Food Price Variation over the SNAP Benefit Cycle

Timothy K.M. Beatty*

Department of Agricultural and Resource Economics, University of California, Davis

Xinzhe H. Cheng†

Department of Agricultural and Resource Economics, University of California, Davis

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*tbeatty@ucdavis.edu.

†xzhhuang@ucdavis.edu.

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Timothy K.M. Beatty[†] and Xinzhe H. Cheng[‡]

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[‡] *Professor, Department of Agricultural and Resource Economics, University of California, Davis, Contact Information: tbeatty@ucdavis.edu)*

[†] *Ph.D. Candidate, Department of Agricultural and Resource Economics, University of California, Davis, Contact Information: xzhhuang@ucdavis.edu*

Abstract

The Supplemental Nutrition Assistance Program (SNAP) is the largest nutrition assistance program in the United States and is a vital part of the social safety net. The monthly lump-sum benefit distribution schedule has led to higher food expenditures and consumption shortly after the date of benefit receipt, and a diminishing food expenditures and associated food consumption pattern towards the end of the benefit month. This has been found to have adverse effects on beneficiaries' dietary outcomes. In this paper, we investigate food purchasing patterns of SNAP households over the month using data from the National Food Acquisition and Purchase Survey (FoodAPS), a newly developed nationally representative survey, and its geographic component. We ask the research question: do SNAP recipients pay more for otherwise similar food at the beginning of the benefit cycle, and substitute less costly food as the month proceeds? We found that the unit cost of food bought declines significantly over the benefit cycle when households make purchases using SNAP benefits. Our results shed light on the optimal policy design of food assistance programs through a better understanding of program participants' food-purchasing behavior.

Key words

SNAP, Benefit Cycle, Food Price

Introduction

The Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program, is the largest nutrition assistance program in the US and is a vital part of the social safety net. SNAP benefits are distributed in a monthly lump-sum payment. Participants' food expenditures are typically high upon benefit receipt and decline over the remainder of the benefit cycle (Shapiro, 2005; Todd, 2015; Wilde and Ranney, 2000). This boom-bust cycle of food spending has been cited as a cause of poor diet quality among SNAP participants (Just et al., 2006). Food expenditure patterns can have a significant influence on the health and food security status of low-income households, and gaining a better understanding of program participants' food purchasing behavior provides insight into the optimal benefit distribution design of food assistance programs. This paper examines the relationship between the monthly benefit cycle and recipients' spending on food. We seek to determine whether the monthly benefit cycle distorts shopping behavior by examining the unit cost of the food recipients purchase as a function of days since benefit receipt.

We use USDA's National Food Acquisition and Purchase Survey (FoodAPS) from April 2012 to January 2013. The survey is unique in that it provides detailed information on food purchased as well as food otherwise obtained from all sources by sample households over a one-week diary period. We first compute the unit price of food (dollars per pound) bought by benefit households, and then we calculate its deviation from the average price in the retail environment provided by FoodAPS' geographic component. We ask: do SNAP recipients pay more for otherwise similar food at the beginning of the benefit cycle, and shift spending toward less costly food as they get further from the date of benefit receipt?

Our article builds on and contributes to two strands of existing literature. One is the literature on the safety net provided by SNAP and the associated benefit cycle phenomenon mentioned earlier. The other strand of literature investigates price searching behavior and the question of whether low-income populations pay more for food (Beatty, 2010; Broda, Leibtag and Weinstein, 2009). Using the FoodAPS data, we make three additional contributions to the literature. First, previous studies were unable to provide both comprehensive information about price actually paid for food from all sources and precise SNAP benefit receipt timing. Unlike retail store scanner data used in the literature, FoodAPS tracked food purchased from all stores that households patronized, as opposed to a single chain. The survey diary documented the actual price paid by households and quantity information for food items, as well as details on coupons and other discounts used. This detailed documentation enabled us to construct the unit price of our interest. FoodAPS is targeted and oversampled low-income, especially SNAP-participating households. It also matched administrative data to verify respondents' participation status and benefit receipt dates. This allowed us to focus on the food purchasing behavior of SNAP households over the benefit cycle. To our knowledge, no study has examined the changing patterns of food price paid by SNAP households over the benefit cycle.

A second feature unique to the FoodAPS data is its geographic component, which provides the precise distance between the food stores visited and each households' residence, as well as the price index for food categories constructed upon the full menu of store prices in the proximate retail environments. This allowed us to control for local retail environment effects and draw a comprehensive picture of possible price search behavior both temporally and spatially.

