Welfare Implications of Increased Retailer Participation in SNAP*

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Abstract

Governments often rely on private vendors to distribute in-kind benefits. The types of vendors that participate can affect beneficiaries, local markets, and program costs. We study the effects of a dramatic increase in the number of non-traditional food stores – club, dollar, drug, and mass-merchandisers – accepting SNAP benefits during the Great Recession. These new authorizations reduced the proximity of SNAP recipients to SNAP-authorized retailers in both geographic and brand space. Newly-authorized retailers also increased their product variety, attracting market share of both SNAP- and non-SNAP shoppers from grocery stores. We do not find evidence this shift in the competitive retail landscape induced adjustments in retail prices. Nevertheless, we estimate that SNAP adoptions reduced aggregate shopping costs (inclusive of time) by an average of 7% for SNAP recipients and 2% for non-recipients.

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 Circana.

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1 Introduction

Many safety net programs provide benefits in-kind, rather than in cash (Currie and Gahvari 2008). Absent its own network of providers, the government must rely on private firms to distribute benefits. A prominent example of this type of arrangement in the U.S. is the Supplemental Nutrition Assistance Program (SNAP), which provides vouchers for food that can be redeemed at participating retailers.[1]

Private vendors serve both recipients and non-recipients and may also compete with businesses that do not distribute public benefits. Their engagement with the government can impact the private markets in which they operate. These spillovers are important considerations when evaluating policies that impact program generosity and/or vendor participation.

In this paper, we study the interplay between SNAP and the food retail market. To identify spillovers, we exploit a dramatic increase in vendor participation during the Great Recession and its aftermath. The number of stores accepting SNAP benefits increased 67% from 2007-2012. Many of the new stores were non-traditional food retailers. Their entry changed both the number and mix of retailers competing for SNAP customers, potentially inducing adjustments to retail prices and variety that affected recipients and non-recipients alike.

We ask how this wave of SNAP adoptions affected retail customers in three ways. First, we characterize the set of stores that start accepting SNAP, and study how access costs (proxied by distance) changed for SNAP recipients. Second, we estimate the causal effects of SNAP adoption on sales, prices and inventory for both the adopting stores and their competitors. Finally, we ask how welfare changed for SNAP and non-SNAP households.

Our analysis relies on a number of detailed, nationally-representative datasets. Our data cover 2008-2012 and include administrative records on all SNAP stores; a large household purchasing panel; a comprehensive dataset of food stores in the U.S.; and weekly, product-

1. In the U.S., government also contracts with private providers to provide subsidized housing (Section 8) and medical care (Medicaid, and Medicare).

level transaction records from a large sample of retailers. Each of these datasets contain precise geographic information that allow us to merge them together based on distance. In addition, by merging the records on SNAP stores to the data on all food stores, we can differentiate between a store opening (which has its own effects on local markets) and stores adopting SNAP.

We find that the wave of SNAP adoptions reduced the distance to the nearest SNAP store for recipients by 16%, moreso for non-traditional food retailers, such as drug, dollar, club, and mass merchandisers. New adopters added new products and saw 5% increases in sales. Nearby incumbents saw 1-2% lower sales, explained entirely by reductions in SNAP receipts, but did not respond to the competition for SNAP customers by adjusting prices or variety at the store or chain level.

To quantify the welfare impacts of these SNAP adoptions on recipients and non-recipients, we estimate a retail demand model whose structure is motivated by the reduced-form results. Specifically, the model permits both SNAP recipients and non-SNAP recipients to value stores differently depending on their SNAP-acceptance policy. We estimate this valuation non-parametrically using chain-by-SNAP acceptance fixed effects. While these parameters allow for the perceived quality of retailers to change when they start accepting SNAP, they are not time-varying otherwise, so do not allow for any adjustments in the perceived quality of retailers that do not adjust their SNAP acceptance policy in response to nearby stores adopting SNAP.

The demand estimates show that the average consumer prefers to shop at a store accepting SNAP benefits but consumers eligible for SNAP have approximately twice the preference for SNAP-accepting retailers. We estimate that the wave of SNAP adoptions between 2008 and 2012 reduced shopping costs for SNAP-eligible households by around 7%, and for SNAP-ineligible households less than 3%.

Our analysis faces a few important limitations. For one, we focus on short-term, rather than long-term, effects (in particular, 6 months before and after SNAP adoption). Longerterm effects may be more relevant from a welfare perspective and could differ if, for example, there are adjustment costs. A second limitation is that the share of low-income and SNAP eligible households in the purchasing panel is relatively low, limiting our power to detect effects in some cases.

Our analysis contributes to several strands of the economics literature. Most closely related is a nascent literature examining the behavior of food stores in the context of nutrition assistance programs in the U.S. Recent examples include analyses of grocery store responses to SNAP (Bitler, Beatty, and Van Der Werf 2019; Goldin, Homonoff, and Meckel 2022; Leung and Seo 2022), the National School Lunch Program (Handbury and Moshary 2021) and the Special Supplemental Nutrition Assistance Program for Women, Infants, and Children (Meckel 2020; Meckel, Rossin-Slater, and Uniat 2021).[2] This literature emphasizes that the incidence of SNAP benefits depends in part on grocer pricing and participation decisions. We contribute to this literature by estimating the effects of food store participation in the SNAP program. We also analyze the role of non-grocer stores, who are the focus of current policy debates.[3]

More broadly, our study is related to several papers analyzing the effects of the SNAP program on food purchasing behavior of low-income households. Studies find that SNAP participation causes an increase in food spending and that, among current beneficiaries, the marginal propensity to consume (MPC) food out of benefits exceeds the MPC out of cash (Hoynes 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,

2. Specifically,Bitler, Beatty, and Van Der Werf (2019) look at the effects of the introduction of SNAP in the 1970s on the local retail environment; Goldin, Homonoff, and Meckel (2022) study within-month variations in benefit issuance timing on grocer pricing and sales; and Leung and Seo (2022) study the effects of variation in program size across states and time on grocery pricing.

