothesis by examining changes in outcomes among users in the top quartile of Fresh EBT use relative to users in the bottom three quartiles. Figure 2 shows the distribution of Fresh EBT use per month. The seventy-fifth percentile is defined by users who check Fresh EBT at least twelve times per month. Table 10 shows no consistent and significant patterns of effects by this variable.

5.2.3 Benefit Amounts

A small proportion of SNAP users rely on SNAP benefits for all of their food consumption. It has been estimated that roughly 16% of SNAP enrollees do not spend additional cash on food (Hoynes & Schanzenbach, 2016). It is possible that Fresh EBT solves a more pressing challenge for this subgroup of users. The data are consistent with that hypothesis. Recipients in the top quartile of deposit amounts receive \$511 in benefits per cycle. This amount equates to the maximum benefit for a household of three.

Table 11 documents the impacts of Fresh EBT on users in this subgroup. The coefficients for impacts on AUC show significant and positive differences relative to individuals outside of this group of roughly ~0.01, or around twice the average benefit across the sample. The coefficients for the number of days spent with less than five dollars and amount saved are consistent with this difference in impact, though not all statistically significant.

5.2.4 Pre-Adoption AUC

From a policy perspective, a key question is whether tools like Fresh EBT help individuals who tend to spread out benefits throughout the month more than individuals who do not. That is, does the tool help those in the bottom of the distribution of AUC prior to adoption, those at the top, or both equally? Individuals in the bottom of the distribution of AUC prior to adoption have an AUC of 0.16 or less. The average for the entire sample is 0.28.

Table 12 shows that by the third period, individuals in the bottom quartile of AUC show a significant increase of 0.014 over the 0.005 shown for other Fresh EBT users. Fresh EBT seems to help those least likely to be smoothing prior to adoption, by a factor of about three relative to those in the rest of the distribution. This difference is concentrated on the measure of AUC, however - it does not show up significantly for the number of days spent with less than \$5 (column 2).

6 Discussion

The event study suggests two primary conclusions about the effect of Fresh EBT on spending within a deposit cycle. The first is that there is a small, but statistically significant impact on the time period over which SNAP recipients spend their benefits. On the most general measure, AUC, the impact is around 4%. On a more intuitive measure - the number of days spent with less than five dollars of the original deposit amount - there is a similarly sized effect. The second conclusion I derive from the data is that the effects on smoothing are correlated with a number of indicators for financial need - the size of SNAP benefits received, recently entering SNAP, and pre-period tendency to spend down benefits quickly. The heterogeneity analysis suggests impacts for the subgroups are between 50% and 100% greater than the average impact observed in the full sample. Fresh EBT shows no significant effects on a variety of non-time related outcomes such as retailer choice and frequency of shopping.

Why does Fresh EBT impact the time horizon over which individuals spend SNAP benefits? One clue may be the impacts it has on amount of benefit left over at the end of the month. Though small, the effect suggests Fresh EBT may raise the salience of spending down benefits. It is useful to keep the counterfactual in mind. Prior to adopting Fresh EBT, SNAP recipients were able to check their remaining balance by either logging into a website - manually entering in login credentials each time, typically on a desktop computer, calling a phone line and waiting to learn their balance through an automated system, or saving past receipts. Fresh EBT removes small, but real barriers to accessing balance and previous spending history. Given that most balance checks happen prior to a transaction, it is likely the availability of balance information increases the salience of the cost to such transactions: a reduced, or zero, balance.

The idea that balance availability increases the salience of costs to a transaction is consistent with a variety of evidence and theory on how salience can influence behavior (Bordalo et al., 2013; Chetty et al., 2009). Fresh EBT highlights the cost of transactions - a reduced window over which SNAP benefits will be available - increasing the horizon over which benefits are available. One element of this empirical context that is different from other contexts in which salience is studied - in posting calories for food, for example

(Bollinger, Leslie, & Sorensen, 2011) or in reminders - is active choice. The counterfactual of behavior without Fresh EBT is a balance likely coming to mind, but not being readily available. With Fresh EBT, recipients make an active choice to observe the balance. This distinction may imply that memory interacts with salience to produce the observed effects.

Why do the impacts correlate with indicators of financial need? Naturally, any interpretation of the heterogeneous effects should come with caveats. There are many correlates with the variables that define the subgroups examined. The results are suggestive, at least, of a potential role for scarcity. The groups that show the largest effects are precisely those groups that one might expect to be balancing SNAP budgeting with a variety of other cognitive demands - managing a family on a tight budget and adapting to new economic circumstances with eligibility for SNAP.

The concepts of salience and scarcity provide a frame in which to consider the implications of Fresh EBT for policymakers. Software such as Fresh EBT provides important information and simplifies the financial management of benefits at a relatively small additional administrative cost. In 2014, the administrative costs of SNAP to the Federal government were $3.6 billion (*Supplemental Nutrition Assistance Program (SNAP)*, 2017); the resources required to support tools like Fresh EBT are small in comparison.

Of additional interest, to researchers and policymakers alike, is the ways in which such applications may be optimally designed to assist beneficiaries with financial management. Experiments on the impacts of financial literacy training show mixed evidence at best and the costs of such approaches are not well understood (J. S. Hastings, Madrian, & Skimmyhorn, 2013). There is evidence that SNAP recipients treat benefits as distinct from cash (J. S. Hastings & Shapiro, 2017; Beatty & Tuttle, 2015), consistent with a mental accounting model. Further research could explore how tools like Fresh EBT might be used in conjunction with these models to support recipients' financial management needs.

7 Conclusion

I study the adoption of a software application allowing SNAP recipients to check their benefit balances in a convenient and salient way. An event study of 23,393 SNAP recipients reveals small but statistically significant impacts on the time horizon over which recipients are able to smooth their spending of benefits. The effects are higher for those new to SNAP, those who receive the most benefits, and those who prior to adoption tended to spend down benefits the quickest. Seen through the lens of salience and scarcity, the results suggest that software tools like Fresh EBT may be one way for policymakers to deliver important information and support beneficiaries trying to stretch scarce resources throughout a benefit cycle.