Finally, our research fits into a broader topic that is not limited to the discussion tied to the SNAP benefit cycle. This field of research studies how consumers change their food shopping behavior in response to income changes more generally. Prior work has explored food price searching behavior in response to income changes after retirement (Aguiar and Hurst, 2005), and in response to macroeconomic crises (McKenzie, Schargrodsky and Cruces, 2011). Even though our research investigates short-term income resource volatility, that is, the monthly arrival of welfare benefits, the subjects of our research may have insufficient resources to consume a healthy diet, and therefore even a small income change could have a critical impact on their food consumption, nutritional intake, and food security. Understanding how, why and when they chose food with different unit prices could help policy makers design their programs to promote better dietary outcomes.

Background

While many previous articles investigate benefit recipients' food expenditure and consumption patterns under the SNAP benefit cycle, our research focus on the variation in food prices paid by consumers over the cycle. We investigate two competing theories of price variation. One possibility is that benefit households pay less for the same quantity of food at the beginning of the month than later in the month. Some studies show that spikes in food expenditures are largely driven by the increase in the food quantity purchased (Hastings and Washington, 2010), and that buying in larger quantities can reduce per-unit costs (Beatty, 2010). Thus, the higher food expenditure at the beginning of the month may allow the households to pay less per unit of food. The alternative hypothesis is that households purchase higher-cost foods when they feel relatively wealthy right after benefit receipt, and substitute for lower-cost foods as their benefit is exhausted toward the end of the month, due to time-inconsistent preferences such as short-time impatience. Other than consumer choice, retailers were also found to set prices higher shortly after the benefit delivery and vary prices pro-cyclically with demand (Hastings and Washington, 2010). However, this finding is drawn from earlier data in a state with a single-day distribution window and is less relevant now because most states have already switched to staggered distribution schedules in recent years. We expect the prices we observe to reveal more about consumer behavior than retailer strategy.

In addition to finding when lower food prices emerge during the SNAP benefit month, the mechanisms households with limited resources use to obtain lower food prices are also a subject of active research. Since food is a necessity and food insecurity is still common among poor families in the United States, having the consumer competence to procure food at an economical price level is critical for both individual and national welfare. In addition, there is public concern about the "food deserts" phenomenon under which low-income households have to face prices higher than the national average, exacerbating the lack of access to affordable food.

The mechanisms that low-income households use to procure lower food prices have been researched in several prior works. One mechanism is to increase shopping frequency to search for lower prices. This includes shopping more days per week, shopping at a wider variety of stores (McKenzie, Schargrodsky and Cruces, 2011), making repeated trips to the same stores, and devoting more time in individual grocery shopping trips (Aguiar and Hurst, 2005). A second mechanism that low-income households use to procure lower food prices is to shop at cheaper stores such as supercenters (Broda, Leibtag and Weinstein, 2009). These cheaper stores may require leaving the neighborhood and traveling further distances. In addition, lower prices are often achieved by consumers who are less specific and more flexible in their eating habits. For example, households save money by switching from premium brands to generic brands, from preferable full-priced items to ones on sale with coupons, and from small packages to more economic large packages (Beatty, 2010; Kaufman et al., 1997).

In addition to answering our main research question about price variation over the benefit month and to contribute to our understanding of the mechanisms households use to obtain lower prices, we also explore benefit households' price searching behavior. Specifically, we examine their shopping frequency, store choice, and use of coupons and discounts, and we discuss potential cyclical patterns over the benefit month.

Data

FoodAPS is the first nationally representative survey to collect comprehensive data about American household food purchases and acquisitions, both for at-home and away-from-home consumption over the course of one week. The survey also collected rich information about the socio-demographic characteristics of the participating households. A total of 4,826 households participated in the survey between April 2012 and January 2013, which included 1,581 households that had at least one member currently on SNAP, other low-income households not participating in SNAP ("eligible non-participants"), and higher income households.

The primary respondent for each household—the main food shopper or meal planner—provided information about stores visited for primary food shopping (referred as primary store) and typical transportation mode used to get to the primary store, as well as other information about the household and individuals in the households through two in-person interviews. During the survey week, households were asked to document the location and date for each food-at-home (FAH) or food-away-from-home (FAFH) acquisition occasion, as well as the payment type, which revealed whether SNAP households used Electronic Benefit Transfer (EBT) cards or "out-of-pocket" income to make the transaction. In terms of FAH, which is our specific research interest for this paper, households were also asked to scan Universal Product Codes (UPC), keep receipts, and write down information in food books when they could not scan the barcodes or a receipt was missing. Thus, FoodAPS contained extraordinarily detailed information about individual food items from both collection and post-processing, including price, coupon and store saving information, and quantity. This makes our empirical investigation possible.