3. Recent work has also studied the role of government-funded options on private markets outside the U.S. (see, e.g., Atal et al. (2024) andCunha, De Giorgi, and Jayachandran (2019)).

Homonoff, and Meckel 2022). Additionally, attention has been paid to how SNAP affects the composition of purchases (Hastings, Kessler, and Shapiro 2021). Our findings suggest that store participation in SNAP affects shopping patterns, which may be explained by travel costs.[4]

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.

The rest of the paper proceeds as follows. Sections 2 and 3 describe the institutional setting and data sources. Section 4 presents some facts on the wave of SNAP adoptions between 2008 and 2012 and section 5 studies their impact on local retail supply. Section 6 estimates demand for SNAP retailers in order to quantify the benefits eligible and ineligible households enjoyed from the adoption wave. Section 7 concludes.

2 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 $120 billion in 2022 (USDA-FNS 2024). On the supply side, the private food retail sector

4. Since SNAP benefits and cash are interchangeable, a nearby store accepting SNAP should not, theoretically, change shopping behavior, unless participants derive a specific benefit from being able to spend SNAP dollars at the new store. Given fixed travel costs, bundling SNAP and non-SNAP dollars together on the same trip is preferable.

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.

The landscape of authorized food retailers in a beneficiary's area can directly impact consumer welfare through the proximity of authorized retailers and the variety of store formats and products available to the beneficiary. Furthermore, SNAP authorization may impact the revenues, pricing, stocking, and other competitive decisions of retailers.

2.1 Cost of Adoption

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). 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 the application process is relatively costless for the store, two important types of fixed costs are thought to limit retailer participation. These are: (1) required stocking of fresh and perishable inventory and (2) the implementation of Electronic Benefit Transfer (EBT) payments.

To be eligible to participate in SNAP, individual stores must satisfy one of two inventory requirements: (1) carry a minimum stock of "staple foods" (bread, meat, dairy, and fruits and vegetable) and perishable goods or (2) sales of "staple foods" comprise more than 50% of gross sales.[5] Perishable foods are defined as those that spoil within two weeks at room temperature. In a grocery store or superstore, these types of foods are generally found in two areas: (1) produce, meat, and bakery departments around the perimeter of the store and (2)

5. The latter qualification allows specialty food stores (such as meat markets) to participate. In practice, the former requirement is far more relevant as less than 5% of benefits are processed by specialty stores during our sample period. See https://www.fns.usda.gov/snap/retailer-eligibility-clarification-of-criterion for detailed definitions of staple foods and clarification of the requirements.

frozen and refrigerated aisles. For a non-grocer such as a convenience store, there are no such "perimeter departments" and, as such, perishable goods are generally frozen or refrigerated. Thus, satisfying the inventory requirements involves having a certain amount of cold storage for staple goods that are perishable. The costs of doing so may include investing in cold storage (refrigerators and freezers) or removing other chilled or frozen items (e.g., beverages or frozen desserts).

The other main cost for stores is the installation of EBT technology. EBT is an electronic system that allows a SNAP beneficiary to pay for food using SNAP benefits at retailers. Retailers bear both the acquisition cost of EBT hardware/software and processing cost of SNAP benefit transactions.[6] All EBT systems are procured through third-party vendors with whom retailers negotiate and enter into private contracts, and which potentially allow for volume discounts for large retail chains.[8]

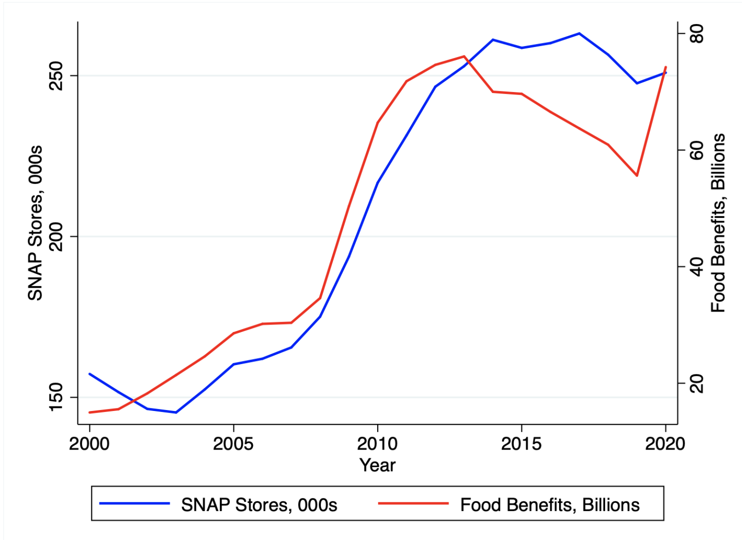
Additional costs that may include training employees to ensure compliance and adherence to SNAP regulations and installing required signage provided by the USDA. These are likely less burdensome, however.

Given that participation in SNAP involves fixed, upfront costs with relatively low ongoing costs, we expect stores to continue participating in SNAP after joining. Stores on the margin of participating may be those with limited food sales, limited product variety, or a small share of SNAP customers. In these cases, the upfront costs of participating — investing in EBT technology and/or expanding product inventory — may outweigh any increase in sales to SNAP customers.

6. 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 [7].

8. Implementing EBT payments may involve additional costs for large chains, however, due to the fact that they often operate checkout technology that is developed in-house (proprietary).

Figure 1: Total SNAP Stores and SNAP Benefits



Notes: Data is drawn from FNS Annual Reports by the Benefit Redemption Division. Retailer counts represent total retailers authorized on September 1. Wayback Machine (https://archive.org/web/) was used to recover early reports.

2.2 Wave of Adoptions during the Great Recession

In Figure 1, we graph total SNAP stores over time, as well as total benefit expenditures. Benefit expenditures expanded greatly during the late 2000s as a result of increasing poverty levels (i.e., increased household eligibility) and legislated benefit expansions during the Great Recession.[9] The resulting increase in SNAP food sales should have made it more attractive for retailers to participate in SNAP.