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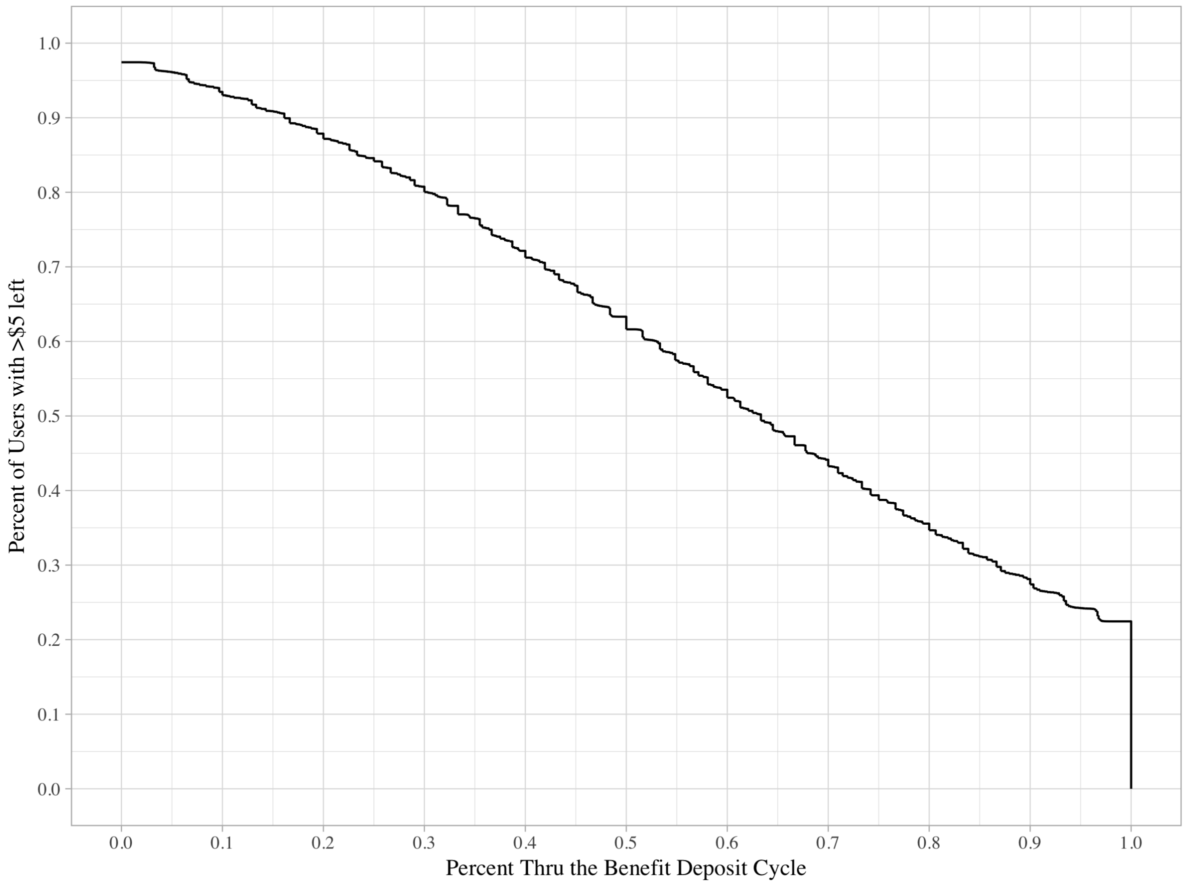
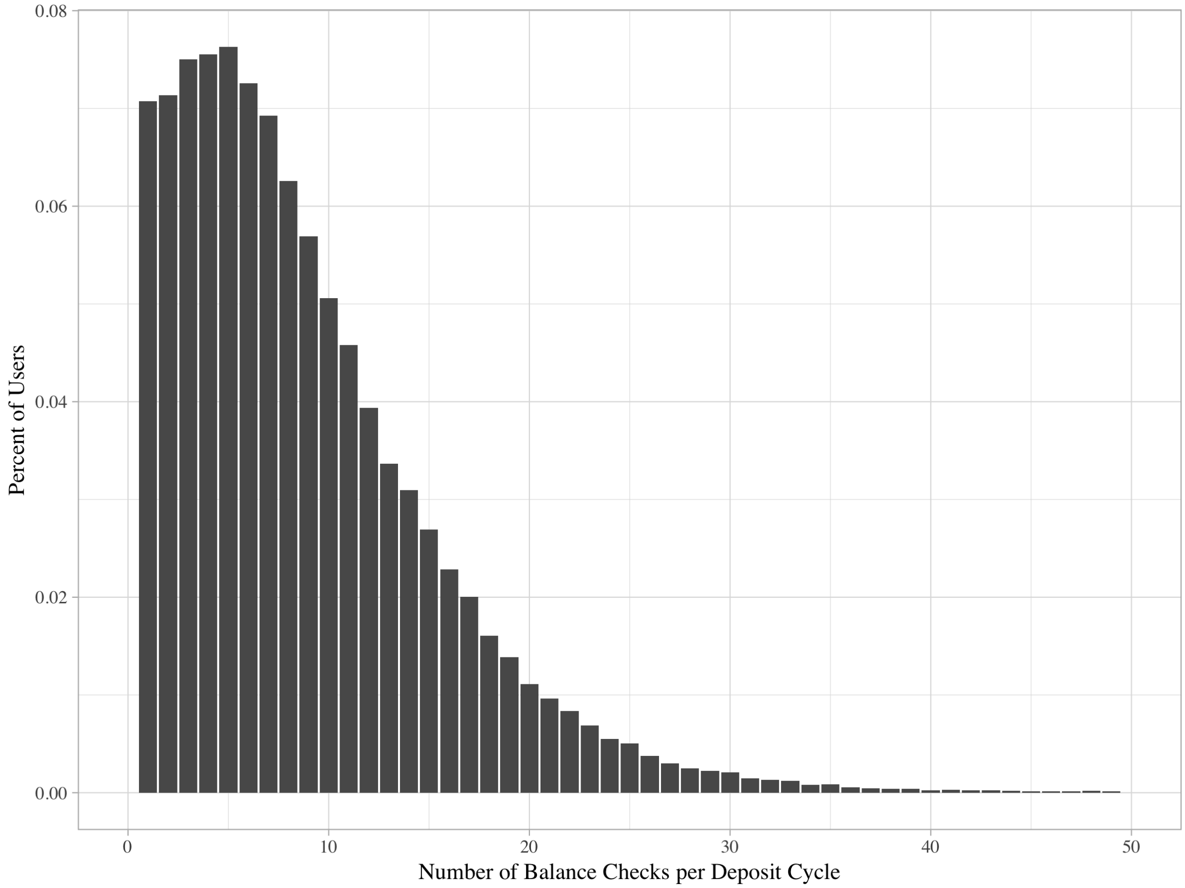
8 Figures