Another important feature of FoodAPS which benefits our research is its geographic component, which uses various measures of food access and food price indexes to characterize the local food environment. Geographic details provide precise locations of respondents' primary stores, stores actually visited in the survey week, and the nearest SNAP-authorized stores. The straight-line distances from each household's residence to the stores were estimated using geocoded data and were collected and processed after the interviews. Crucial to our research question about price variation, the geographic component of FoodAPS contains price indexes constructed from weekly UPC-level store sales from the Information Resources, Inc. (IRI) retailer scanner data, which enabled us to compare price and options available to households across different geographic locations.

Households were asked about their current SNAP participation status and the most recent benefit receipt date during the initial interview prior to the survey week. FoodAPS also compares self-reported survey responses against the SNAP administrative database. We use the dates from the administrative database only in cases where the primary respondent did not provide a last receipt date. There are some cases where respondents were near the end of their benefit cycle during the initial interview. If it is assumed that they received SNAP benefits on the same date the following month, they were supposed to receive their benefit during the data collection week. For these households, we assumed that they received SNAP benefits on the same calendar day every month and recalculated the time since SNAP was received for data collection day. Using this date and the diary dates, we calculated the number of days since benefit receipt. In this paper, we use day 1 to indicate the day of benefit arrival and day 31 to indicate the last possible day of the cycle. In the final sample, we have 1,431 SNAP-participating households after excluding households that reported their most recent benefit receipts more than one month prior to the initial interview.

Descriptive Statistics

We start our descriptive statistics by exploring the FAH expenditure patterns over the benefit month in the FoodAPS data. Figure 1 presents graphical evidence of decreasing food spending patterns across the month and is consistent with previous literature (Hastings and Washington, 2010; Shapiro, 2005; Wilde and Ranney, 2000). Taking advantage of additional data collected on payment methods in the FoodAPS data, we plot average daily food expenditures from SNAP income by using EBT cards and expenditures from "out-of-pocket" income by non-EBT payment methods separately. On the day of benefit receipt, the average SNAP household spends \$99.44 out of SNAP income on FAH, while only \$11.21 from non-SNAP income. As the month proceeds and their benefit drains, the average household spends decreasing amounts from SNAP benefits on food and increasing amounts from non-SNAP income on food. During the last two weeks of the benefit month, "out-of-pocket" food expenditure exceeds food expenditure transacted with EBT cards.[1] Different spending patterns from distinct transaction methods motivate us to take a close look at the way that households pay for food and the influence of payment method on food price.

To better understand whether any potential price searching behavior exists, we first investigate the store location choice over the benefit cycle. This may be related to how far households travel for grocery stores.[2] Figure 2 presents the mean distance to food stores SNAP households actually traveled to for grocery shopping over the SNAP benefit month.[3] Since transportation mode can influence where a household shops for groceries, we classify households into three groups depending on travel mode to their primary stores: (1) driving own vehicle; (2) using someone else's car or getting a ride from someone; and (3) walking, biking, public transit or others, and we report the mean distance to stores for each group of households. For households shopping at their primary stores with their own vehicles, mean distance to food stores visited falls from 4.79 miles in the first week slightly to 3.99 miles in the second week, but increases in the third and fourth week to 5.7 miles and 5.87 miles separately. None of these mean distances are statistically different from the one in the first week, but this suggests that SNAP recipients are less likely to make short trips to nearby local stores when their benefit is running out. The mean distance between grocery stores and home is shorter for the second group of households who rely on someone else's car for primary shopping trip compared with people who shop with their own vehicles. There is no clear pattern for this group over the benefit month. Not surprisingly, households who walk, bike or use public transit to primary stores travel the shortest distance to grocery stores in all four weeks, and we see no dramatic change over the course of the month.

[1] We plot this figure using "finer" item-level data in FoodAPS, which excludes any non-food items. We also plot the same figure using food-event level data as a robustness test, which includes all items acquired during a food event and perhaps non-food items, such as paper towels, toothpaste, and so on from food stores. We observed similar spending patterns.

[2] Store distances are straight-line distances between survey respondent's home and the food stores. It does not necessarily represent the actual distance traveled, since households do not necessarily go directly from home to store. Without a detailed time diary on household activities, we cannot tell whether grocery shopping originated from home or not.

[3] We drop outliers where the straight-line distance exceeded 200 miles.

Next, we count the number of stores visited by households to infer the household's shopping intensity. Figure 3 shows that the average household visits approximately 0.55 stores per day in the first week, and make significantly fewer visits to food stores as months goes on.[4] However, the larger number of stores visited in the first week of the benefit month does not necessarily reveal that shoppers are exhibiting low price searching behavior, since this is at least partly driven by the higher likelihood of doing grocery shopping when the SNAP benefits remain. In general, only observing shopping frequency may be a noisy measurement of shopping intensity in that time per trip may not be constant. Unfortunately, the data set did not include information on how long each grocery trip took nor observe households for a period long enough to consider repeat visits to the same store.