Indeed, there was a large increase in the number of food stores participating in SNAP during this period (from approximately 150,000 to 250,000).[10]

As benefit expenditures contracted in the wake of the Great Recession, the number of participating stores stayed elevated, as expected. In addition, the increase in store partici-

9. The American Reinvestment and Recovery Act increased the maximum benefit level for SNAP recipients by 14%. Source: https://www.ers.usda.gov/amber-waves/2019/august/snap-households-adjust-their-expenditures-and-how-they-spend-their-time-in-response-to-changes-in-program-benefits/.

10. Media reports described this increase in store participation in 2009. For example: "More Retailers Say Yes to Food Stamps," ABCNews. July 28, 2009.

pation is driven by "non-traditional food stores" (i.e., non-grocer retailers), including dollar stores, drug stores, mass merchandisers, convenience stores, and club stores. As expected, these stores either have limited food sales and variety (dollar, drug, mass merchandisers, and convenience stores) or have a limited share of low-income customers (club stores).

In this paper, we aim to assess the causal effects of this large increase in retailer participation during 2008-2012 on SNAP participants, non-participants, and food stores. To do so, we require detailed data on food stores (location, opening and closing dates, SNAP participation spells) and food shoppers' expenditure patterns. We describe these data in the next section.

3 Data

We combine several sources of data to measure the local food retail environment and the response of shoppers and retailers to SNAP adoption. These data include proprietary retail panels from NielsenIQ and Circana, as well as administrative data on SNAP receipts from FNS. We merge these data to obtain a panel spanning 2008-2012.

NielsenIQ's TDLinx dataset provides information on all food retailers in the U.S. with more than $1 million in sales per year (from both food and non-food products). For each store, the data include name, geocoded address, parent company name, opening date, and store channel. See Cho et al. (2019) for more detailed information on TDLinx data.

FNS's Store Tracking and Redemption System (STARS) provides information on all SNAP-authorized stores. For each store, these data report: name, geocoded address, market channel, and a unique identifier. Store name, address, and channel are self-reported by stores 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 spent at that store). We define a store's SNAP adoption date as the earliest month in which they have redemptions greater than 0.

The Circana Omnimarket Core Outlet data provide weekly, product-level transactions of all food products for a panel of 44,000 food stores, covering 51% of grocery food sales in the US. For each transaction, we observe the price, the number of units sold, and any discounts or coupons. For each store, we observe the name, geocoded address, parent company, and a unique identifier.

The Circana Consumer Panel is drawn 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 food 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, including income, household size, and Census block group of residence. Although these demographic variables are reported annually, we only observe them in 2012 (the last year of our data). Thus, any demographic measures we use do not change over time.

For each shopping trip, we observe the date, the store name, 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. Circana validates prices using scanner data they collect independently from retail chains. See Muth et al. (2016) for more detailed information on both Circana outlet and consumer data.

3.1 Analysis Samples

We combine our data sources to assemble two analysis samples, which we refer to as the "Household Store Choice Dataset" and the "Retailer Panel." We use the first to analyze the effects of nearby SNAP store adoption on household purchasing behavior. We use the second to study retailer responses to their own SNAP adoption as well as adoption by their competitors. In this section, we describe the construction of these datasets.

3.1.1 Household Store Choice Dataset

A main focus of our paper is to analyze the shopping responses of SNAP and non-SNAP households to SNAP adoption by nearby retailers. The Consumer Panel provides data on shopping behavior but does not record SNAP participation. Instead, we create a proxy for SNAP eligibility using household income (reported in brackets) and family size, applying the federal gross income test.[11] Because income is bracketed and we only observe household demographic information in 2012, our measure for SNAP-eligibility contains some error.

About 6% of households in our data are imputed to be SNAP-eligible — by comparison, in 2012, around 14% of households participated in SNAP in 2012.[12] This difference aligns with previous evidence that, although the Consumer Panel is designed to be nationally representative, it tends to undersample low-income households (Lusk and Brooks 2011).

For analysis, we collapse the panel to the household-quarter level, generating the following outcomes: total expenditures, total trips, expenditures by chain, and trips by chain. We sum across SNAP households to the chain level and identify the top 100 chains by total expenditures. We focus all of our analyses on these chains going forward, as doing so increases the tractability of our computations. In total, these chains comprise 80% of SNAP household food spending from 2008-2012.

We use our store datasets to characterize the retail environment faced by Consumer Panel households. We start with the TDLinx data restricted to the top 100 chains. We link these data at the store level to the administrative records on SNAP stores (STARS). The linkage, described fully in Appendix A.3, is based on geocoded address, name, and opening/closing dates. This linkage allows us to observe whether and when TDLinx stores started participating in SNAP. Importantly, because TDLinx records a store's opening date, we can differentiate between SNAP adoptions that are concurrent with openings (which we

11. Household income is reported in brackets of $5,000 to $10,000, and we impute the income level using the upper bound of the income bracket to avoid mis-coding SNAP-eligible households as SNAP-ineligible.

12. Source: https://www.census.gov/content/dam/Census/library/publications/2020/demo/acsbr20-01.pdf.

expect to have independent effects on shopper behavior) and those that happen at already-open stores.

We use the centroid of each household's Census Block to match them to all retailers within 15 miles. We consider this set of stores to be the food retail environment for households in the given Census Block. The Consumer Panel does not identify the location of shopping trips, only the store name. Thus, to match shopping trips to stores in the retail environment, we assume individuals shop at the nearest location within a chain. Lastly, we calculate the distance between a household's Census Block and each store it visits.

3.1.2 Retailer Panel

Our second analysis sample is a monthly panel of retailers, which we use to analyze how a store's sales, prices, and product offerings adjust when it adopts SNAP, as well as how its' competitors respond to this adoption. We start with the Core Outlets retailer panel – of our top 100 chains, 38 are present in this panel, so our sample includes those retailers. Importantly, the Core Outlets data excludes club retailers (a type of food store that started accepting SNAP during this period), so we are unable to analyze how their sales, pricing, and inventory adjust upon adoption.