Figure 1: SNAP Benefit Spending



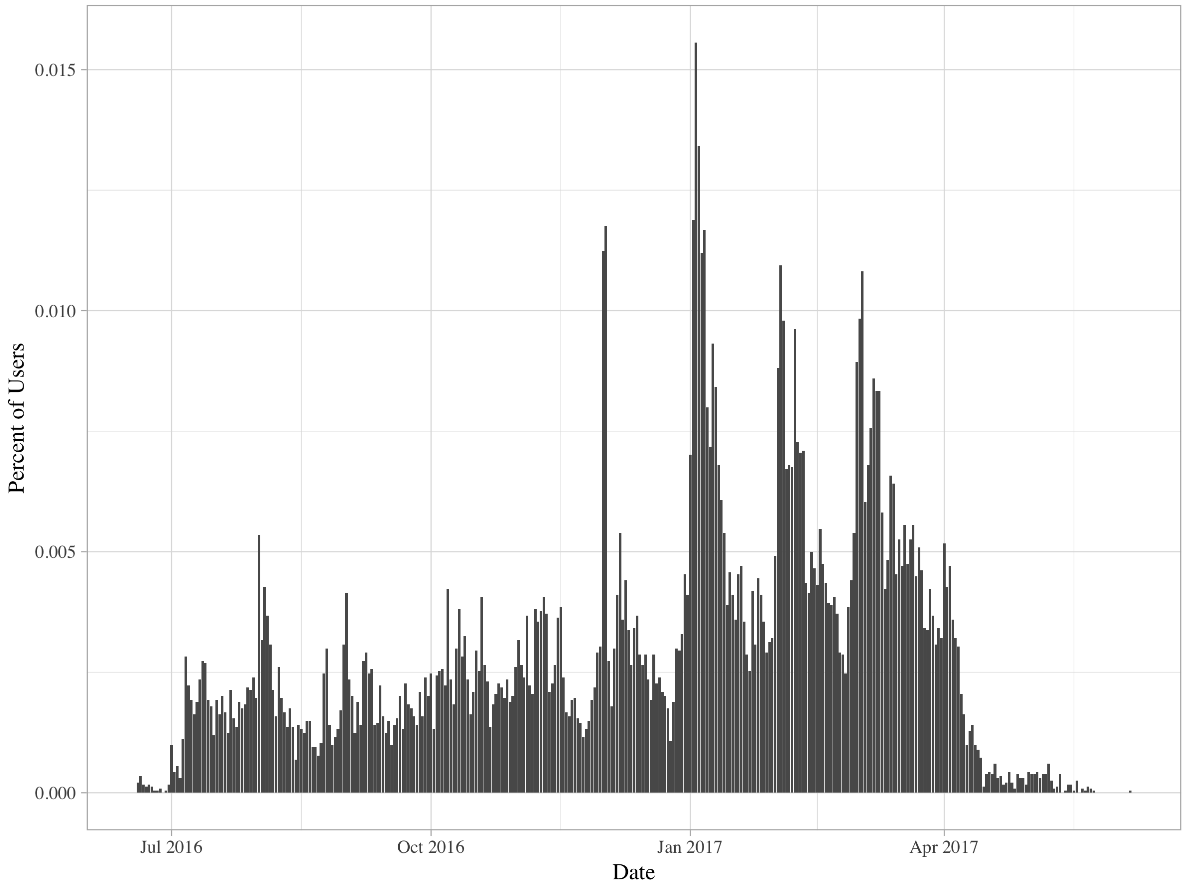
The figure shows the average percent of SNAP recipients on Fresh EBT who have less than $5 remaining at various times throughout a deposit cycle, measured in terms of percentage of the cycle.

Figure 2: Balance Checks per Cycle



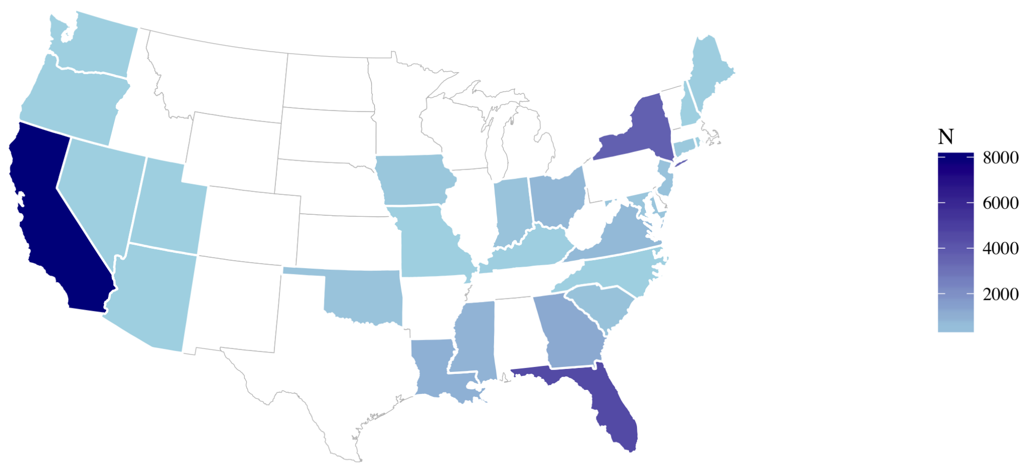
The figure shows the distribution of balance checks by users of Fresh EBT. A balance check corresponds to opening Fresh EBT and observing the balance of SNAP benefits available to the user. Balance checks are logged no more than once every twenty four hours.

Figure 3: Join Dates for Fresh EBT



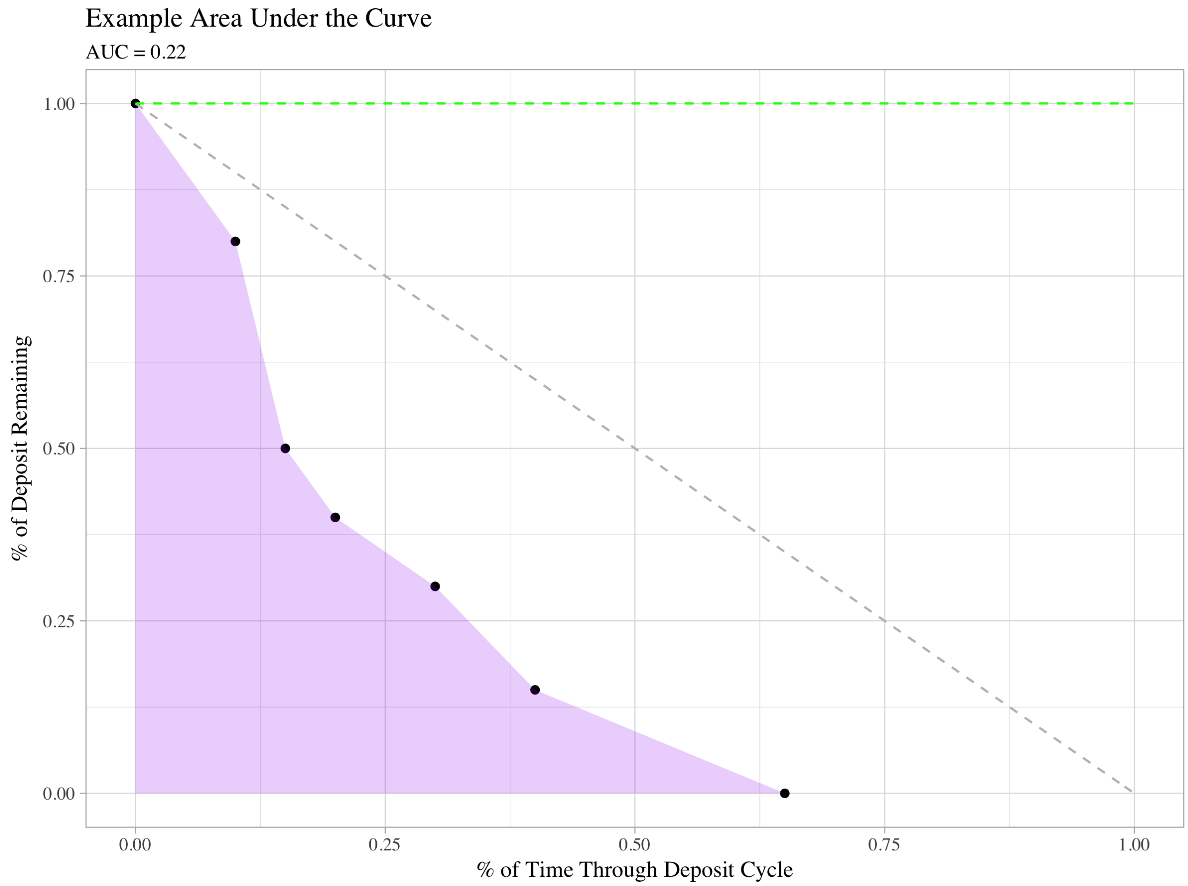
The figure shows the dates at which users in the sample joined Fresh EBT. Fresh EBT became available in June 2016.

