Retailer SNAP Adoption and Household Expenditure Patterns∗

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Abstract

Many social safety net programs in the U.S. provide in-kind benefits, relying on private vendors to distribute these transfers. Yet we know relatively little about the implications of vendor participation decisions for beneficiary welfare. We study the Supplemental Nutrition Assistance Program (SNAP), the second-largest anti-poverty program in the U.S., which provides vouchers for food that can be redeemed at participating food retailers. We first document an increase in retailer participation during the Great Recession, when the SNAP program expanded in size. This increase was driven by large chains from the following channels: dollar, drug, club, and mass merchandiser. We then show that SNAP-eligible households shifted their food expenditures towards these retailers when they started accepting benefits. We explore several explanations, finding little evidence for price changes, increases in program take-up, or that households were previously constrained. Additional analyses suggest that travel costs are important for some households and that some stores increased their inventory of fresh foods. Our findings imply that increases in program size can yield welfare benefits to program recipients through retailer response.

Disclaimers: (1) The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy. (2) The analysis, findings, and conclusions expressed in this report should not be attributed to NielsenIQ TDLinx. (3) The analysis, findings, and conclusions expressed in this report should not be attributed to IRI.

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1 Introduction

Many safety net programs in the U.S. provide transfers in-kind, rather than in cash, and rely on private vendors to distribute benefits. As beneficiaries have preferences for vendor attributes, such as location, pricing, and product offerings, vendor participation decisions may have important welfare implications. Yet there is relatively little research on vendor participation decisions in these programs.

In this paper, we study vendor participation in the Supplemental Nutrition Assistance Program (SNAP), the second largest anti-poverty program in the U.S. SNAP provides vouchers for food that can be redeemed at participating food retailers, and most retailers that carry food are eligible to participate. Participation involves non-trivial upfront technology costs but ongoing costs are low, so most retailers continue participating after initial authorization.

We first document a few facts about retailer participation in SNAP over the past couple of decades. To do so, we combine administrative records on the universe of SNAP retailers with microdata on all food stores in the U.S. First, we find that the number of retailers participating in SNAP increased greatly during the Great Recession (and did not subsequently decrease) and that new entries were concentrated around the timing of a benefit increase that occurred under the American Reinvestment and Recovery Act (ARRA). Thus, we conclude that retailer engagement is responsive to program size. Third, the majority of benefits redeemed at these new SNAP retailers are redeemed by outlets belonging to eight national chains. These chains belong to the following channels: club, dollar, drug, and mass merchandiser, some of which carry limited food offerings.

Next, we study the effects of SNAP adoption by these chains on food expenditures among SNAP households. To do so, we draw on data from a large, nationally representative consumer panel that contains detailed information on all food purchases, from any outlet. The panel also includes detailed household demographic information, such as income and household size, which we use to proxy for SNAP eligibility. We find that, on aggregate, SNAP-eligible households shifted their food expenditures towards the new SNAP chains when they
started accepting benefits. We find no similar increase for non-SNAP households. Thus, it appears SNAP recipients derive value from being able to spend their SNAP benefit dollars at these chains.

There are several reasons SNAP households might increase spending at a given store when it starts accepting benefits. One reason is that households were previously constrained, meaning they wanted to spend more than their cash budget at the store before it accepted benefits, but couldn’t. Second, it could be that stores alter aspects of their environment (e.g., prices or inventory) when they join SNAP. Third, if households face important travel costs associated with shopping, they may prioritize stores that accept both cash and SNAP benefits. Finally, SNAP recipients could prefer shopping at different outlets when using cash vs. SNAP benefits — thus, non-fungibility of cash and benefits could be an explanation.

The eight chains mentioned above expanded SNAP adoption across their outlets quickly, creating well-defined adoption “events.” We use these SNAP adoption events to identify the causal effects of retailer SNAP adoption on food expenditures of households living nearby. We match households in our consumer panel to nearby outlets based on location geocodes. We then estimate two specifications: a difference-in-differences model, which uses variation across stores in the timing of SNAP adoption, and a triple differences model, which additionally compares SNAP and non-SNAP households. Our specifications include household fixed effects, so that our estimates reflect within-household spending changes.

We find that when a store starts accepting SNAP, nearby SNAP households increase their share of food expenditures spent at the new SNAP store by 0.4 percentage points (pp). This effect represents a 12% increase in food expenditures at these retailers and is similar across our two specifications. We also consider effects on the share of shopping trips that occur at the SNAP-adopting store and find that this outcome increases by 0.3 pp, or about 10%. We find little evidence of a change in total expenditures or trips to any outlet. Combined, these findings suggest that SNAP households are reallocating their food expenditures across retailers, rather than an increasing their total food spending.
Next, we estimate effects separately by chain. We find that the overall increase in expenditure share at SNAP-adopting outlets is largely driven by particularly strong effects at one of the dollar chains and one of the club chains. In particular, we estimate that SNAP-eligible households spend 0.2pp (67%) more at nearby outlets belonging to the dollar chain when they start accepting benefits and 0.4pp (7%) more at nearby outlets belonging to the club chain when they start accepting benefits. We focus on these chains individually to understand the mechanisms behind these effects.

We first consider whether households might be constrained. Using a detailed survey of food purchasing and consumption habits, we find that fewer than 10% of SNAP households that shop at club and dollar stores identify them as their primary food shopping store, suggesting that the majority are not constrained by whether these stores accept benefits. Next, we consider whether SNAP adoption by retailers causes households nearby to enroll in SNAP. We rule out this explanation because we do not find evidence of an increase in total food expenditures among SNAP-eligible households in response to SNAP adoption by nearby retailers.

Third, we consider whether retailers change their pricing or product variety when they start to accept SNAP benefits. To do so, we use a panel of transaction-level data that covers the majority of food retailers in the U.S. These data exclude the club chain, so this analysis is limited to the dollar chain. We employ the same econometric methods described above, replacing household fixed effects with store fixed effects. We find no evidence that the dollar chain changes its prices after it starts accepting SNAP benefits. We do find that its outlets are more likely to carry produce products, however. In particular, we estimate a 5% increase in the likelihood an outlet belonging to the dollar store carries any produce.

Finally, we consider whether fixed costs of travel might contribute to the increases in expenditure share we find. If fixed costs of travel are important, then households may prefer to do the majority of their food spending at an outlet that accepts both cash and SNAP benefits. When outlets start accepting benefits, SNAP-eligible shoppers may re-time shopping trips
to fall just after the SNAP adoption date. We find evidence of this behavior for the club chain — during the adoption quarter, the likelihood of SNAP-eligible households making at least one trip increases 13%, and subsequently declines.

These results contribute to several literatures by presenting insights into how nutritional programs shape the evolving food retail landscape, shift household purchasing patterns, and impact household welfare.

First, a large and growing literature has documented the purchasing patterns of SNAP beneficiaries and how these patterns are affected by facets of the program. Studies have shown how SNAP benefits increase food expenditures at the household level (Hoyes and Schanzenbach 2009; Beatty and Tuttle 2015; Hastings and Shapiro 2018). With its monthly distributions, there is a well-documented monthly cycle of SNAP expenditures where beneficiaries tend to spend a large portion of their benefits in the first few days after receipt and reduce both purchases and consumption later in the month (Wilde and Ranney 2000; Shapiro 2005; Hastings and Washington 2010; Damon, King, and Laibtag 2013; Goldin, Homonoff, and Meckel 2022). Additionally, attention has been paid to how SNAP affects the composition of purchases (Hastings, Kessler, and Shapiro 2021). We add to this literature by providing new evidence on the impacts of store participation on SNAP household expenditures.