Finally, we analyze SNAP households' expenditures on food purchased on sale or with coupons over the benefit month. Purchasing goods on promotion is an explicit price-reducing activity. We discuss both how widely households used this mechanism and how deep discounts were obtained. Figure 4 plots the propensity of SNAP households to use any coupon or buy any food with store savings on a day over the benefit month. It reveals no clear pattern over the month. Next we compute the food expenditure share saved by coupons and store savings, by dividing total dollars saved through discounts by the daily total food expenditure, in order to measure how deep the discount is. The share saved by discounts is greater in the second half of the month than the first, but small in magnitude and not statistically significant.[5] This does not provide an additional piece of evidence in support of the view that SNAP households tend to purchase more discounted food items at either the beginning or the end of the benefit month.

Empirical Methods

In the empirical work, we estimate price paid by SNAP households as a function of time since benefit receipt. Our identification strategy is based on the idea that the date of benefit receipt is randomly assigned to the household—in many instances it is driven by the last digit of an individual's social security number—and that the benefit receipt date is exogenous to the FoodAPS survey day. By

[4]In this figure, we include days when households made zero food purchases and document it as zero stores visited.

[5]We examine an additional measures of the discounts usage—the fraction of daily purchase (food expenditures in dollars) on promotional items and plotted it over the benefit month. The analysis is robust.

estimating the linear relationship between price paid and time since benefits were received, we are able to test whether the price paid in the last week of month is lower or higher than the price paid at the beginning of the month.

To measure the price of food paid by households, we use two sets of dependent variables. We first divided the expenditure for each food category purchased by a household on a day by the quantity (how many pounds) to yield a unit value (dollars per pound).[6] Then we use the log of price per pound as the first dependent variable of interest. In order to control for the local retail environment, the second set of dependent variables is constructed based on the price index provided by FoodAPS geographic data. Using data from the geographic component of FoodAPS, we link the weekly-store level price index constructed from IRI scanner data to the distance information of IRI stores which are within 20 miles from the population-weighted centroid of census block groups.[7] Then, we compute four sets of block group level mean weekly price for each food category, by using only prices from stores within a certain distance from the block group centroid. We include four different distances—1 mile, 5 miles, 10 miles, and 20 miles—as a robustness check.[8] To construct the dependent variable, we take the deviation of price actually paid by SNAP households from the mean weekly price of the block group in which households reside and at the time they did the grocery shopping, and then divide it by the sum of price actually paid and regional mean price.[9] Since the price index from the FoodAPS geographic component is built on IRI scanner data which contains the full menu of prices from which households were able to choose, the price deviation we calculated captures whether the price paid by households is relatively more or less expensive than the price in the local retail environment.

For each set of dependent variables Y_{hjt} of food category j bought by household h on day t, we estimate the model below:

$$Y_{hjt} = \alpha + \sum_{i=2}^{4} \gamma_i \; Week_{it} \; + \sum_{i=1}^{4} \theta_i \; Week_{it} \; * \; EBT_{hjt} + \phi(t) + \tau_h + \delta_j + \epsilon_{hjt} \tag{1}$$

[6]We use USDA 4-digit food categories to classify individual food item purchased by households into 160 food categories.

[7]Price index is constructed with 2012 IRI scanner data. For details about price index construction and an undercoverage problem with IRI stores, please refers to the FoodAPS Geographic Component codebook.

[8]Food category here refers to USDA Thrifty Food Plan (TFP) food categories which is provided in the FoodAPS geographic component data. This food category classification is different from USDA 4-digit food categories. There are 29 categories in the TFP.

[9]Since price index is constructed from 2012 IRI data, we limit our sample to the households observed in 2012.

where is a set of indicators corresponding to $Week_1$ (day 1 to day 7), $Week_2$ (day 8 to day 14), $Week_3$ (day 15 to day 21) and $Week_4$ (day 22 to day 31). EBT_{hjt} takes the value of one if the transaction was done with EBT, and zero if the transaction is done with cash, debit cards, or credit cards. By interacting $Week_i$ and EBT, we set the baseline group to be the food purchased with out-of-pocket money in the first week, right after benefit receipt. $\phi(t)$ is a set of indicators specific to the food purchased day t, including whether the day t was a weekend day, a holiday, and from which month of the year. τ_h is a row vector of household fixed-effects, and δ_j is a row vector of food category fixed-effects. This allows us to control for the unobserved effects within different households and over different food categories. ϵ_{hjt} is an individual error term.