We link the Core Outlets retailer panel to the STARS administrative records at the store level, using geocoded location, store name, and dates of operation, as described in Appendix A.3. This linkage allows us to observe when a retailer in the retailer panel adopts SNAP, and the share of food sales (observed in the retailer panel) that were paid for with EBT (observed in the STARS data).

Next, we generate the following monthly outcomes for each retailer: total food sales, total EBT sales, a price index of food products, and two measures of variety among food products. The price is constructed as an inflation index for continuing UPCs, following Beraja, Hurst, and Ospina (2019). Continuing UPCs are those sold in a given store in every month in the current year and at least one month in the previous years. This index allows us to measure changes in the price of a fixed bundle of goods, limiting bias due to changes in the composition of products sold, while also incorporating the majority of food products. The calculation steps are described in Appendix Section A.4.

The Beraja index allows for (limited) changes in product composition over time, as it holds fix the set of products purchased in the previous year. To hold the set of products fixed during our entire sample period (thereby completely eliminating any price fluctuations due to changes in product composition), we consider a balanced subset of store-products (i.e., store-products with positive sales in each month in our data).

Our measures of variety include weighted store-level UPC and product counts. While UPCs are the most dis-aggregated product unit, "products" are groups of items aggregated one level above UPC in the Circana product. Each UPC or product is weighted based on its share of national sales in 2008, so that the index is more responsive to price fluctuations in frequently-purchased products.

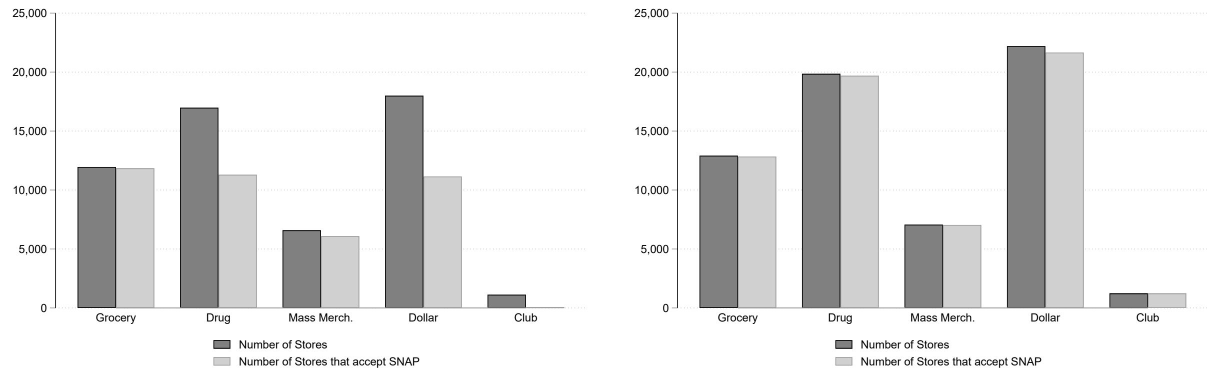
Lastly, we define a subset of competitors for each store. We do so by using the shopping patterns of the households in our Household Retailer Choice dataset, following a revealed preference approach. The household dataset is too sparse to directly identify competitors for each store in the Retail Panel. Instead, we model household demand for each of the 38 chains as a function of distance and predict expenditure weights for households living in the same Census block as the focal store. The outcome for the demand model is expenditures per chain and the inputs include distance, channel, and chain effects. Appendix A.6 provides a complete description.

4 Stylized Facts

Before moving on to our causal analysis, we use our analysis samples to document (1) the increase in retailer SNAP adoption between 2008 and 2012, (2) associated changes in household access to SNAP stores, and (3) the evolution of EBT payments after a retailer adopts SNAP.

Figure 2: Store Count by Channel and SNAP Adoption Status

(a) 2008 (b) 2012



Notes: Shows the number of total stores and SNAP participating stores by retail channel in 2008 and 2012.

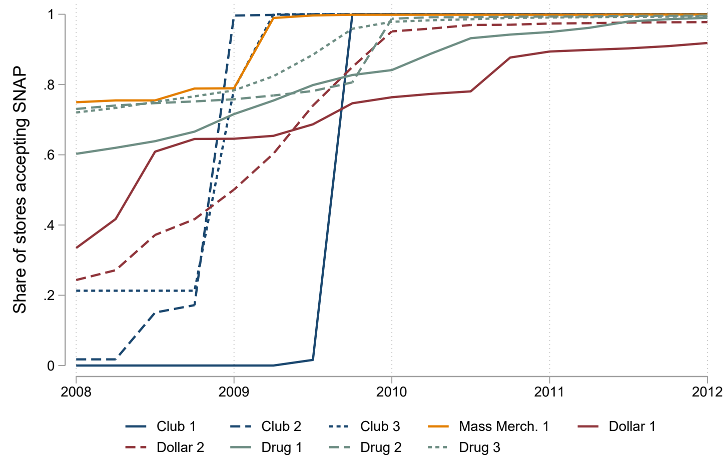
4.1 Retailer SNAP adoptions, 2008-2012

We start with the retail environment dataset described above, which links administrative records on SNAP stores to a census of food stores. Figure 2 displays counts of food stores in 2008 and 2012, by retail channel and SNAP participation status. The light gray bars depict counts of total stores, whereas the dark gray bars depict the subset that participate in SNAP. Panel A shows that almost all grocery stores and the vast majority of mass merchandisers were already participating in SNAP at the start of our sample in 2008. In contrast, fewer than two-thirds of the drug and dollar stores and none of the club stores in our sample participated.

Expansions of drug and dollar chains from 2008-2012 led to higher numbers of these stores in 2012 (Panel B), while the other channels remained relatively constant. In addition, in all non-grocer channels, the share of stores participating in SNAP reached nearly 100% by 2012.

In the previous section, we predicted that stores on the margin of participating would be those with limited food retail or those that cater to higher-income customers. Indeed, drug, dollar and mass merchandisers traditionally carry a limited selection of foods, as their retail

Figure 3: SNAP Adoption by Chain



Notes: Plots the share of stores that have adopted SNAP over time for nine anonymized chains between 2008 and 2012.

offerings included a large share of non-food goods. Club stores, which charge a membership fee to shoppers, tend to cater to higher-income households.