Second, our study is also related to work on the changing food retail landscape, which emphasizes the entry of non-traditional food retail stores, such as supercenters, club stores, dollar stores, and drug stores (USDA-ERS 2021; Courtemanche and Carden 2014; Bauner and Wang 2019). Martinez (2007) found that the share of expenditures at traditional grocery retailers fell from 81.7% in 1994 to 67.4% in 2005, while the share of expenditures in nontraditional retailers grew from 17.1% to 31.6% over the same period. Most of the studies on non-grocery food retailers have focused on supercenters, and impact of shifts in the retail landscape on SNAP beneficiaries remains an understudied topic. Our findings further address this gap in the literature by analyzing the role of non-supercenter, non-grocery food
retailers and their specific relationship to the SNAP population.

Our paper is also related to a few recent papers on dollar stores. Chevalier et al. (2022) note the accessibility of dollar stores for low-income, rural, and minority populations. Furthermore, dollar stores have a demonstrable impact on the food landscape, especially in areas of low food access. Chenarides et al. (2021) show that once a dollar store enters a food desert, that area is more likely to remain without access to supermarkets. Dollar stores are becoming key players within the food retailing environment, but they have received little attention in the economics literature. Our findings offer new insights into this trending retail channel.

In addition, our results contribute to a broader literature on the interaction of nutritional programs and food retail stores and their welfare implications. To that end, SNAP is not the only federal food assistance program that can have an impact on food sales. Indeed, Handbury and Moshary (2021) show that expansions in the National School Lunch Program reduce local retail food sales and lower prices more broadly, while Meckel (2020) and McLaughlin, Saitone, and Sexton (2019) demonstrated differentiated pricing behavior among authorized retailers for the Women, Infants, and Children Program (WIC). The present study contributes to this body of work by demonstrating how the expansion of SNAP into non-grocery retailers impacts both retailers and SNAP beneficiaries.

Finally, we contribute to the store choice literature on how food store attributes such as quality, product variety, and store format impact welfare. We show that whether a store accepts SNAP benefits is an important store quality attribute for consumers’ store choice (Matsa 2011). Taylor and Villas-Boas (2016) find that consumers are willing to pay more for certain outlets (e.g. supercenters) than others, suggesting that store attributes are a critical component to welfare.

The rest of the paper proceeds as follows. Section 2 describes the institutional details behind retail SNAP participation and Section 3 describes the data sources used. Section 4 and Section 5 summarizes aggregate trends in retailer participation in SNAP, household
EBT redemption, and household spending patterns around the time of the ARRA expansion. Section 6 describes our econometric approach and Section 7 includes our main results. This is followed by a discussion of mechanisms at play in Section 8. Section 9 concludes.

2 Institutional Background on the SNAP Program and SNAP Retailers

The Supplemental Nutrition Assistance Program (SNAP) is the largest domestic food and nutrition assistance program for low-income Americans. In the past decade, SNAP has grown substantially. In 2009, SNAP distributed $50 billion in benefits, and distributions increased to $108 billion in 2021 (USDA-FNS 2022). On the supply side, the private food retail sector plays an integral role in SNAP implementation as SNAP participating households receive monthly lump sum benefits that can be spent at authorized retail stores for eligible food items.

In order to participate in SNAP and accept SNAP benefits, each individual store location must be separately authorized by the U.S. Department of Agriculture (USDA) Food and Nutrition Service (FNS). The main SNAP participation requirements for retailers involve product offering and sales of staple food products. To qualify, individual stores must satisfy one of two inventory requirements: (1) carry a minimum stock of “staple foods” (bread, meat, dairy, and fruits and vegetable) or (2) sales of “staple foods” comprise more than 50% of gross sales. The latter requirement allows specialty food stores (such as meat markets) to participate. Applications for individual stores are directly submitted to FNS along with required documentation to initiate the process. Applications are accepted on a rolling basis and FNS authorization decisions are made within 45 days. An expedited process exists for owners of more than 10 stores.

While the application process is relatively costless for the store, the actual implementation of Electronic Benefits Transfer (EBT) is not. Electronic Benefits Transfer (EBT)
is an electronic system that allows a SNAP beneficiary to pay for food using SNAP benefits at retailers, and the retailer bears both the acquisition cost of EBT hardware/software and processing cost of SNAP benefit transactions. All EBT systems are procured through third-party vendor with whom retailers negotiate and enter into private contracts, and which potentially allows for volume discounts for large retail chains. Additional costs include training employees on SNAP rules to ensure compliance and adherence to SNAP regulations. Once store locations are authorized to accept SNAP benefits, a sticker or decal is often placed in the window to advertise the retailer’s status. The FNS website also maintains an easily accessible database for all currently authorized SNAP retailers. When a beneficiary shops at a SNAP authorized retail store, their SNAP EBT account is debited to reimburse the store for food that was purchased. EBT has been the sole method of SNAP issuance since June of 2004 and is in use in all 50 states, the District of Columbia, Puerto Rico, the Virgin Islands, and Guam.

3 Data

We draw on several different data sources to analyze the effects of retailer participation in SNAP on program beneficiaries.

3.1 IRI Consumer Network

To study the effects of retailer SNAP participation on household food spending behavior, we use data from the IRI Consumer Network dataset for the years 2008-2016. The Consumer Network data is compiled by IRI from the National Consumer Panel, a shopper panel that includes approximately 120,000 households per year and is designed to be representative of households nationwide and within individual markets throughout the United States. Participants provide data on all products they buy, at any outlet, using an in-home barcode scanner. To incentivize participation, panelists are awarded points for data submission that can be exchanged for prizes. Households also provide detailed demographic information, such
as income and household size. Although demographic information is provided annually, we observe these variables only for 2012.

For each shopping trip, we observe the date, the store, and the total amount spent. In addition, for all food products purchased, we observe the unit price, the quantity purchased, and whether any discounts were awarded. IRI validates prices using scanner data they collect independently from retail chains.

Our main interest is in the shopping behavior of SNAP households. The Consumer Network data do not record SNAP participation, however. Therefore, we create an indicator for SNAP eligibility as a proxy for take-up. We impute eligibility using household income and family size by applying the federal gross income test.\footnote{We cannot apply the SNAP asset test because the Consumer Network does not report data on household assets. Because we only observe household demographic information in 2012, our indicator for SNAP-eligibility does not change over time.} Finally, we collapse the household panel to the level of household, year, and quarter, generating the following outcomes: total food spending, food spending per chain, total trips, and total trips per chain. Trips are included if they have a positive amount of food spending.

3.2 Administrative Data on SNAP Stores

We obtain information on all SNAP-authorized retailers between 2006 to 2016 from FNS’s Store Tracking and Redemption System (STARS). These data contain the following information on stores: name and address, market channel, SNAP authorization date, and a unique identifier. Stores report their name, address, and channel to FNS and this information is verified periodically through audits. In addition, the STARS data include monthly EBT redemptions for each store, i.e. the amount of SNAP benefits used at that store.

We use store name to identify outlets belonging to the eight chains studied in this article. Because store names are self-reported, there are occasional errors (e.g., spelling mistakes),
so we use string-cleaning techniques to standardize the name field. We use the unique store identifier to link stores across years.

### 3.3 IRI Retail Scanner Data

To study retailer behavior, we use the IRI Infoscan dataset from 2009 to 2012. These data consist of product-level transactions records for over 41,000 food retailers in the U.S. Our data include retailers from the following market channels: convenience, dollar, drug, grocery, and mass merchandiser. We do not have data on club stores or liquor stores. For each store, we observe the name, address, parent company, and a unique identifier.

Each observation in our data is a store, month, and product (Universal Product Code, or UPC). We observe sales volume and volume-weighted average price for each product sold in a given store-month. The price we observe incorporates retailer discounts and specials, such as coupons or loyalty card price reductions, but does not reflect discounts from manufacturer coupons (e.g., a manufacturer rebate). Our data are limited to food products.