Figure 4: States in Fresh EBT Data



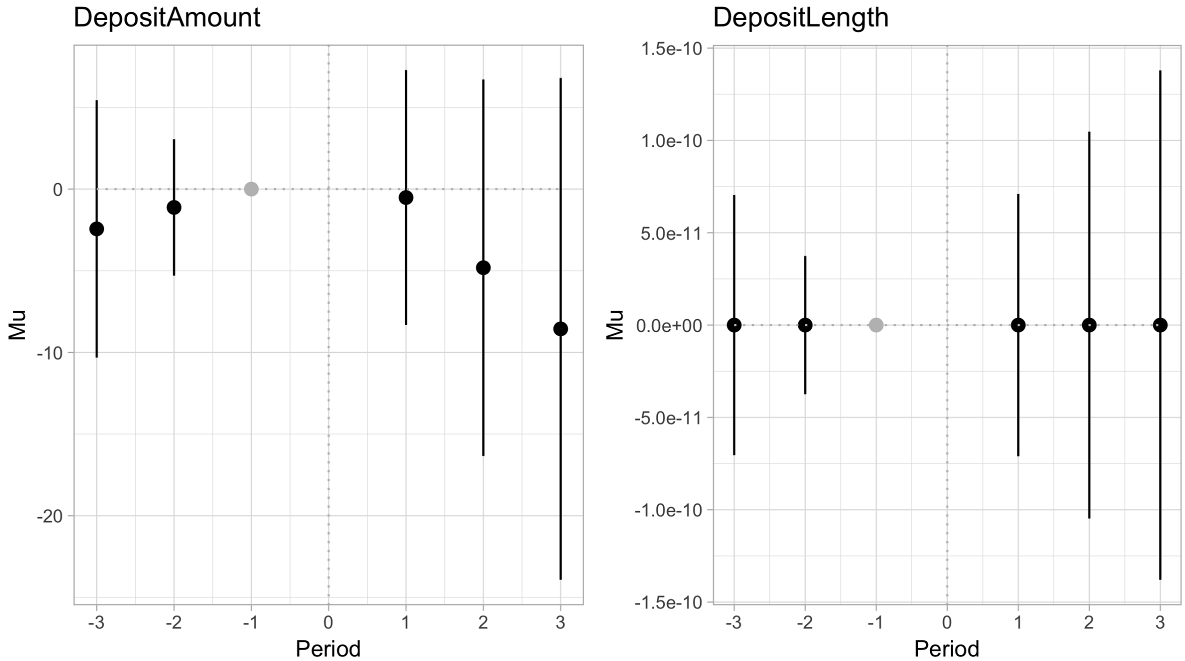
The map shows the states users come from in the sample, colored by the number of users per state.

Figure 5: Area Under the Curve (AUC)



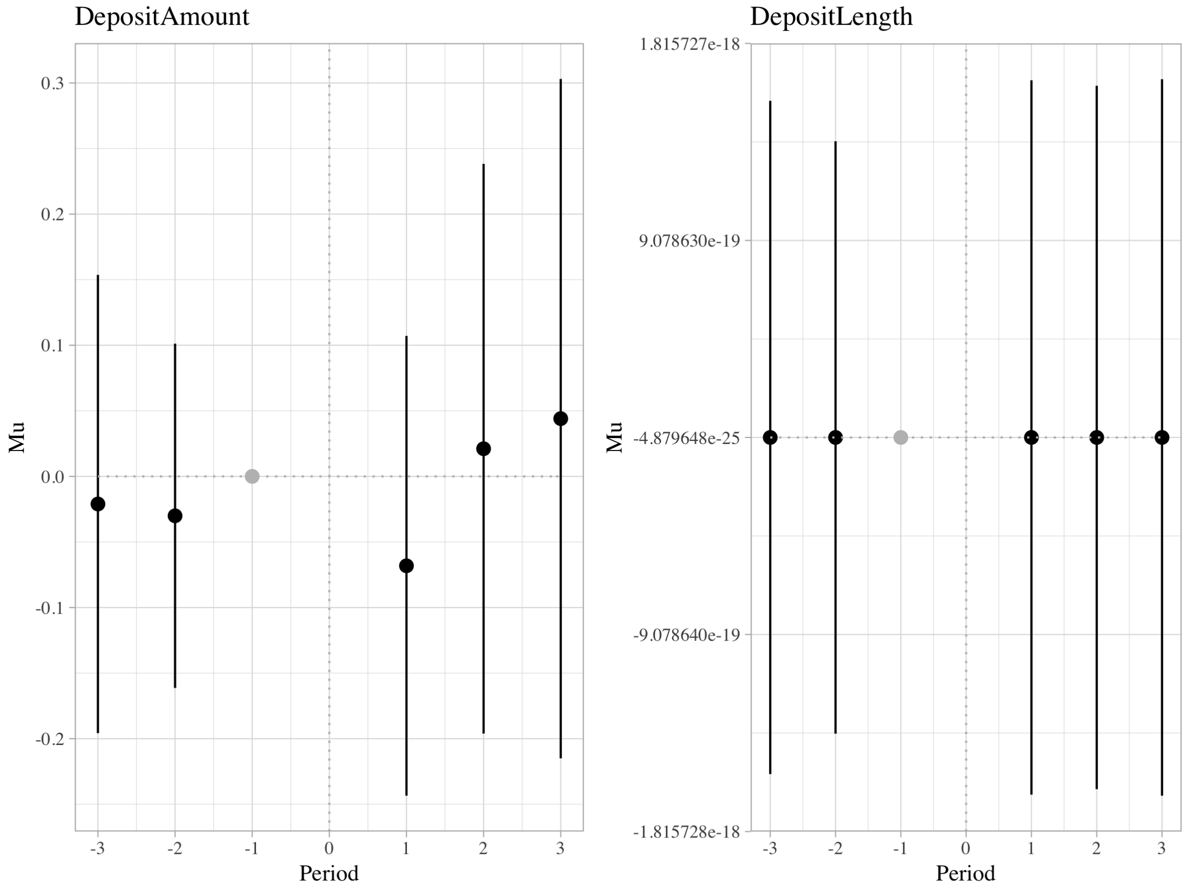
The graph shows an example measure of "area under the curve" (AUC). AUC is computed as the purple area - the area under the points formed by plotting each transaction within a deposit cycle according to where it falls in time and how much of the initial deposit has been spent.