The increase in SNAP adoption in non-grocer retail channels is in fact driven by nine national chains.

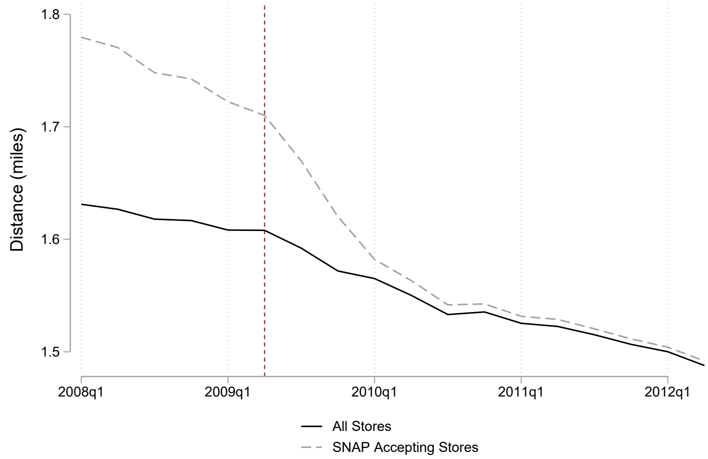
In Figure 3, we graph the time pattern of SNAP adoption among stores in these nine anonymized chains. While some chain adoptions are concentrated in a single wave (Club 1-3, Mass Merchandiser 1, Drug 2), others roll out adoption across their outlets more gradually (Dollar 1, Dollar 2, Drug 1, and Drug 3. As described in the next section, we use variation in SNAP adoption at both the store- and chain-level to identify causal effects.

4.2 Travel Distance for SNAP-eligible Households

The key goal of our paper is to quantify the benefits, if any, of increased store SNAP adoption on SNAP, as well as non-SNAP, households. SNAP recipients could, for example, be relatively unaffected if their usual grocer always accepted SNAP. This could occur if SNAP adoption is concentrated among stores in high-income areas.

To begin to understand effects on SNAP households, we calculate the distance to the nearest SNAP store for SNAP-eligible households in our Household Store Choice dataset. In

Figure 4: Distance to the Nearest Retailer and the Nearest SNAP-Authorized Retailer



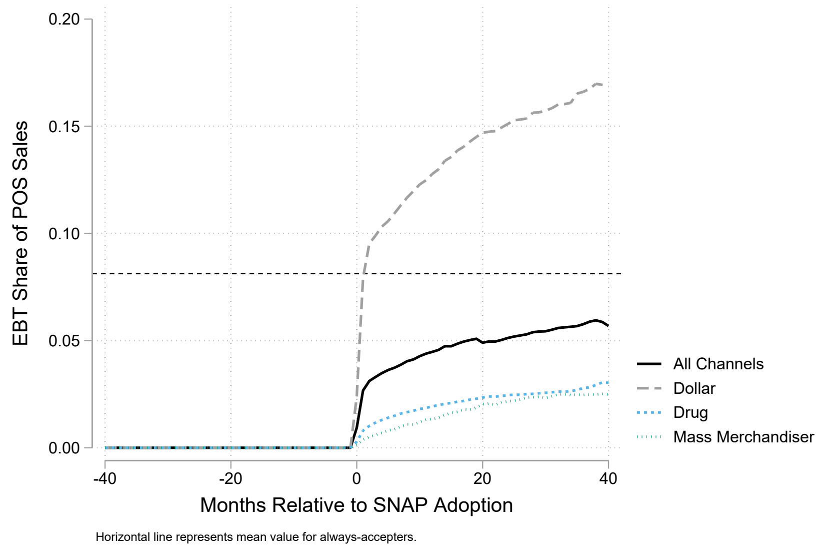
Notes: Mean distance for consumer panel households to nearest store location in selected top chains. SNAP accepting stores are the subset of these stores in a given period that accept SNAP benefits. The dotted red vertical line represents the onset of the ARRA when SNAP benefits expanded. Only includes households with at least one chain within 15 miles.

Figure 4, we plot the average distance for these households over time. Note that reductions in distance to the nearest SNAP store can be caused either by new stores opening (and accepting benefits) or existing stores deciding to accept SNAP. We also graph the average distance to any food store, which is only affected by new stores opening.

The average distance to the nearest food store falls from 1.63 to 1.49 miles (an 8.5% decrease) from 2008-2012. This decrease reflects the expansion of dollar and drug store chains during this period shown in Figure 2. By comparison, the average distance to the nearest SNAP store falls from 1.78 miles to 1.49 miles from 2008-2012 (a 16% decrease). The distance to the nearest SNAP store falls more sharply after benefits are expanded in 2009Q2.

Thus, increased store SNAP adoption resulted in important decreases in the minimum distance SNAP households had to travel to spend their benefits. These changes may have reduced travel burdens for these households, rendering important welfare benefits. We examine this hypothesis further below by studying SNAP shopper shopping patterns.

Figure 5: EBT Sales as a Share of Total Stores Sales Before and After SNAP Authorization



Notes: Mean monthly EBT payments as a share of food sales for each month relative to SNAP adoption.

4.3 Evolution of EBT payments after SNAP Adoption

As a final descriptive analysis, we look at the evolution of EBT payments after a store starts adopting SNAP. In Figure 5, we graph monthly EBT payments as a share of food sales against the number of months after SNAP adoption (Figure A.1 shows the corresponding EBT totals). Across all channels, there is a sharp increase right after adoption followed by a gradual increase up to 40 months later. The fact that payments continue to increase over time may reflect frictions for the consumer or store — SNAP customers may acquire information about new stores gradually or face costs in changing their shopping patterns; stores may also adjust their product attributes (price, variety, etc.) slowly in response to new customers.