In order to identify which retailers in IRI participate in SNAP (and when), we perform a linking procedure between the IRI database and the SNAP administrative records on stores (described above). In both datasets, we observe geocoded location, store address, and store name, although these fields can differ somewhat due to a variety of factors (e.g., spelling mistakes or differences in geocoding methodology). Thus our linking procedure is based on proximity between stores as well as similarity between the name and address fields. We describe this procedure in detail in Appendix Section A1.

We create two different analysis samples: one at the store-month level and one at the store-month-product level. For the first sample, we calculate the following outcomes for each store-month: total food sales, an indicator for any produce sales, and a price index. The indicator for any produce sales is a proxy measure for inventory (i.e., whether the store carries any fresh produce), which is not reported in the Retailer Panel.

Next, we create a price index at the store-month level. Because supermarkets typically stock thousands of products, we construct an inflation index to capture changes in the price
of a fixed bundle of goods, whereby avoiding any product heterogeneity biases. Following [Beraja, Hurst, and Ospina (2019)] we measure inflation for continuing UPCs: those sold in a given store in every month in the current year and at least one month in the previous year. The calculation proceeds in two steps. First, for each product module $j$, we calculate a month-on-month arithmetic inflation index for each store $s$. Let $u$ denote a particular product (UPC), and $U_{j,s,m}$ be the set of products sold in store $s$ in group $j$ in month $m$. Product-module level inflation for a given month is defined as:

$$P_{s,j,m} = \frac{\sum_{u \in U_{j,s,m}} p_{u,s,m} q_{u,s,y(m)} - 1}{\sum_{u \in U_{j,s,m}} p_{u,s,m-1} q_{u,s,y(m)-1}}$$

where $p_{u,s,m}$ is the unit price at which UPC $u$ is sold in store $s$ in month $m$ and $q_{u,s,y(m)-1}$ is the quantity of UPC $u$ sold in store $s$ in the calendar year preceding month $m$.

We then aggregate across product modules using a Tornqvist index:

$$P_{s,m} = \prod_{j \in J} \left( P_{s,j,m,y} \right)^{S_{s,j,m} + S_{s,j,m-1}}$$

where $S_{s,j,m}$ denotes the expenditure share of product module $j$ in store $s$ in month $m$. Store-level monthly inflation is therefore a Tornqvist aggregate of Laspeyres-style lagged-weight arithmetic indexes at the product module-store level. To obtain the price level of each store $s$ in month $m$, $P_{s,m}$, we take a rolling average of store-level monthly inflation from January 2010, during which the index is set to 1.

Our second analysis sample is at the store-month-product level and includes 10 top-selling UPCs at Dollar Chain #1. We choose these products by aggregating food sales across all months and outlets belonging to Dollar Chain #1 and calculating which UPCs have the highest expenditure share. The 10 products include soda, juice, lunch meat, and canned and boxed meals.
3.4 TDLinx

NielsenIQ’s TDLinx dataset provides information on all food retailers in the U.S. For each store, the data include name and address, corporation and parent company name, opening date and closing year, and store channel and subchannel.

3.5 FoodAPS Survey

To shed further light on the shopping habits of SNAP households, we use the USDA’s National Household Food Acquisition and Purchase Survey (FoodAPS). FoodAPS is a nationally representative survey that collects comprehensive data about household food purchases and acquisitions over a 7 day period. The sample includes 4,826 households. Importantly for our purposes, the data indicate which households participate in SNAP (based on administrative records) as well as information on how they allocate their SNAP and out-of-pocket food expenditures across stores.

4 Aggregate Trends in Retailer Participation in SNAP

We start our analysis of retailer participation in SNAP by plotting aggregate trends. In Figure 1, we plot net store entry per month from 2006 to 2014. We define “net entry” as total newly authorized SNAP stores minus total stores exiting SNAP. In the same figure, we also plot a version of this measure that weights stores according to their average SNAP EBT redemptions per month.

Figure 1 reveals a few important findings. First, net entry is positive over this time period, indicating that the total number of SNAP retailers is increasing. Note that an increase in SNAP retailers may be due to greater participation among pre-existing stores or newly opened stores joining the program. Second, Figure 1 shows that the months with highest retailer entry are close in timing to the expansion of SNAP benefits that occurred under the ARRA, in May 2009. Thus, the graph suggests that retailer engagement is a function

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4. A SNAP store’s exit date is defined as the month of its last EBT redemption.
of program size. Finally, Figure 1 reveals that entry around the ARRA expansion was dominated by stores with especially high EBT revenues (i.e., large national chains).

We next investigate which large chains expanded their acceptance of SNAP benefits around the time of the ARRA. Using media reports, we identified eight large retailers that either started accepting SNAP benefits for the first time or expanded benefit acceptance to the remainder of their outlets around the time of the ARRA. These eight chains are not traditional food stores (i.e., grocery stores) and include dollar stores, mass merchandisers, club stores, and drug stores. Notably, in 2009, new SNAP stores belonging to these eight chains redeemed 56% of the EBT payments redeemed by all new SNAP stores.

Going forward, we refer to these eight chains as the “SNAP-adopting chains” and the time period over which they rapidly increased SNAP adoption among their outlets as their “SNAP adoption period.”

In Figure 2, we graph the SNAP adoption period by chain, displaying total new SNAP outlets per month in green. Vertical gray lines denote the start and end month of each store’s authorization event, in event time. Each of the SNAP adoption periods happens over a relatively short time period, ranging from a single month to 4 years, depending on the chain. In addition, we graph total new stores (i.e., openings) for each chain, in red, to demonstrate that the increase in SNAP authorization is not driven by the chain opening new stores.

5 Retailer Participation in SNAP and Household Spending

So far, we have documented that, around the time of the ARRA expansion in SNAP, there was a large increase in SNAP outlets, driven by an increase in SNAP adoption by eight large, non-grocery chains. What we are principally interested in, however, is what effect, if any, this increase in SNAP stores had on SNAP participant welfare. To analyze effects on

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6. Media reports from this time period suggest national retailers were aware of the expansion in the SNAP and sought to increase revenues by accepting SNAP benefits. Source: “More Retailers Say Yes to Food Stamps,” ABCNews. July 28, 2009.

7. By comparison, the overall EBT share belonging to these chains in 2009 was only 5%.

8. Data privacy requirements prevent us from displaying calendar months on these graphs, so we instead plot event-time on the x-axis, where 0 denotes the first month of the authorization event.
participant welfare, we investigate whether SNAP households increased their expenditures at the new SNAP stores. An increase in spending at the new SNAP outlets would indicate that SNAP recipients derive particular value from being able to spend their SNAP benefit dollars at these chains.

Why might a SNAP household increase spending at a given store when it starts accepting SNAP benefits? One reason is that the household might be constrained, meaning that they wanted to spend more than their out of pocket budget (cash) at the store before it started accepting benefits. When the store starts participating in SNAP, these households would therefore increase their total spending (= SNAP benefits + cash) at that store.

Second, stores that start accepting SNAP benefits might change their environment in order to attract more SNAP customers. For example, they might change their inventory or reduce their prices (if SNAP households are more price sensitive than non-SNAP shoppers). Third, if households face a fixed cost of shopping (e.g., due to travel), it may only be worth it to shop at stores that accept both cash and SNAP benefits.

Fourth, SNAP recipients may not view cash and SNAP benefits as fungible due to mental accounting or other behavioral biases (as in Hastings and Shapiro 2018). For example, if SNAP recipients are less price-sensitive when using EBT to pay for food, as opposed to cash, they may shift EBT spending to a high cost (but otherwise desirable) store when the store starts accepting SNAP benefits. This logic can be generalized by considering stores as products differentiated by attributes such as distance, price, variety, and other quality attributes. Then, cash and SNAP benefits are non-fungible if households prioritize some attributes when spending SNAP benefits and other attributes when spending cash.