Figure 6: Deposit Cycle Characteristics: Individual Fixed Effects



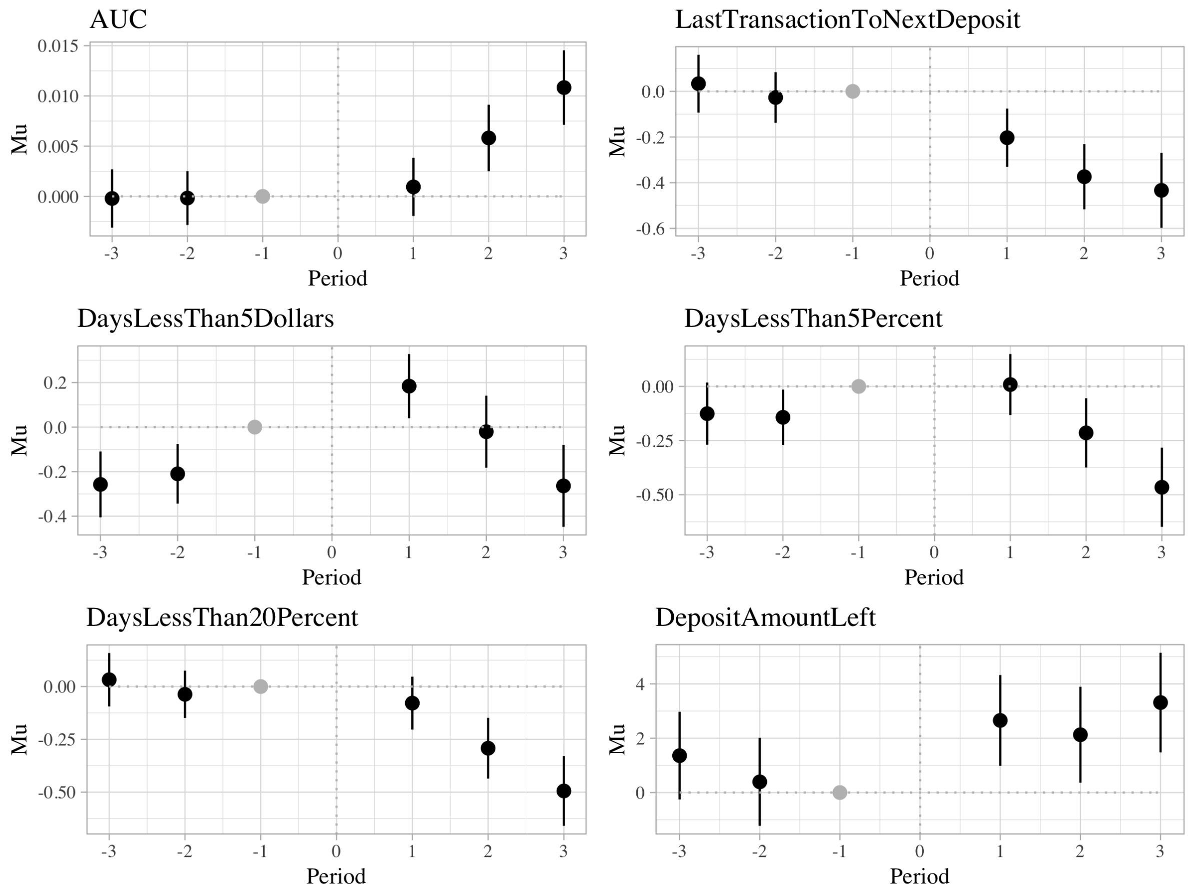
The figure plots coefficients for μ_r from Equation 1. The model includes fixed effects for individual recipient, state, and deposit cycle. The left panel shows the amount of the deposit within the deposit cycle as the outcome. The right panel shows the length of the deposit cycle as the outcome. Both models cluster standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Figure 7: Average Effects: Deposit Cycle Characteristics