EBT comprises around 5% of food sales across all adopting stores. For dollar stores, the share is around 15%, whereas for mass merchandisers and drug stores, it is around 2.5%. This variation across channels likely reflects a combination of (1) differences in food sales volume, with drug and dollar having relatively low sales, and (2) differences in shopper preferences across channels.

5 The Causal Effects of SNAP Adoption on Retailer Outcomes

Next, we analyze the causal effects of SNAP adoption on sales, prices, and inventory. The growth in EBT payments documented above does not imply growth in food sales — SNAP shoppers could simply be replacing one tender (cash) with another (EBT) for foods they were already buying at these stores. Further, growth in food sales might not imply that SNAP adoption attracts new demand to a store, which may change its own prices or inventory to appeal to its new customer base. Additionally, existing SNAP stores may respond to an increase in SNAP adoption among their competitors by changing prices or inventory to retain their SNAP customers. We test these hypotheses with a single identification strategy that incorporates variation in the timing of SNAP adoption for a given store as well as its competitors.

In a separate analysis (Appendix A.7), we consider the possibility that pricing and inventory are set at the chain, rather than store level, following recent evidence of chain-wide decision-making (Adams and Williams (2019), DellaVigna and Gentzkow (2019), Hitsch, Hortacsu, and Lin (2019)).

5.1 Identification Strategy

We use an event-study approach to estimate dynamic treatment effects of SNAP adoption. Our analysis of EBT payments above suggests a gradual change in expenditure patterns among a store's customers following its entry into SNAP. Event-study graphs depict the gradual impact of SNAP adoption on store-level outcomes, controlling for confounding trends.

In our setting, an event is a month-to-month change in SNAP adoption – either of a given store or the stores it competes with. Our setting thus involves several different treatments, including those that are discrete ("turning on" in a single month) and those that are continuous (varying in intensity over time). To model the effects of both continuous and discrete treatment variables, we employ the generalized event-study approach of Schmidheiny and

Siegloch (2023), estimating all treatment effects simultaneously.

For store i in month t, our model is given by:

$$Y_{i,t} = \sum_{\ell} [\beta_{1\ell}\text{StoreAdopt}_{i,t-\ell} + \beta_{2\ell}\text{CompetitorsAdopt}_{i,t-\ell}] + \mu_i + \theta_{cty(i),t} + \gamma_{ch(i),t} + \epsilon_{i,t} \quad (1)$$

.

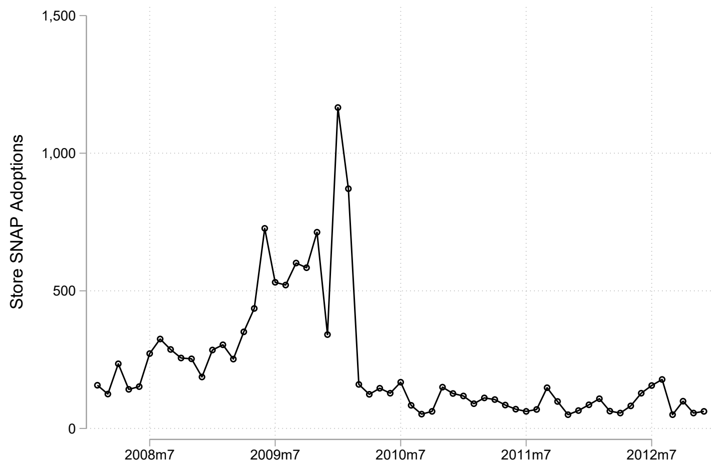
The outcome $Y_{i,t}$ is one of log sales, log EBT, log price, or log variety. Relative time, the number of months relative to period t, is given by ℓ. $\text{StoreAdopt}_{i,t-\ell}$ is an indicator for whether store s adopted SNAP ℓ months before month t. $\text{StoreCompetitor}_{i,t-\ell}$ denotes the month-on-month change in the share of competitors that accept SNAP ℓ months before month t. We include 6 months of leads and 12 months of lags and bin observations outside of this event window.

The model includes store (μ_i) fixed effects and the pre-period coefficients ($\beta_{1\ell}$ and $\beta_{2\ell}$ for $\ell = -1$) are normalized to zero, so the event coefficient estimates can be interpreted as the average level of the outcome variable in periods around the event time, relative to the level in the same store in the period before the event.

County*month ($\theta_{cty(i),t}$) and channel*month ($\gamma_{ch(i),t}$) fixed effects control for confounding shifts in local or channel-specific trends occurring during the time-frame around SNAP adoptions. We cluster standard errors at the Census block level, at which we define the competitor adoption variable.

The event study graphs depict the estimated coefficients on the leads and lags of each treatment variable. For the discontinuous treatment variable, $\text{StoreAdopt}_{i,t-\ell}$, we plot the coefficients on the leads and lags against relative time. For the continuous treatment variables, we plot the change in the outcome variable estimated to be associated with a 1 standard deviation change in treatment against relative time. These figures have a similar interpretation to standard event study graphs. To interpret the estimates as causal impacts of SNAP

Figure 6: SNAP Adoptions Over Time



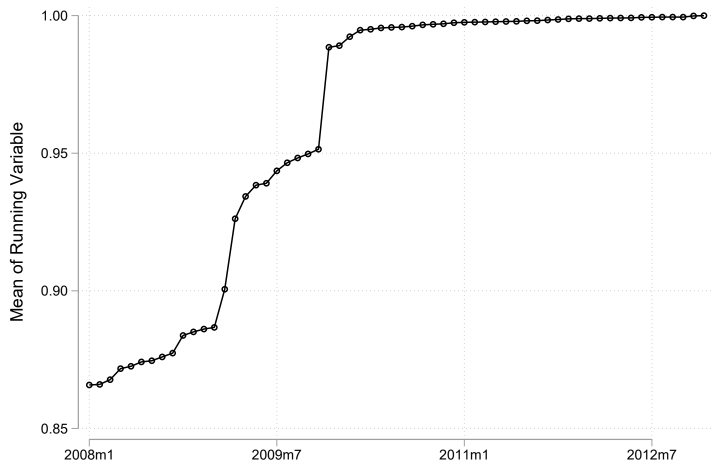
Notes: Number of stores in the store analysis dataset that adopt SNAP in a given year-month.

adoption, we must assume that,conditional on controls, counterfactual trends in the outcome variables would not have been correlated with treatment intensity absent treatment. While it is impossible to definitively prove the validity of this assumption, the coefficients on the leads of our treatment variables provide evidence as to the presence of a correlation between trends that existed prior to treatment and the intensity of treatment.