If households shift their food spending to the new SNAP stores, then we should see this change reflected in national expenditures. In Figure 3 we graph the share of SNAP benefits (EBT) redeemed at these the SNAP adoption chains on the left axis. On the right axis, we graph the share of household food expenditures that occurs at these chains, separately for SNAP-eligible and non-SNAP-eligible households. The EBT share increases from about 0.5%
to 5% from 2006 to 2016, with a sharp increase in 2009, corresponding to the increase in stores in Figure 1. We see a similar sharp increase in the share of food expenditures at these chains among SNAP-eligible households, but no corresponding expenditures for non-SNAP households (although spending is trending upwards for non-SNAP households). Thus, Figure 3 suggests that SNAP households shifted food spending towards these chains after the chains started accepting SNAP benefits.

To shed additional light on which types of chains are driving this change, we re-create Figure 3 by channel. The results are shown in Appendix Figure A1. The share of SNAP-eligible households’ food expenditures at club chains and dollar chains belonging to one of the eight SNAP adoption chains increases markedly after 2009, but there is no similar increase for non-SNAP eligible households. Thus, Appendix Figure A1 suggests that SNAP households shifted their food spending towards dollar and club stores when they started accepting SNAP benefits. For the mass merchandiser, we see larger growth in sales among non-SNAP households, which reflects a concurrent reformatting by this chain that involved adding fresh foods at the same time they were expanding SNAP acceptance.

Still, it is somewhat difficult to draw firm conclusions from these graphs due to the presence of other macro events, such as the concurrent expansion in the SNAP program under the ARRA reform. In the next section, we describe our method for testing whether retailer participation in SNAP had a causal effect on household spending patterns.

6 Empirical Method

In order to identify the causal effects of retailer SNAP adoption, we exploit variation across stores in the timing of SNAP authorization. We focus on stores belonging to the SNAP adopting chains that started accepting benefits during their chain’s adoption event. We refer to these stores as “SNAP-adopting stores.” We drop stores that opened up at any point during their chain’s adoption period to avoid confusing the effects of SNAP acceptance with market entry.
6.1 Outcome: Household Spending

We first investigate the effects of retailer SNAP adoption on household expenditure patterns. We construct our analysis sample by matching households in the Consumer Network data to SNAP-adopting stores located nearby. Specifically, we match households to SNAP-adopting drug and dollar stores located in their ZIP code of residence. We match households to SNAP-adopting mass merchandiser and club stores located within 10 miles of their residence. We choose a wider radius than ZIP code for mass merchandisers and club stores based on evidence that households travel farther to shop at these stores (Taylor and Villas-Boas 2016; Ellickson, Grieco, and Khvastunov 2020).

We drop households that are not matched to any SNAP-adopting store. Although these households could serve as a control group, it is possible, given variation in local market size, that some shop at their nearest SNAP-adopting stores and thus are treated. When estimating specifications separately by chain, we use the sample of households that live near SNAP-adopting outlets in that chain. When estimating the effects of the SNAP-adopting chains together, we limit the sample of households to those living near an outlet from at most one SNAP-adopting chain.

Our baseline econometric model is a difference-in-differences specification that compares changes in household spending before and after a nearby store adopts SNAP. We estimate this specification separately for SNAP-eligible and non-SNAP eligible households. The specification is as follows:

\[ Y_{it} = \beta \text{Adopt}_{it} \ast \text{Window}_{it} + \lambda \text{Window}_{it} + \psi_i + \phi_t + \epsilon_{it} \]  

(1)

where the outcome \( Y_{it} \) is a measure of food spending for household \( i \) in year-quarter \( t \). \( \text{Adopt}_{it} \) is a vector of two indicators: one for whether the nearby SNAP-adopting store’s

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9. SNAP households in the FoodAPS data who identified a club store as their primary food shopping store live an average of 7.6 miles away from the store (standard deviation: 4.6). This calculation is based on 16 households. Only one SNAP household identified the dollar store as their primary food shopping store and that household lives under a mile from the store.
adopts SNAP in year-quarter $t$ and one for whether it adopts SNAP before $t$. We dummy out the quarter of adoption because the month of adoption varies within that quarter, so we expect a smaller effect.

$\psi_i$ are household fixed effects, which control for time-invariant differences across households, including the characteristics of their nearest store. $\phi_t$ are year-quarter fixed effects, which adjust for time trends in spending that are common across SNAP households. $\text{Window}_{it}$ is an indicator for whether year-quarter $t$ is within 3 quarters (before or after) of the nearby store’s authorization date. By interacting this indicator with $\text{Adopt}_{it}$, we ensure that $\beta$ is estimated using a sample of time periods close to the authorization event, whereas the fixed effects are estimated using the full time series. We cluster the error term, $\epsilon_{it}$, at the level of ZIP code of residence.

Our exogeneity assumption is that the exact timing of EBT adoption is unrelated to pre-existing trends. Under this assumption, $\beta$ measures the causal effect on $Y_{it}$ of having a nearby store start accepting SNAP. With regards to the exogeneity assumption, it is reassuring that the SNAP adoption schedules were determined by each chain’s headquarters and not by individual stores (who would be more sensitive to local factors).

Another potential confounding factor is store-level policies a chain implements at the same time as SNAP adoption. In fact, this issue arises with the mass merchandiser in our sample. This chain reformatted their stores to carry a full line of fresh groceries at the same time they were expanding SNAP authorization. This reformatting caused a large increase in food sales, more so for non-SNAP households than SNAP households (Appendix Figure A1). Thus we focus on the seven remaining chains going forward.

A common method for detecting the presence of pre-trends is to estimate event-time figures. In our setting, event-time $q$ is defined as the difference between year-quarter $t$ and the quarter in which the nearby store started accepting SNAP. Because our sample is unbalanced

10. Recall that we do not observe moves across locations because our demographic information is from one year – 2012.
11. For completeness, we report results from a version of Eq. 1 that omits the window term in the Appendix.
in event-time, coefficient estimates for large or small values of event-time will tend to give unequal weight to households living near stores that adopt SNAP relatively early or late in the sample. It is therefore important to define a range of event-time values in which the sample of households is balanced (Kline 2011). We keep households for which we observe at least 3 quarters before and after the SNAP authorization date of their nearby store. We use this sample to estimate both the event-time regressions and our main specification (Eq. 1).

Next, we define the following event-time indicators: $q < -3$, $q = -3$, $q = -2$, $q = 0$, $q = 1$, $q = 2$, $q = 3$, $q > 3$. The omitted (reference) indicator is $t = -1$, the quarter before store SNAP adoption. Bracketing event-time values outside the window reduces collinearity between event-time and year-quarter fixed effects. We re-estimate Eq. 1 replacing $\text{Adopt}_{it} \ast \text{Window}_{it} + \text{Window}_{it}$ with event-time indicators, and graph the resulting coefficients from $q = -3$ to $q = 3$.

For some chains, there are very few adoption dates. For example, for one club chain, all outlets start accepting SNAP in the same quarter. In this case, we cannot separately identify $\text{Adopt}_{it}$ from trends over time ($\phi_t$). Thus, for these chains we take one of two approaches. First, we estimate Eq. 1 but omit the date (year-quarter) fixed effects. Second, we estimate a triple differences specification in which we compare outcomes between SNAP-eligible and non-SNAP-eligible households. Let $\text{SNAP}_i$ denote SNAP eligibility for household $i$. Then, the triple differences specification is as follows:

$$Y_{it} = (\gamma \text{Adopt}_{it} \ast \text{SNAP}_i + \rho \text{Adopt}_{it} + \omega \text{SNAP}_i + \nu) \ast \text{Window}_{it} + \psi_i + \phi_t + \epsilon_{it}. \quad (2)$$

The parameter of interest is $\gamma$, which measures the effect of a nearby store adopting SNAP for SNAP households relative to non-SNAP households. The other controls are defined as above in Eq. 1.
6.2 Outcome: Retailer Pricing, Variety, and Sales

In order to test whether stores change their environment after adopting SNAP, we estimate store-level regressions using the IRI Retailer Panel, which contains information on pricing and product variety. We also use these data to verify that sales increase when the stores start accepting SNAP benefits.