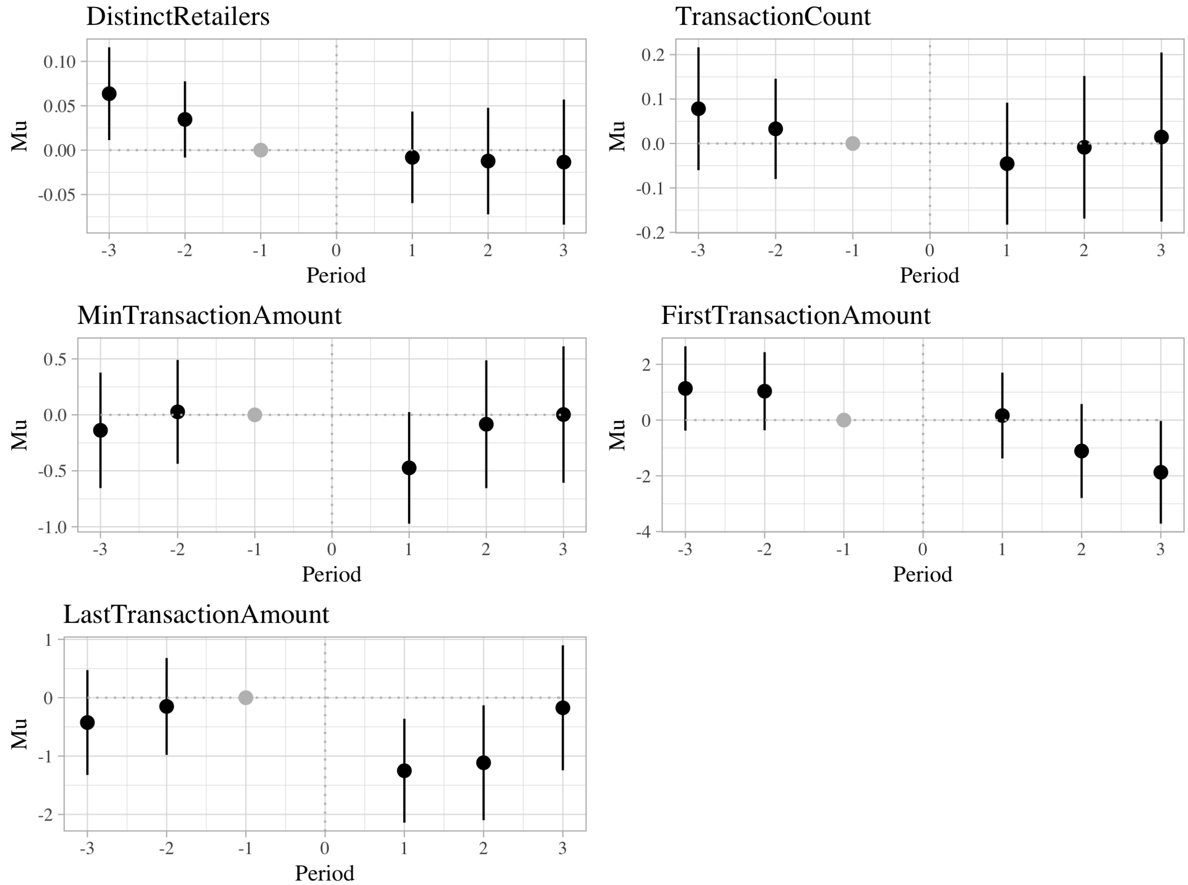
The figure plots coefficients for μ_r from Equation 2. The model includes fixed effects for deposit amount, state, and deposit cycle. The left panel shows the amount of the deposit within the deposit cycle as the outcome. The right panel shows the length of the deposit cycle as the outcome. Both models cluster standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Figure 8: Average Effects: Time Outcomes



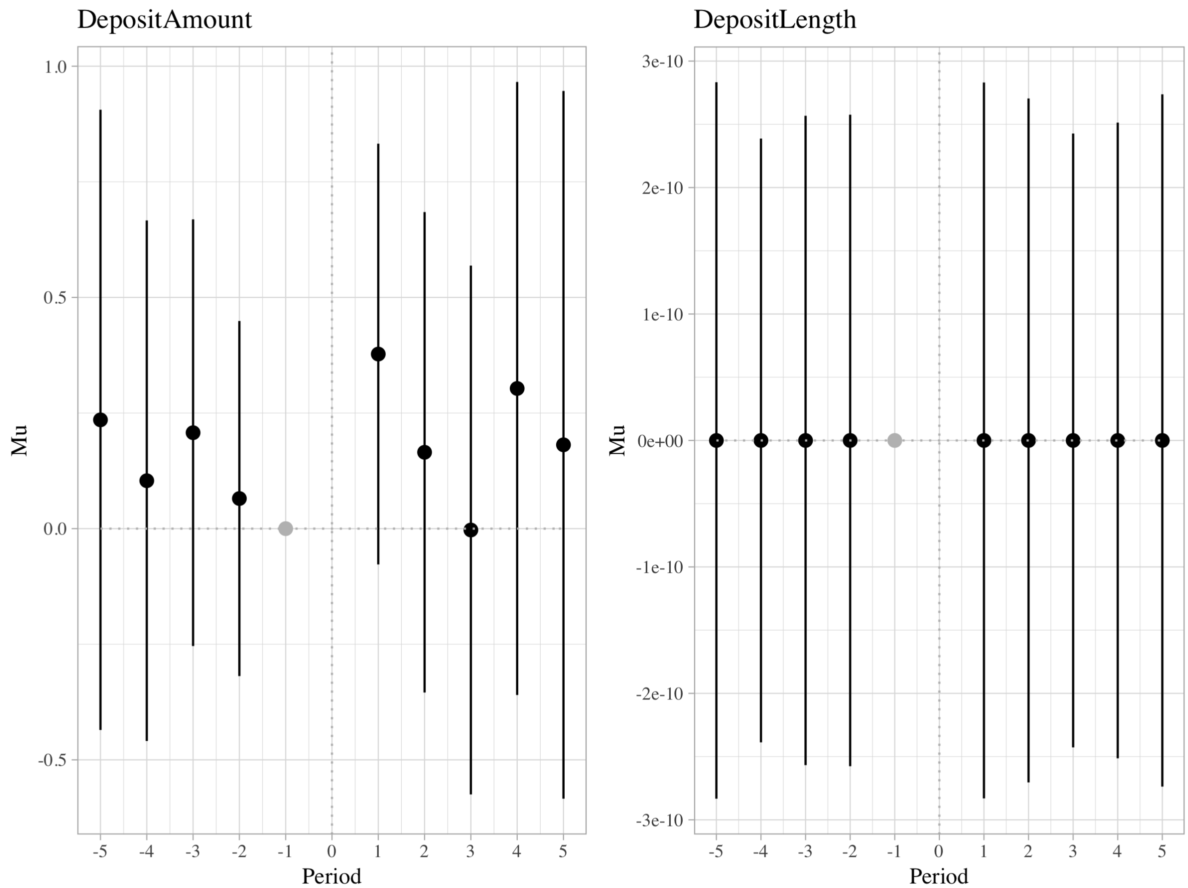
The figures plot coefficients for μ_r from Equation 2. The model includes fixed effects for deposit amount, state, and deposit cycle. Each outcome is described in section 4. All models cluster standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Figure 9: Average Effects: Spending Behavior Outcomes