Results

Table 1 presents estimation results for the model using the log of unit price as the dependent variable. We cluster robust standard errors at the household level to adjust for unobserved factors within each household. Our result reveals that prices fall by 11.5% in the third week and decrease by 12.9% in the last week with EBT card transaction, both statistically significant, compared to the food purchased with "out-of-pocket" money in the first week. Price paid with non-EBT transaction in the third week is also significantly lower than the price paid in the same way but in the first week of the month, but we find no significant difference in the fourth week.

Table 2 are the estimation results from regressions of price deviation from the mean price in the local retail environment. Each column contains different dependent variables, using price deviation constructed by comparing to stores with different distances to the centroid of the census block group. Consistent with Table 1, we find the lowest relative prices appear in the last week using EBT cards with all dependent variables, and they are statistically significantly lower than the price deviation paid in the first week with out-of-pocket income. Again similar to Table 1, food purchased with EBT cards in the third week yields the second lowest prices, when comparing to the weekly mean price of stores within 5 miles, 10 miles, and 20 miles from the block group centroid. Interestingly, we also find slightly, but still statistically significantly lower price paid in the first week by EBT cards than the price paid with non-SNAP incomes purchased in the same week. This corresponds to the different expenditure patterns by EBT versus non-EBT shortly after the benefit receipt, as captured in Figure 1. In summary, our regression results show that unit price paid by households are decreasing along the benefit month.

Conclusion

The way that benefit recipients utilize the transfers from the government assistance programs is a question that always brings our attention. Using the FoodAPS data, we investigate the food purchasing behavior of households who participate in SNAP, the largest federal safety net program in the United States. Specifically, this paper studies the food price paid by SNAP households over the benefit month. We find that SNAP households tend to purchase higher-cost food right after they receive a benefit transfer, and then select progressively cheaper food as they approach the end of benefit cycle.

In addition, our research fits into the literature about how households with limited resources change their food purchasing behavior in a response to income change. Other than finding the changing patterns in food purchase price, we also discuss whether any possible price searching behavior exists in the sample. In the future, we aim to further investigate which specific mechanisms SNAP households utilize to obtain lower food prices at the end of month. We also seek to answer the question: do SNAP participants pay more for the unit cost of a certain nutrient (e.g. protein, fat and so on) closer to the date of benefit receipt, and switch to a less-costly source of this nutrient later of the month. Determining how the unit value paid for different nutrients changes over the benefit cycle can help policymakers understand how changes to policy design can impact healthy eating behaviors, dietary outcomes, and recipients' well-being.

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Figure 1: Average daily FAH expenditures over the benefit month