Each observation in the data is a store-month. Because we linked the IRI Retailer Panel to administrative records on SNAP stores, we are able to observe the SNAP adoption date for stores in our sample, and we use this date to define treatment. We include store fixed effects in our regressions since we are interested in pricing and variety changes that occur within stores after they start accepting benefits. When analyzing prices at the product level, we additionally control for product fixed effects.

Our specification is otherwise similar to Eq. (1) and is given as follows:

\[ Y_{it} = \gamma \text{Adopt}_{it} \ast \text{Window}_{it} + \text{Window}_{it} + \xi_i + \omega_t + \nu_{it} \]  

(3)

where \( Y_{it} \) is a measure of price, variety, or sales for store \( i \) on date (year-quarter) \( t \). When the outcome is the price index, store variety, or sales, our dataset is at the store-month level, and \( \xi_i \) are store fixed effects. When the outcome is product-level pricing or sales, our dataset is at the store-month-product level, and \( \xi_i \) represents two separate vectors of store and product fixed effects. \( \omega_t \) are year-quarter fixed effects.

We weight each observation by average food volume per store. We cluster standard errors at the store level.

Note that we exclude from our estimating sample stores other than those in the SNAP adoption sample. Although these other stores could serve as a control group, it is also possible that they are directly affected by the retailer SNAP adoption events. For example, a non-adoption store might lose customers when a store nearby starts accepting SNAP benefits (and attracts new customers). Thus, these non-adoption stores are not an appropriate control
Finally, we restrict the sample such that it consists of a balanced sample of stores from 6 months before to 12 months after the SNAP adoption date. We use a shorter “pre” window than when using the Consumer Network Data because our Retailer Panel sample starts later (in 2009).

7 Results

7.1 SNAP Household Expenditures

We first estimate the effects of retailer SNAP adoption on food expenditures among SNAP eligible households living nearby. We consider SNAP adoption by outlets belonging to any of the SNAP-adopting chains. Our sample consists of households living near at most one SNAP-adopting outlet. We estimate Eq. 1 setting $Y_{it}$ to the following outcomes: share of food expenditures at the SNAP-adopting outlet; share of shopping trips at the SNAP-adopting outlet; total food expenditures at any outlet; and total shopping trips at any outlet. We also present corresponding estimates from Eq. 2, the triple differences specification that uses non-SNAP households as a control group, for comparison.

The results are shown in Table 1. Odd-numbered columns contain estimates from Eq. 1 for the sample of SNAP-eligible households and even-numbered columns contain estimates from Eq. 2 for both SNAP-eligible and non-SNAP-eligible households. The main coefficients of interest are “After Adoption Quarter” and “After Adopt Qtr*SNAP Elig.”

We find that the share of SNAP households’ food expenditures spent at the nearby SNAP-adopter increases by 0.389 percentage points when the store starts accepting benefits. This point estimate represents an increase of 12% of the mean expenditure share of 3.21. Our triple difference estimate in Column (2) is identical, implying that the result in Column (1) is not driven by a change in non-SNAP household expenditures. For shopping trips, we find that the share of SNAP households’ trips at the nearby SNAP-adopter increases by 0.304 percentage points when the store starts accepting benefits, a 10.6% increase relative to the
sample mean. Our triple difference estimate is similar.

In Columns (3) and (4), the effects on total food expenditures are relatively small in magnitude, inconsistently signed, and not statistically distinguishable from 0. Thus, it appears that SNAP-eligible households are re-allocating their spending across retailers, rather than spending more on food overall.

As for total shopping trips, we find suggestive evidence of a small increase. In Column (8), which presents estimates from the triple-differences specification, the point estimate is 0.402, representing a a 2% increase from the sample mean of 23 trips per quarter.. This effect is marginally significant at the 10% level. The corresponding estimate in Column (7) is smaller in magnitude and imprecise.

Finally, Columns (4) and (8) show that non-SNAP-eligible households spend slightly less and take fewer trips to SNAP-adopting outlets after adoption. Event study figures show that this reflects a secular downward trend in non-SNAP-eligible activity at these stores over the whole period, which may be related to declines in shopping activity during the Great Recession.

Next, we estimate effects separately for each of the SNAP-adopting chains. Because some of these chains expand SNAP adoption to their outlets in a single quarter, we estimate the triple differences specification Eq. 2. The analysis sample for each chain consists of all households that live near a SNAP-adopting store belonging to that chain, excluding a limited number of cases in which a store entry from that chain also occurred nearby.

Table 2 reports the results. The point estimates reveal that SNAP households increase their food spending at Dollar Chain #1 and Club Chain #2 when they start accepting SNAP benefits (Columns (1) and (4), respectively). In particular, SNAP households spend 0.2 percentage points more at a nearby outlet from Dollar Chain #1. This effect represents a 67% increase from the sample mean of 0.3 percent. For Club Chain #2, the coefficient is 0.4 percentage points, a 7% increase relative to the mean. We also estimate positive effects for both Drug chains as well as Club Chain #1, but these effects are not statistically significant.
For Dollar chain #2 and Club Chain #3, we estimate negative effects that are small in magnitude and imprecise.

At the bottom of Table 2, we report, for each chain, the share of shoppers in 2008 that are SNAP eligible. These statistics provide some insight into how the customer base for each chain varies. Shoppers at the dollar stores are the most likely to be SNAP-eligible, followed by shoppers at the drug chains, and then shoppers at the club chains. These differences likely reflect variation in location, as dollar stores are more likely to be located in low-income areas. We may expect stores with larger shares of SNAP-eligible customers to experience larger expenditure shifts or make larger changes to their store offerings to attract these customers. In fact, there is no clear pattern between the impact of adopting SNAP on SNAP-eligible household expenditure share changes and the store’s ‘exposure’ to SNAP-eligible households. That said, within the Dollar and Club categories, we find the strongest effects for the chains with the largest share of SNAP-eligible customers.

Motivated by our results in Table 2, we further explore the effects of Dollar Chain #1 and Club Chain #2 adopting SNAP on food expenditures of SNAP households living nearby. We decide to investigate each chain individually because differences in location, inventory, and pricing strategies suggest that SNAP shoppers may be shifting their expenditures towards these chains for different reasons.

First, for Dollar Chain #1, Figure 4 presents event-time estimates corresponding to Eq. 1. We estimate the event-time specifications separately for SNAP and non-SNAP households living near SNAP-adopting outlets belonging to Dollar Chain #1. In Panel (a), the outcome is the expenditure share allotted to the nearby dollar store. In Panel (b), the outcome is the share of the household’s food shopping trips per quarter that occur at the nearby dollar store. In both panels, there is a clear increase after the SNAP adoption date for SNAP households but not for non-SNAP households. As expected, the increase occurs over the

12. This statistic is calculated using the Consumer Network Data and is equal to the average of our SNAP eligibility indicator across all households that visit the chain at least once in 2008.
13. Here, food shopping trips are defined as any trip that involves at least one food purchase.
first two quarters, as the first quarter is partially treated. Finally, there is no evidence of a pre-existing trend in either figure, providing support for our exogeneity assumption.

In Table 3, we present corresponding coefficients from estimating Eq. 1 for the sample of SNAP households living near SNAP-adopting outlets from Dollar Chain #1. In addition to expenditure share and trip share, we consider the following outcome: whether a given household makes at least one trip to the nearby dollar store in the given quarter. All three measures are in percentage points.

The point estimate on “After Adoption Quarter” in Column (1) is similar to the triple difference coefficient in Table 2, which is unsurprising given that there does not appear to be a change in expenditure shares for non-SNAP households. The point estimate for trip share is 0.223, or 12.3% of the sample mean and marginally statistically significant. The estimated change in the likelihood of making any trip in column (3) after adoption is small relative to the sample mean (3%) and imprecise, suggesting that our effects on expenditure shares and trip shares are driven by households that already shopped for food at the nearby Dollar Chain #1 outlet.