We graph monthly variation in retailer SNAP adoption — our identifying variation — in Figures 6 and 7. Figure 6 shows the number of SNAP adoptions per month from 2008-2012 in our retailer panel. Most adoptions occur by mid-2010, with over 1,000 adoptions on 1/2010, although adoptions continue at a rate of around 100 per month in 2011 and 2012. Figure 7 depicts variation over time in SNAP adoption among the competitors of each retailer in our panel. The share increases from just over 85% at the start of 2008 to approximately 100% by the start of 2011.

Lastly, to estimate a single post-period treatment effect, we drop the leads and lags from Eq. 1 and add a weighted average of the lagged treatment indicators. The coefficient on this measure represents the causal effect on $Y_{i,t}$ during the full post period. We also estimate variants of this regression in which we estimate separate effects for lagged periods 0-6, 6-12,

Figure 7: Mean Store Local Market SNAP Adoption



Notes: Average value of the indirect local SNAP exposure measure for stores in the store analysis dataset.

and 12+, as well as leads 1 to 3, to test for anticipation effects.

5.2 Results

5.2.1 Effects on Own Store Outcomes

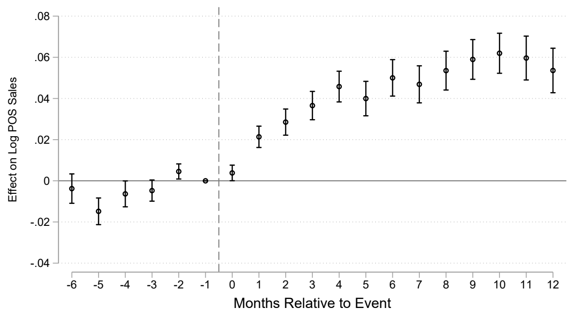
We first examine the effects of SNAP adoption on a retailer's own food sales, as well as its pricing and product variety decisions. Figure 8 displays event-study figures, showing $\beta_{1\ell}$ from Eq. (1) estimated for each of these outcomes, using the full sample of retailers. Figure 9 graphs DiD estimates and 95% confidence intervals for each retailer channel, separately. Appendix Table A.5 reports the corresponding point estimates.

Figure 8(a) reveals a sharp increase in food sales one month after adoption that continues at a more moderate rate over the first year. Sales level off at approximately 6% above their pre-adoption level between 9 and 12 months after adoption. In contrast, the event-study coefficients for the months prior to SNAP adoption are very small ($|\beta_{1\ell}| < 0.02$) and inconsistently signed. This lack of "pre-trend" provides support for our identifying assumption that the exact timing of SNAP adoption is unrelated to pre-existing trends.

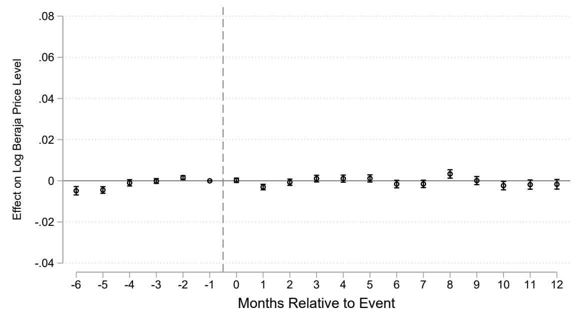
The impact of SNAP adoption on sales varies across different retailer channels. Figure 9