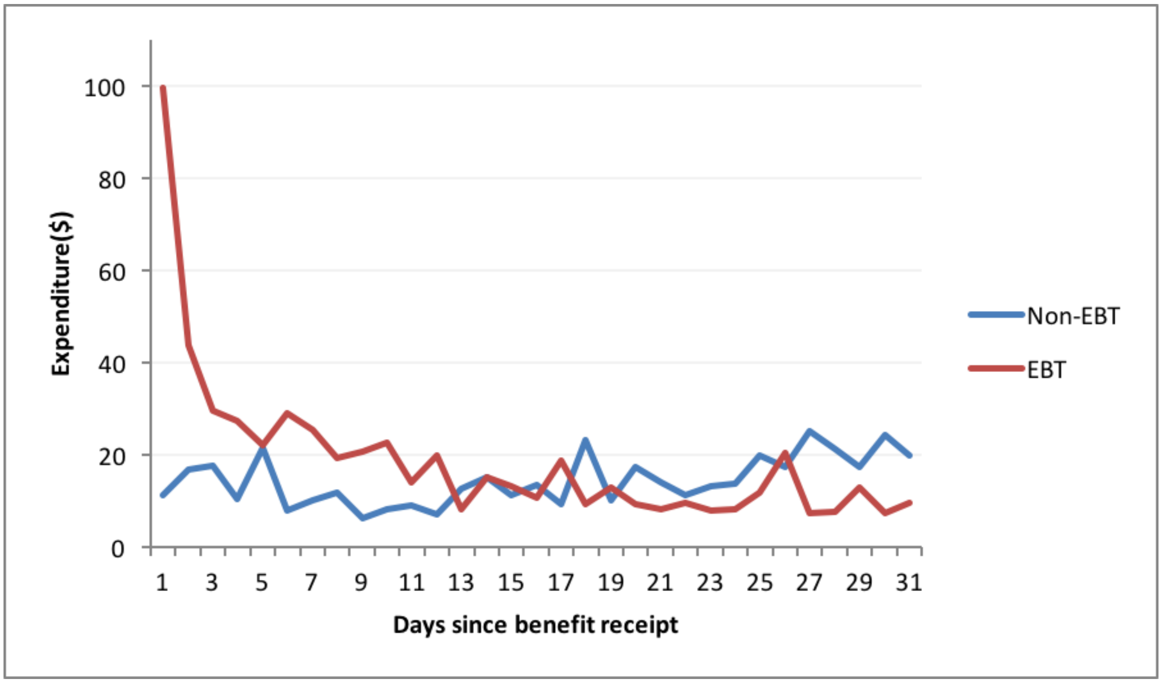

Figure 2: Distance to food stores visited over the benefit month by transportation mode to primary stores