Next, we estimate the same set of results for Club Chain #2, as shown in Figure 5 and Table 4. One difference, however, is that because Club Chain #2 has a single SNAP adoption date, we omit date fixed effects, which are collinear with our treatment indicator. 5 reveals an increase in expenditure share at the club chain among SNAP households, but also a downward trend throughout the event-time window in expenditure shares for non-SNAP households. Given the lack of time controls, the trend for non-SNAP eligible households may reflect a general time trend in expenditures (in which case the causal increase for SNAP-eligible households would be amplified).

In Table 4, we find a marginally significant increase in expenditure share equal to 0.282, or 10% of the sample mean. There is also an increase in trip share, at 0.151, or 8% of the sample mean, but it is imprecise. Interestingly, there is a large and precisely estimated increase in the likelihood SNAP households make any trip to the club chain in the quarter
of SNAP adoption (2.125, or 13% of the mean). If households face an important travel cost associated with shopping at the club chain, so that bundling shopping with cash and EBT into the same trip is preferred, then we would expect to see this type of bunching behavior in shopping trips around the quarter of SNAP adoption.

8 Mechanisms

In this section, we investigate different reasons why SNAP households might increase their expenditures at retailers that start accepting benefits.

8.1 Are Households Constrained?

One reason why SNAP households might increase their food spending at a store when it starts accepting benefits is that they were previously constrained. In this context, households are constrained if they want to spend more than their cash food budget at the store but cannot do so until the store starts accepting EBT payments. Therefore, if households are constrained by whether a given store accepts SNAP, it should be that they spend all of their cash food budget at that store.

We test this hypothesis using the FoodAPS data, the 7-day food expenditure survey. We first limit the sample to households that currently participate in SNAP (1,316 out of 4,826 households). We then keep households that have shopped for food during the last 30 days at dollar stores and club stores, as a proxy for those with access to these types of stores. These restrictions result in 520 households with access to dollar stores and 190 households with access to club stores.

FoodAPS asks households to identify their primary food store, defined as the store where the household does most of their food shopping. It seems reasonable to assume that households spend most of their cash food budget at their primary store, especially since cash is a large share of overall food spending for SNAP households. Among households with access to dollar stores, only 1 identifies the dollar store as their primary food store (0.9% with

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14. In the FoodAPS, cash accounts for 36% of SNAP households’ spending on food-at-home.
household weights applied). Thus, it seems unlikely that SNAP households are constrained by whether nearby dollar stores accept EBT. This result is perhaps unsurprising given that dollar stores offer a limited range of foods and are not often classified as food stores.

Among SNAP households that shop at club stores, a larger share identify them as their primary store — 6.4%, with household weights. Therefore, there may be some that are constrained by whether club stores participate in SNAP.

### 8.2 Does the Store Environment Change?

When stores start accepting SNAP benefits, they may change certain attributes in order to cater to SNAP customers. For example, retailers with limited food offerings might expand their fresh offerings. Other stores might change their pricing, depending on the relative price sensitivity between SNAP shoppers and their non-SNAP customers. These changes can affect both SNAP and non-SNAP shoppers.

We evaluate the effects of SNAP adoption on prices and product variety using the IRI retailer panel. Because these data do not include club chains, our investigation is limited to outlets belonging to Dollar Chain #1. We also examine effects on total food sales. Because we found that SNAP-eligible shoppers spent more at Dollar Chain #1 (but expenditures by non-SNAP-eligible shoppers did not change), total food sales at these outlets should increase.

As discussed above, we constructed two different datasets using the IRI retailer panel. The first one is at the store-month level and contains the following outcomes: log food sales, the price index, and an indicator for any produce sales. The second is at the store-month-product level, includes the top 10 products for Dollar Chain #1, and contains the following outcomes: log price per unit and log sales.

We estimate Eq. 3 for each of these outcomes. Regressions estimated with the store-month-product dataset include product fixed effects. Our results are presented in Table 5.

In accordance with our previous results, we find that food sales increase after stores adopt SNAP. The magnitude of the increase, both across all products and within the top 10 products is 5% (Columns (1) and (4)). In Column (2), we estimate a very small increase
in the price index of 0.2% – our standard errors allow us to rule out an increase larger than 0.4% with 95% confidence. Using the product level dataset, we do not find evidence of a change in prices.

Lastly, we find that SNAP adoption increases the probability that outlets belonging to Dollar Chain #1 sell any fresh produce in a given month. The point estimate is 1.8 percentage points, which is 5% of the sample mean of 35%. The sample mean of 35% implies that the majority of outlets sell no fresh produce during our sample. Because this outcome is a proxy for inventory, this result suggests that SNAP adoption leads to an increase in dollar stores carrying fruits and vegetables.

Thus, we find that SNAP adoption by Dollar Chain #1 leads to an increase in sales, has no appreciable effect on prices, and increases the likelihood outlets carry produce.

8.3 Does Benefit Take-Up Increase?

It is also possible that when stores start accepting SNAP benefits, eligible households nearby join the program. Then, their food expenditures would increase because their food budget would increase. However, we do not find evidence of an increase in household food expenditures as a result of nearby stores adopting SNAP in Table 1 (Columns 3 and 4). In fact, the effects are negative, although small in magnitude and noisy. Thus, it does not appear that retailer SNAP adoption leads to an increase in benefit take-up. This finding is perhaps unsurprising given the large number of retailers that participate in SNAP, so that the marginal store entrant is unlikely to significantly change access to nearby SNAP stores. (Oliveira et al. 2018).

8.4 Fixed Cost of Travel

If households face an important fixed cost of travel associated with shopping at certain outlets, then they may prefer to do the majority of their food spending at that outlet in a single trip (e.g., on a monthly or quarterly basis). This type of behavior approximately describes households shopping at club stores. In the FoodAPS data, households who identified
a club store as their primary food shopping destination lived an average of 6.6 miles away from that store (median: 5.4 miles).\textsuperscript{15} In the Consumer Network Data, among SNAP-eligible households with at least one trip to Club Chain #2 in 2008, the average number of trips to that Chain in 2008 is 6.0 (median: 5.0), or approximately quarterly.\textsuperscript{16}

Thus, SNAP households who shop at Club Chain #2 may time shopping trips to fall just after the club starts accepting benefits, in order to be able to bundle their EBT and cash spending together. Then we should see an increase in the likelihood of shopping for these households during the SNAP adoption quarter. In fact, this is what we find in Table 4.

9 Conclusion

The participation, stocking, and pricing decisions of private vendors are key components of public benefit programs that rely on in-kind transfers. Yet we have relatively little evidence on these margins. We study vendor participation in the context of SNAP and food retailers and their implications for household welfare.

We find that the number of retailers participating in SNAP greatly increased during the Great Recession, particularly for eight national club, dollar, drug, and mass merchandiser chains. To measure the causal effect of store SNAP adoption on household expenditure decisions, we match households in a large, nationally representative, consumer panel to SNAP-adopting stores located nearby. Using a difference-in-differences model that uses variation across stores in the timing of SNAP adoption and a triple differences model comparing SNAP-eligible and non-SNAP-eligible households, we find that SNAP-eligible households respond by shifting expenditure and trip share towards these SNAP-adopting chains. We do not find an impact for non-SNAP-eligible households and find no evidence of overall expenditure trends driving our results.

When separating our results out for the individual SNAP-adopting chains, we identify

\textsuperscript{15} By comparison, households that identify a dollar store as their main food store live an average of 1.6 miles away (median: 0.8 miles).