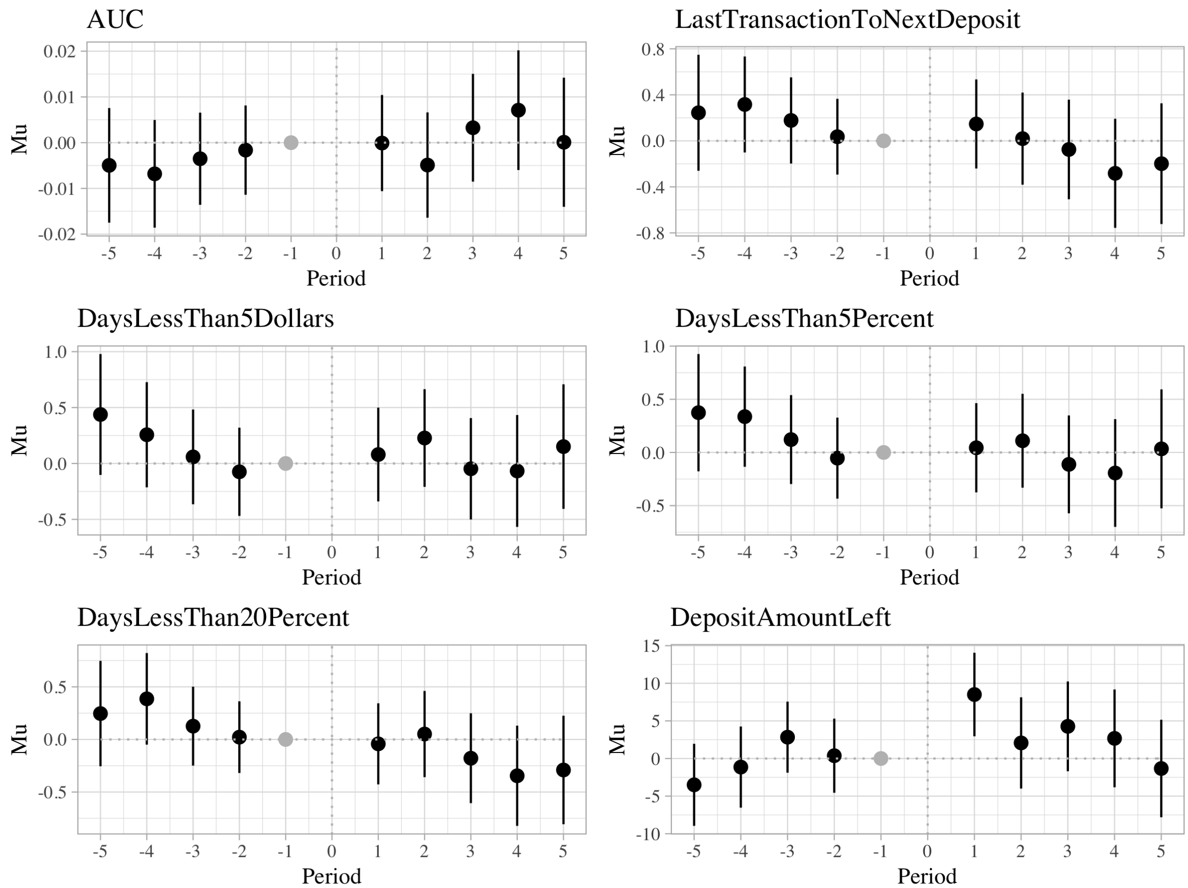
The figures plot coefficients for μ_r from Equation 2. The model includes fixed effects for deposit amount, state, and deposit cycle. Each outcome is described in section 4. All models cluster standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Figure 10: Heterogeneity: Length on SNAP



The figure plots coefficients for μ_r from Equation 2 with two additional deposit cycles added pre and post adoption. The model includes fixed effects for deposit amount, state, and deposit cycle. The left panel shows the amount of the deposit within the deposit cycle as the outcome. The right panel shows the length of the deposit cycle as the outcome. Both models cluster standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Figure 11: Heterogeneity: Length on SNAP



The figures plot coefficients for μ_r from Equation 2 with two additional deposit cycles added pre and post adoption. The model includes fixed effects for deposit amount, state, and deposit cycle. Each outcome is described in section 4. All models cluster standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

9 Tables

Table 1: SNAP Income Eligibility Limits

Household Size	Gross Monthly Income	Net Monthly Income
	(130 percent of poverty)	(100 percent of poverty)
1	$1,287	$990
2	1,736	1,335
3	2,184	1,680
4	2,633	2,025
5	3,081	2,370
6	3,530	2,715
7	3,980	3,061
8	4,430	3,408
Each additional member	451	347

The table shows the gross and net income eligibility limits for SNAP recipients. Source: US Department of Agriculture Food and Nutrition Service

Table 2: SNAP Benefits by Household Size FY 2016

Household Size	Maximum Monthly Benefit	Estimated Average
1	$194	$142
2	$357	$260
3	$511	$382
4	$649	$471
5	$771	$536

The table shows the maximum and average SNAP benefits for recipients with varying household sizes for 2017. Source: Center on Budget Priorities (2016)

Table 3: Fresh EBT

Balance		**$119.94**
Recent Transactions		
Safeway	06/04	- $60.18
711	06/02	- $9.56
Walmart	06/01	- 167.32
Benefit Deposit	06/01	+ $357.00
Joe's Convenience Store	05/20	- $16.44
Safeway	05/14	- $45.53
...	...	...

The table shows an example of the information Fresh EBT provides to SNAP recipients through their mobile phone.

Table 4: Deposit-Level Summary Statistics

Statistic	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
DepositAmount	370.706	219.254	194.000	357.000	511.000
DepositLength	28.598	6.807	28	30	31
AUC	0.280	0.198	0.122	0.249	0.405
DistinctRetailers	6.048	3.570	3	5	8
TransactionCount	13.095	9.831	6	11	18
DaysLessThan5Dollars	11.065	9.384	2	10	18

The table displays summary statistics at the deposit cycle level for the 70,179 observations in the event study prior to the adoption of Fresh EBT. Each variable is described in depth in Section 4.

Table 5: Average Effects: Deposit Amount

	Dependent variable:		
	DepositAmount		
	(1)	(2)	(3)
Post	0.002		−0.303
	(0.105)		(0.275)
RelativeTime:Post			0.046
			(0.063)
RelativeTime		0.011	0.011
		(0.045)	(0.045)
p1		−0.083	
		(0.129)	
p2		−0.005	
		(0.174)	
p3		0.008	
		(0.220)	
Mean Pre Adoption	370.7	370.7	370.7
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:	*p<0.1; **p<0.05; ***p<0.01		

The table shows regression results for Equations 3-5 for the amount of deposit in each deposit cycle. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 6: Average Effects: AUC

	Dependent variable:		
	AUC		
	(1)	(2)	(3)
Post	0.005***		−0.023***
	(0.001)		(0.005)
RelativeTime:Post			0.005***
			(0.001)
RelativeTime		0.0001	0.0001
		(0.001)	(0.001)
p1		0.001	
		(0.002)	
p2		0.006*	
		(0.003)	
p3		0.010***	
		(0.004)	
Mean Pre Adoption	0.2799	0.2799	0.2799
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:	*p<0.1; **p<0.05; ***p<0.01		

The table shows regression results for Equations 3-5 for AUC, a measure of smoothing throughout a deposit cycle. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 7: Average Effects: Days < \$5

	Dependent variable:		
	DaysLessThan5Dollars		
	(1)	(2)	(3)
Post	0.146**		1.721***
	(0.070)		(0.224)
RelativeTime:Post			−0.353***
			(0.051)
RelativeTime		0.129***	0.129***
		(0.038)	(0.038)
p1		−0.049	
		(0.117)	
p2		−0.383**	
		(0.151)	
p3		−0.756***	
		(0.187)	
Mean Pre Adoption	11.06	11.06	11.06
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:			*p<0.1; **p<0.05; ***p<0.01