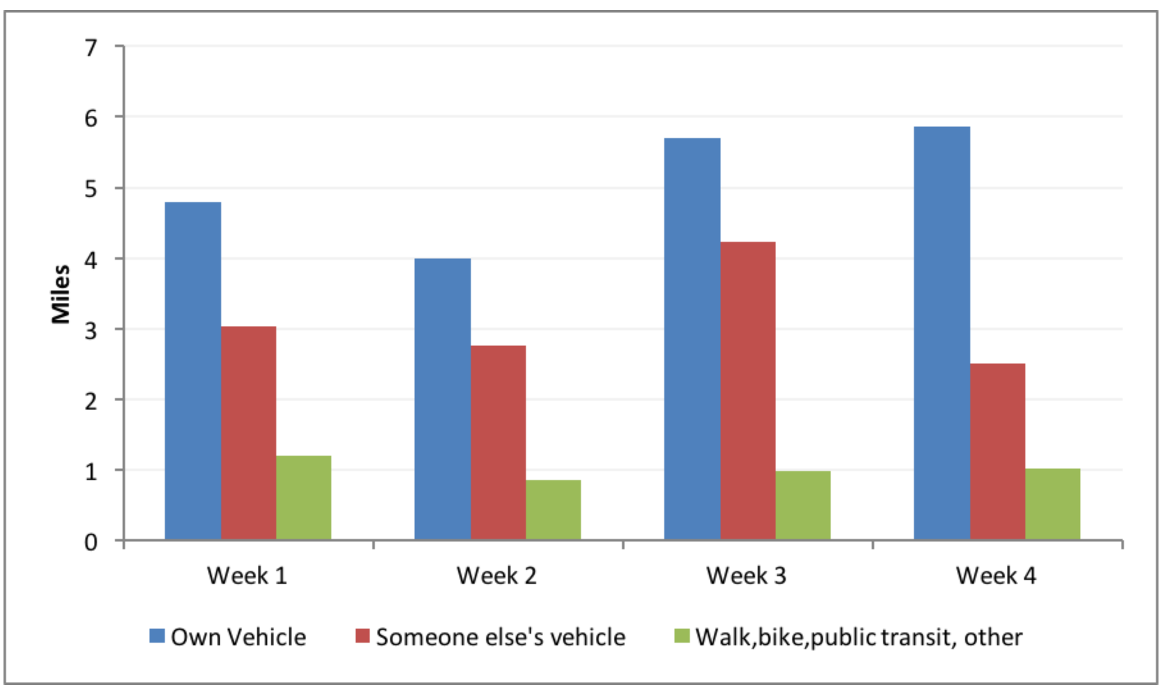

Figure 3: Number of food stores visited per day over the benefit month

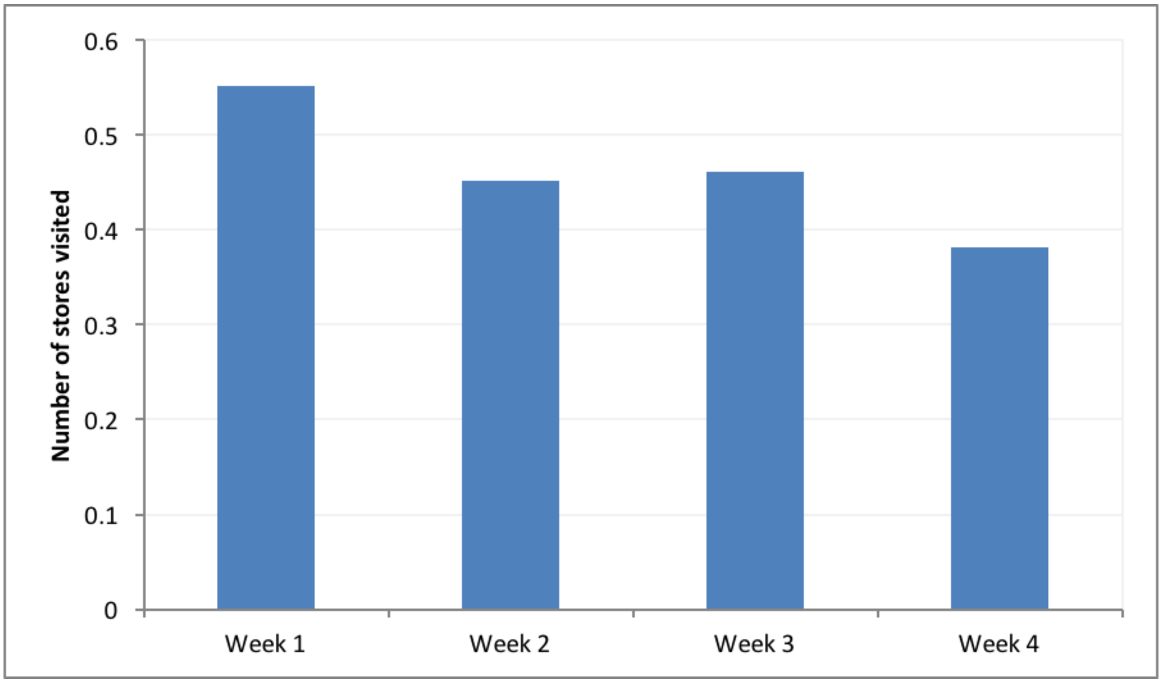

Figure 4: Propensity to purchase food with coupons or store savings over the benefit month

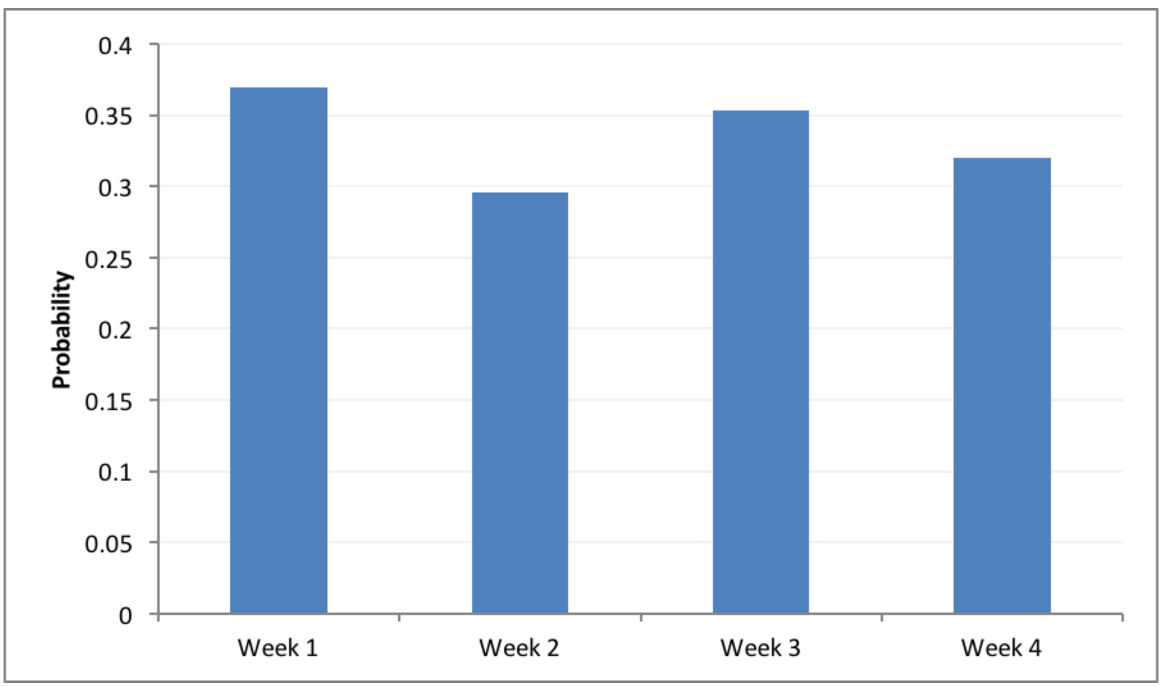

Figure 5: Food expenditure share saved by coupons or store savings over the benefit month