\textsuperscript{16} By comparison, SNAP-eligible households with at least one trip to Dollar Chain #1 in 2008 made 4.8 trips in that year to Dollar Chain #1. Recall that the Consumer Network data does not capture non-food shopping trips, which likely comprise the majority of trips to dollar chains.
one dollar store and one club chain that largely drive our results. We focus on these chains individually to understand the mechanisms at play behind these changes in household expenditure patterns. We rule out the possibility that households are constrained by where they can redeem their in-kind SNAP benefits. We also rule out that increases in the presence of SNAP-adopting stores drives increases in SNAP participation. We utilize store level data for our dollar store retailer to investigate changes in store characteristics, and find that the dollar chain does change its prices after starting to accept SNAP but is 5% more likely to carry produce products. Lastly, we find suggestive evidence that fixed costs of travel may be important, particularly for households shifting towards our club store.
References


Handbury, Jessie, and Sarah Moshary. 2021. “School food policy affects everyone: Retail responses to the national school lunch program.” *NBER No. w29384.*


Figure 1: Trends in Retailer Participation in SNAP, 2006-2014

Notes: Net entry is defined as the number of new SNAP outlets in a given month minus the number of outlets exiting SNAP in that month. The blue series counts each outlet equally, while the red series weights each outlet by its average EBT redemptions per month. Counts of new and exiting SNAP stores are calculated using the USDA-FNS Store Tracking and Redemption System dataset.
Figure 2: SNAP Adoption Periods by Retail Chain

(a) Dollar #1
(b) Dollar #2
(c) Club #1
(d) Club #2
(e) Club #3
(f) Mass Merchandiser
(g) Drug #1
(h) Drug #2

Notes: The green series shows the number of new SNAP outlets per month, while the orange series shows the number of new stores per month. Counts for new SNAP outlets are calculated using the USDA-FNS Store Tracking and Redemption dataset. Counts for new stores are calculated using the TDLinx dataset.
Notes: Shown above are EBT shares and household expenditure shares for the eight retailer chains we analyze in this article. EBT share is defined as the share of SNAP benefits redeemed at these chains in a given quarter, out of all benefits nationwide. EBT share is calculated using the USDA-FNS Store Tracking and Redemption System dataset. Household expenditure share is the share of total food expenditures households spend at these chains in a given quarter. Household expenditure share is calculated using the IRI Consumer Network data, separately for SNAP-eligible and non-SNAP eligible households.
Figure 4: Effect of SNAP Adoption by Dollar Chain #1 on Household Food Expenditures

(a) Expenditure Share

![Expenditure Share Chart]

(b) Trip Share

![Trip Share Chart]

Notes: Shown above are point estimates and 95% confidence intervals from the event-time version of Eq. 1. The dependent variable in subfigure (a) is household food expenditure share, in percentage points, at the nearby outlet from dollar chain #1. Regressions are estimated separately for SNAP-eligible and non-SNAP-eligible households. Controls include household, year-quarter, and year-quarter*SNAP Eligible FE. The data is the IRI Consumer Network Data. The sample is limited to households living within the same ZIP code as a SNAP-Adopting outlet from Dollar Chain #1. Households are dropped if they live in a ZIP code in which an outlet from Dollar Chain #1 opens during 2008-2011. The sample is also limited to households for which we observe 3 quarters before and after the entry quarter. Standard errors are clustered at the level of ZIP.
Figure 5: Effect of SNAP Adoption by Club Chain #2 on Household Food Expenditures

(a) Expenditure Share

(b) Trip Share

Notes: Shown above are point estimates and 95% confidence intervals from the event-time version of Eq. 1. The dependent variable in subfigure (a) is food expenditure share at the nearby outlet from Club Chain #2. Regressions are estimated separately for SNAP-eligible and non-SNAP-eligible households. Controls include household FE. The data is the IRI Consumer Network. The sample includes households living within 10 mi. of a SNAP-Adopting outlet from Club Chain #2. Households are dropped if they live within 10 mi. of an outlet from Club Chain #2 that opens from 2008 to 2011. The sample is limited to households for which we observe 3 quarters before and after the adoption quarter. Standard errors are clustered at the level of ZIP.
Table 1: Effects of Retailer SNAP Adoption on Household Food Expenditures

<table>
<thead>
<tr>
<th></th>
<th>Expenditures</th>
<th>Shopping Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SNAP-Adopter %</td>
<td>Total</td>
</tr>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
</tr>
<tr>
<td>After Adoption Qtr</td>
<td>0.389*** -0.000</td>
<td>-4.893 -8.272***</td>
</tr>
<tr>
<td></td>
<td>(0.188) (0.050)</td>
<td>(7.210) (1.941)</td>
</tr>
<tr>
<td>Adoption Quarter</td>
<td>0.044 -0.003</td>
<td>-0.300 4.180*</td>
</tr>
<tr>
<td></td>
<td>(0.150) (0.056)</td>
<td>(8.254) (2.156)</td>
</tr>
<tr>
<td>After Adopt Qtr*SNAP Elig.</td>
<td>0.389*** 3.380</td>
<td>0.256* 0.402*</td>
</tr>
<tr>
<td></td>
<td>(0.195) (7.460)</td>
<td>(0.154) (0.237)</td>
</tr>
<tr>
<td>Adopt Qtr*SNAP Elig.</td>
<td>0.047 -4.480</td>
<td>-0.074 -0.131</td>
</tr>
<tr>
<td></td>
<td>(0.159) (8.437)</td>
<td>(0.163) (0.270)</td>
</tr>
</tbody>
</table>

|                                      | Total              |
|                                      | (5) (6)            | (7) (8)              |
| Observations                         | 16,724 264,000     | 16,724 264,000       |
| Dep. Var. Mean                       | 3.21 5.58          | 634.21 704.38        |
| Total Households                     | 980 14,925         | 980 14,925           |

Note: Each column presents coefficients and standard errors from a separate regression estimating estimating Equation 1 in odd-numbered columns and Equation 2 in even-numbered columns. The data used to estimate these regressions is the IRI Consumer Network Data. The sample is limited to households that live nearby a SNAP-adopting outlet from any of the chains shown in Figure 2, except for the mass merchandiser, and in odd-numbered columns the sample is further limited to only consider SNAP-eligible households. “Living nearby” is defined as residing within the same ZIP code for the dollar and drug outlets and residing within 10 miles for the club stores. The sample is limited to households living nearby at most one SNAP adopting outlet. The dependent variable in columns (1) and (2) is the share of household food expenditures spent at their nearby SNAP-adopting outlet. The dependent variable in columns (3) and (4) is total household food expenditures, at any outlet. The dependent variable in columns (5) and (6) is the share of household shopping trips that occur at their nearby SNAP-adopting outlet. The dependent variable in columns (3) and (4) is total shopping trips, at any outlet. The regressions include household, year-quarter, and year-quarter*SNAP Eligible fixed effects and clusters at the zip level. Standard errors are clustered at the level of ZIP code.
Table 2: Retailer SNAP Adoption and Household Expenditure Share

<table>
<thead>
<tr>
<th>Chain:</th>
<th>Dollar</th>
<th></th>
<th>Club</th>
<th></th>
<th>Drug</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#1</td>
<td>#2</td>
<td>#1</td>
<td>#2</td>
<td>#1</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>After Adoption Quarter</td>
<td>-0.006</td>
<td>0.017</td>
<td>0.069</td>
<td>-0.076**</td>
<td>0.339**</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.017)</td>
<td>(0.103)</td>
<td>(0.038)</td>
<td>(0.056)</td>
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<tr>
<td>Adoption Quarter</td>
<td>-0.001</td>
<td>0.012</td>
<td>0.059</td>
<td>0.140***</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.017)</td>
<td>(0.135)</td>
<td>(0.052)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>After Adopt Qtr*SNAP Elig.</td>
<td>0.208**</td>
<td>-0.050</td>
<td>0.320</td>
<td>0.357**</td>
<td>-0.048</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.088)</td>
<td>(0.362)</td>
<td>(0.154)</td>
<td>(0.236)</td>
</tr>
<tr>
<td>Adopt Qtr*SNAP Elig</td>
<td>0.025</td>
<td>0.104</td>
<td>0.904*</td>
<td>0.088</td>
<td>-0.205</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.073)</td>
<td>(0.541)</td>
<td>(0.194)</td>
<td>(0.207)</td>
</tr>
<tr>
<td>Dep. Var. Mean</td>
<td>0.32</td>
<td>0.29</td>
<td>4.84</td>
<td>4.99</td>
<td>7.84</td>
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<tr>
<td>Observations</td>
<td>172,310</td>
<td>62,660</td>
<td>65,941</td>
<td>432,494</td>
<td>285,251</td>
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<tr>
<td>Total Households</td>
<td>9,691</td>
<td>3,488</td>
<td>3,719</td>
<td>24,724</td>
<td>15,731</td>
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<tr>
<td>% Shoppers SNAP Elig.</td>
<td>13.82</td>
<td>9.68</td>
<td>3.84</td>
<td>4.06</td>
<td>3.43</td>
</tr>
</tbody>
</table>