The table shows regression results for Equations 3-5 for the number of days spent with less than five dollars during a deposit cycle. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 8: Average Effects: Deposit Amount Left

	Dependent variable:		
	DepositAmountLeft		
	(1)	(2)	(3)
Post	2.164***		−1.142
	(0.590)		(2.765)
RelativeTime:Post			0.995*
			(0.598)
RelativeTime		−0.677*	−0.678*
		(0.411)	(0.411)
p1		4.096***	
		(1.377)	
p2		4.248**	
		(1.755)	
p3		6.110***	
		(2.139)	
Mean Pre Adoption	-1.322	-1.322	-1.322
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:	*p<0.1; **p<0.05; ***p<0.01		

The table shows regression results for Equations 2-5 for the amount of the initial deposit amount available at the end of the deposit cycle. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 9: Heterogeneous Effects: Length on SNAP

	Dependent variable:		
	AUC	DaysLessThan5Dollars	DepositAmountLeft
	(1)	(2)	(3)
Time	-0.002^{**}	0.225^{***}	-0.590
	(0.001)	(0.058)	(0.659)
LongTimeRecipient	-0.018^{***}	0.860^{***}	-0.849
	(0.003)	(0.177)	(1.946)
p1	0.002	0.028	1.917
	(0.003)	(0.183)	(2.141)
p2	0.013^{***}	-0.461^{**}	5.291^{**}
	(0.004)	(0.235)	(2.693)
p3	0.018^{***}	-0.892^{***}	5.122
	(0.005)	(0.289)	(3.316)
Time:LongTimeRecipient	0.004^{***}	-0.152^{**}	-0.145
	(0.001)	(0.072)	(0.837)
LongTimeRecipient:p1	-0.003	-0.147	3.624
	(0.005)	(0.234)	(2.775)
LongTimeRecipient:p2	-0.015^{**}	0.138	-2.600
	(0.006)	(0.303)	(3.555)
LongTimeRecipient:p3	-0.015^{**}	0.243	0.988
	(0.007)	(0.372)	(4.320)
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:			*p<0.1; **p<0.05; ***p<0.01

The table shows regression results for Equation 2 when an indicator for being on SNAP for longer than four deposit cycles prior to adoption is interacted with non-fixed effects variables. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 10: Heterogeneous Effects: Use of Application

	Dependent variable:		
	AUC	DaysLessThan5Dollars	DepositAmountLeft
	(1)	(2)	(3)
Time	−0.0003	0.184***	−0.832*
	(0.001)	(0.043)	(0.470)
TopQuartileAppUse	−0.022***	1.627***	−4.475**
	(0.003)	(0.174)	(1.832)
p1	−0.001	−0.062	4.080***
	(0.003)	(0.135)	(1.567)
p2	0.005	−0.467***	4.997**
	(0.003)	(0.176)	(2.002)
p3	0.010**	−0.921***	7.020***
	(0.004)	(0.216)	(2.440)
Time:TopQuartileAppUse	0.002	−0.215***	0.607
	(0.001)	(0.070)	(0.838)
TopQuartileAppUse:p1	0.006	0.029	0.149
	(0.005)	(0.237)	(2.985)
TopQuartileAppUse:p2	0.001	0.300	−2.955
	(0.006)	(0.300)	(3.713)
TopQuartileAppUse:p3	0.002	0.641*	−3.668
	(0.007)	(0.368)	(4.519)
No. Individuals	23,393	23,393	23,393
Observations	140,346	140,346	140,346
Note:			*p<0.1; **p<0.05; ***p<0.01

The table shows regression results for Equation 2 when an indicator for being in the top quartile of Fresh EBT use is interacted with non-fixed effects variables. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 11: Heterogeneous Effects: Benefit Amounts

	Dependent variable:		
	AUC	DaysLessThan5Dollars	DepositAmountLeft
	(1)	(2)	(3)
Time	0.0005	0.115***	−0.312
	(0.001)	(0.044)	(0.405)
TopQuartileBenefits	−0.025***	0.659***	−24.619***
	(0.004)	(0.181)	(2.416)
p1	−0.002	0.008	2.014
	(0.003)	(0.137)	(1.325)
p2	0.003	−0.353**	3.808**
	(0.004)	(0.177)	(1.712)
p3	0.008*	−0.758***	5.261**
	(0.004)	(0.218)	(2.077)
Time:TopQuartileBenefits	−0.002	0.070	−1.876*
	(0.001)	(0.069)	(1.020)
TopQuartileBenefits:p1	0.010**	−0.225	8.076**
	(0.005)	(0.233)	(3.564)
TopQuartileBenefits:p2	0.009*	−0.138	2.438
	(0.006)	(0.296)	(4.462)
TopQuartileBenefits:p3	0.011	−0.037	4.769
	(0.007)	(0.362)	(5.445)
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:			*p<0.1; **p<0.05; ***p<0.01

The table shows regression results for Equation 2 when an indicator for being in the top quartile of SNAP benefit amounts is interacted with non-fixed effects variables. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.

Table 12: Heterogeneous Effects: Pre-Adoption AUC

	Dependent variable:		
	AUC	DaysLessThan5Dollars	DepositAmountLeft
	(1)	(2)	(3)
Time	0.001	0.075^{*}	-0.570
	(0.001)	(0.039)	(0.517)
BottomQuartileAUC	-0.141^{***}	6.826^{***}	3.205^{**}
	(0.003)	(0.199)	(1.472)
p1	-0.0005	-0.109	5.255^{***}
	(0.003)	(0.125)	(1.753)
p2	0.002	-0.368^{**}	5.127^{**}
	(0.004)	(0.161)	(2.230)
p3	0.005	-0.607^{***}	6.371^{**}
	(0.004)	(0.198)	(2.703)
Time:BottomQuartileAUC	-0.004^{***}	0.287^{***}	-0.427
	(0.001)	(0.085)	(0.656)
BottomQuartileAUC:p1	0.005	0.243	-4.531^{**}
	(0.004)	(0.278)	(2.203)
BottomQuartileAUC:p2	0.010^{*}	0.075	-3.453
	(0.005)	(0.359)	(2.824)
BottomQuartileAUC:p3	0.014^{**}	-0.264	-1.102
	(0.006)	(0.438)	(3.419)
No. Individuals	23,393	23,393	23,393
Observations	140,358	140,358	140,358
Note:			*p<0.1; **p<0.05; ***p<0.01

The table shows regression results for Equation 2 when an indicator for being in the bottom quartile of AUC prior to adoption is interacted with non-fixed effects variables. Each model includes fixed effects for deposit amount, state, and deposit cycle and clusters standard errors by recipient. The omitted category is period -1, the deposit cycle immediately prior to adoption. The period of adoption is dropped from the sample.