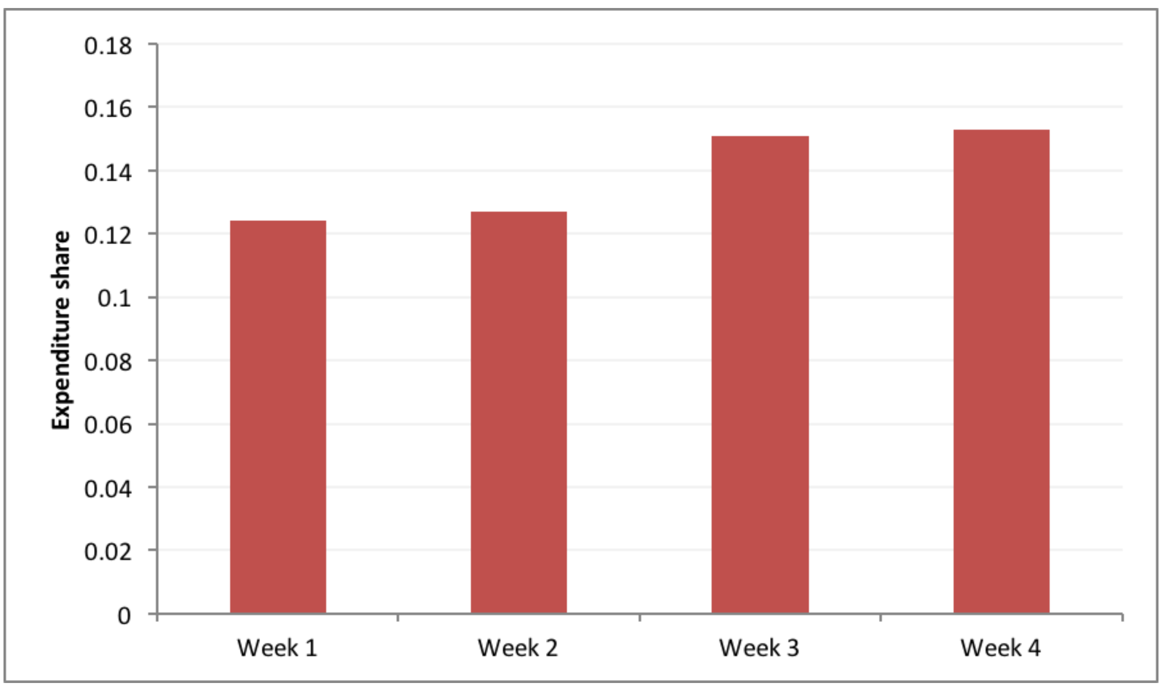

Table 1: Regression on log price

VARIABLES	Log Price
$Week_1 = 1$; EBT = 1	-0.053
	(0.039)
$Week_2 = 1$; EBT = 0	-0.045
	(0.055)
$Week_2 = 1$; EBT = 1	-0.072
	(0.049)
$Week_3 = 1$; EBT = 0	-0.123**
	(0.057)
$Week_3 = 1$; EBT = 1	-0.115**
	(0.058)
$Week_4 = 1$; EBT = 0	-0.067
	(0.045)
$Week_4 = 1$; EBT = 1	-0.129**
	(0.045)
Observations	18,901
R-squared	0.645

Notes: Robust standard errors in parentheses. All regressions include household fixed effects with standard errors clustered at the household level and food category fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Regressin on price deviation

VARIABLES	(1) 1 mile	(2) 5 mile	(3) 10 mile	(4) 20 mile
$Week_1 = 1$; EBT = 1	-0.030	-0.039*	-0.039*	-0.038*
	(0.028)	(0.022)	(0.022)	(0.022)
$Week_2 = 1$; EBT = 0	0.014	0.006	0.007	0.004
	(0.033)	(0.028)	(0.028)	(0.028)
$Week_2 = 1$; EBT = 1	-0.030	-0.036	-0.035	-0.037
	(0.031)	(0.027)	(0.026)	(0.026)
$Week_3 = 1$; EBT = 0	-0.033	-0.044	-0.038	-0.041
	(0.035)	(0.031)	(0.030)	(0.030)
$Week_3 = 1$; EBT = 1	-0.055	-0.067*	-0.066*	-0.067*
	(0.041)	(0.035)	(0.035)	(0.034)
$Week_4 = 1$; EBT = 0	-0.035	-0.045*	-0.036	-0.036
	(0.029)	(0.024)	(0.024)	(0.024)
$Week_4 = 1$; EBT = 1	-0.076**	-0.088***	-0.078***	-0.077***
	(0.034)	(0.029)	(0.028)	(0.028)
Observations	8,901	11,287	11,776	11,970
R-squared	0.313	0.306	0.315	0.313

Notes: Robust standard errors in parentheses. All regressions include household fixed effects with standard errors clustered at the household level and food category fixed effects. *** p<0.01, ** p<0.05, * p<0.1.