Note: Each column above presents coefficients and standard errors from a regression estimating Eq. 2. The dependent variable in all columns is household food expenditure share at the indicated chain, expressed in percentage points. The data used to estimate these regressions is the IRI Consumer Network Data. A household is included in the analysis if it experiences an SNAP-adoption event from the chain of interest between 2008 and the start of 2011 and no entry by that chain during that period. For dollar and drug stores this event must occur within the household’s ZIP code, and for club stores within a 10-mile radius of their zip centroid. Household data must be balanced for the 3 quarters before and after the event date. The regression includes household fixed effects and additional year-quarter and year-quarter*SNAP Eligible fixed effects for the Dollar Store chains and Drug Store #1. The regression clusters standard errors at the zip level.
Table 3: SNAP Adoption and SNAP Household Expenditures, Dollar Chain #1

<table>
<thead>
<tr>
<th></th>
<th>Expenditure Share</th>
<th>Trip Share</th>
<th>Any Trip</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>After Adoption Quarter</td>
<td>0.203**</td>
<td>0.223*</td>
<td>0.600</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.132)</td>
<td>(0.991)</td>
</tr>
<tr>
<td>Adoption Quarter</td>
<td>0.024</td>
<td>-0.109</td>
<td>-0.298</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.117)</td>
<td>(1.281)</td>
</tr>
<tr>
<td>Dep. Var. Mean</td>
<td>0.6</td>
<td>1.81</td>
<td>19.95</td>
</tr>
<tr>
<td>Observations</td>
<td>14,352</td>
<td>14,352</td>
<td>14,352</td>
</tr>
<tr>
<td>Total Households</td>
<td>832</td>
<td>832</td>
<td>832</td>
</tr>
</tbody>
</table>

Note: This regression estimates Equation 1. The dependent variable in Columns (1) and (2) are household expenditure share and shopping trip share for Dollar Store #1 in percentage points. The dependent variable in Column (3) is an indicator for whether the household made at least one trip to dollar store #1 in a given quarter. A household is included in the analysis if it experiences an SNAP-adoption event in their ZIP code of residence by dollar store #1 between 2008 and the start of 2011 and no store entry by dollar store #1 in their zip code during that period. Household data must be balanced for the 3 quarters before and after the event date. The regression includes household, year-quarter, and year-quarter*SNAP Eligible fixed effects. The regression clusters standard errors at the zip level.
Table 4: SNAP Adoption and SNAP Household Expenditures, Club Chain #2

<table>
<thead>
<tr>
<th></th>
<th>Expenditure Share</th>
<th>Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>After Adoption Quarter</td>
<td>0.282*</td>
<td>0.151</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.093)</td>
</tr>
<tr>
<td>Adoption Quarter</td>
<td>0.268*</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Dep. Var. Mean</td>
<td>2.83</td>
<td>1.89</td>
</tr>
<tr>
<td>Observations</td>
<td>23,202</td>
<td>23,202</td>
</tr>
<tr>
<td>Total Households</td>
<td>1365</td>
<td>1365</td>
</tr>
</tbody>
</table>

Notes: This regression estimates Equation 1. The dependent variable in Columns (1) and (2) are household food expenditure share and shopping trip share for Club Chain #2 in percentage points. The dependent variable in Column (3) is an indicator for whether the household made at last one trip to Club Chain #2 in a given quarter. A household is included in the analysis if it experiences an SNAP-adoption event by Club Chain #2 within 10 miles of their zip centroid between 2008 and the start of 2011 and no store entry by Club Store #2 within that time period and distance. Household data must be balanced for the 3 quarters before and after the event date. The regression includes household fixed effects. Time fixed effects are excluded due to Club Store #2 having a single adoption date. The regression clusters standard errors at the ZIP code level.
Table 5: SNAP Adoption and Store Attributes, Dollar Chain #1

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>Log Sales</th>
<th>Log Price</th>
<th>Any Produce</th>
<th>Log Sales</th>
<th>Log Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>After Adoption Qtr</td>
<td>0.052***</td>
<td>0.002***</td>
<td>0.018***</td>
<td>0.051***</td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Adoption Quarter</td>
<td>-0.003</td>
<td>0.002***</td>
<td>-0.004</td>
<td>-0.021***</td>
<td>-0.008***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Dep. Var. Mean</td>
<td>9.75</td>
<td>0.085</td>
<td>0.35</td>
<td>3.02</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>81,301</td>
<td>81,072</td>
<td>81,301</td>
<td>748,563</td>
<td>748,563</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Each Column above reports coefficients and standard errors from separate regressions estimating Eq. 3. The sample is drawn from the IRI Retailer Panel. In Columns (1), (2), and (3), each observation is a store-month. In Columns (4) and (5), each observation is a store-month-product. In Column (1), the dependent variable is the log of total food sales. In Column (2), the dependent variable is a price index constructed across food products sold by a given store. In Column (3), the dependent variable is an indicator for whether the store sold any produce items in the given month. In Column (4), the dependent variable is log of sales for the given product. In Column (5), the dependent variable is the per-unit price for the given product. Controls include fixed effects for store and date (year-month). In Columns (4) and (5), we additionally control for produce fixed effects. Each observation is weighted by average total food sales per store. Standard errors are clustered at the level of store.
Figure A1: Expenditure Shares, by Channel

Notes: Shown above are EBT shares and household expenditure shares for the eight retailer chains we analyze in this article split by channel. EBT share is defined as the share of SNAP benefits redeemed at these chains in a given quarter, out of all benefits nationwide. EBT share is calculated using the USDA-FNS Store Tracking and Redemption System dataset. Household expenditure share is the share of total food expenditures households spend at these chains in a given quarter. Household expenditure share is calculated using the IRI Consumer Network data, separately for SNAP-eligible and non-SNAP eligible households.
A1 Linking IRI Stores with FNS Records on SNAP Stores

To link stores in the IRI database to administrative records on SNAP stores, we take the following steps. First, we generate all possible pairs between IRI stores and SNAP stores that are located within the same state and ZIP code, and calculate the distance between each store within these pairs. Distance calculations are possible because each dataset includes geocoded coordinates for each store. We drop stores that are >10 miles apart. Second, we clean the store names and store addresses, which involves capitalizing all fields and removing symbols and spaces. Third, for each store pair, we generate the following measures: (a) a similarity score for the store name; (b) a similarity score for the street address; (c) an indicator for whether the street address exactly matches; and (d) the inverse distance between the stores, scaled to 0-1 using logistic distribution. We drop any pairs with store name similarity match <0.4 (i.e., the store names are very different). Finally, for each store in the remaining pairs, we chose its “match” through the following ranking procedure: 1st best = perfect matches on measures (a) through (d); 2nd best = perfect street address match; 3rd best = very close in distance (<0.1 miles); 4th best = very high similarity score for store name and street address; 5th best = same street number and similar store name OR same street number and close distance.