Figure 8: Event Study Estimates of Direct Effect of SNAP Adoption: All Channels

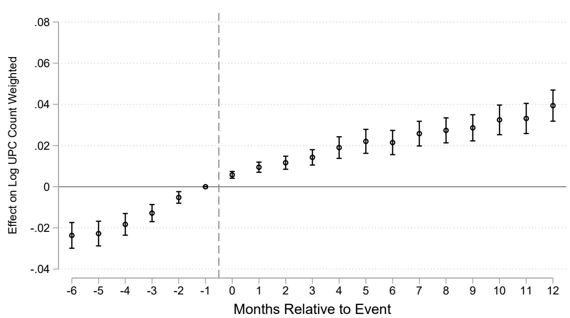
(a) Sales



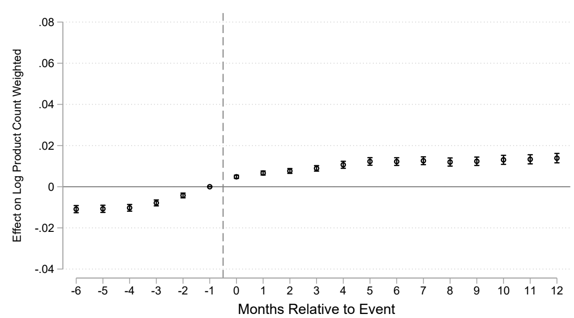
(b) Prices



(c) Weighted UPC Count

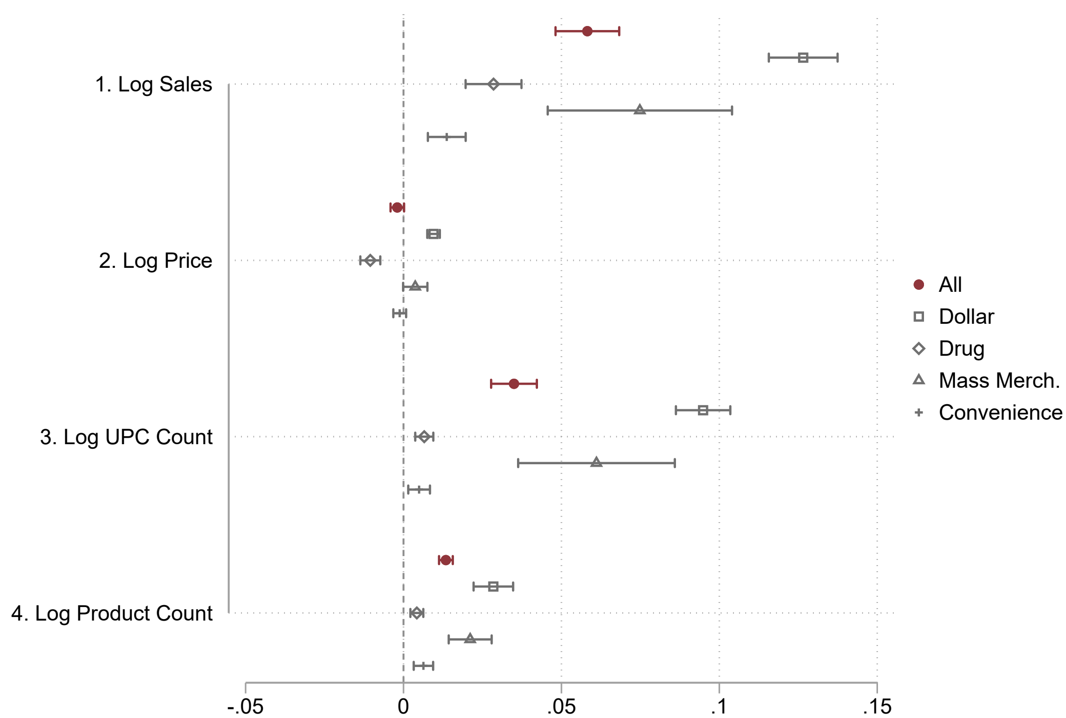


(d) Weighted Product Count



Notes: Difference-in-differences event study estimates of SNAP adoption for all channels combined, studying effects on four outcomes: total store sales, prices as measured by a singular price index, and product variety as measured by national sales-weighted UPC and product counts.

Figure 9: Difference-in-Differences Estimates of Direct Effect of SNAP Adoption by Channel



Notes: Pre-post two period differences-in-differences estimates of the direct effect of SNAP adoption on four outcomes: total store sales, prices as measured by a singular price index, and product variety as measured by national sales-weighted UPC and product counts. Effects are estimated separately for all channels and by each individual store channel.

shows the average estimate in the 12 months after adoption. We find that SNAP adoption leads to the largest increase in food sales for dollar stores (14.2%) and mass merchandisers (14.2%), with smaller increases for drug (4.0%) and convenience stores (1.4%). The estimate for grocers (4.1%) is noisy, reflecting the small number of grocer adoptions during our study period.

The increases in food sales observed at SNAP-adopting outlets are large, and potentially driven by changes in store offerings (such as product variety and prices), in addition to the introduction of a new payment method. We next investigate whether they respond by changing their prices or product variety following SNAP adoption.

In Figure 8(b), we find very little evidence of price changes following SNAP adoption. The event-study estimates of adjustments in store price indexes around adoption are small and display no clear trend. All but one post-adoption coefficient are statistically indistinguishable from zero, and the 95% confidence interval on the largest estimate, eight months after adoption, allows us to rule out price increases greater than 0.6%.

The estimates by retailer channel (Figure 9) show that the change in prices is uniformly small in magnitude (less than 1%) across channels.

Next, we estimate the effects of SNAP adoption on a store's product variety. Figure 8(c)-(d) reveal clear increases in the variety of UPCs and product categories stores offer when they adopt SNAP. A year after adoption, the national-sales weighted UPC count is 4% higher than at adoption. Figure 8(d) shows that over one-quarter of this increase is attributable to new product types, consistent with the requirement that SNAP-authorized retailers carry products in a range of food categories. The outsized effect for variety of UPCs relative to variety of product categories indicates that new products are concentrated in a few categories. Figure 9 shows the largest increases in variety are in dollar stores (12.0%) and mass merchandiser stores (16.7%), where we also find the largest increases in sales.

Figure 8(c)-(d) displays an increasing pre-trend in both measures of product variety, starting around 3 months prior to SNAP adoption. This result aligns with the fact that stores must demonstrate that they carry the required inventory before they can start accepting benefits. We do not observe a pre-trend prior to this "stock-up," however — the inventory coefficients for 6 to 3 months prior to SNAP adoption are similar in magnitude and statistically indistinguishable from one another — indicating that the increase in inventory around the SNAP adoption date is unlikely to be driven by coincident trends unrelated to SNAP adoption.

Including the pre-emptive growth to meet stocking requirements, the increase in variety in SNAP-adopting retailers amounts to a 7% increase in the share of national sales represented by the UPCs offered, and a 2% increase in the share of national sales represented by the product categories offered.

5.2.2 Effects on Competitor Outcomes

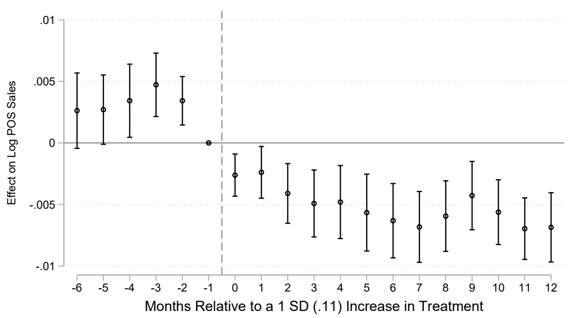
Next, we estimate the effects of retailer SNAP adoption on food sales, pricing, and product inventory among their competitors ($\beta_{2\ell}$ from Eq. 1). Figure 10 displays event-study figures for each of these outcomes. Figure 11 graphs the differences-in-differences coefficients and 95% confidence intervals for each retailer channel separately, and Appendix Tables A.5-A.9 report the corresponding point estimates.

Figure 10(a) reveals a moderate decrease in sales following competitor SNAP adoption. The estimates indicate that a 1 std. dev. increase in the market share-weighted rate of SNAP acceptance among a store's local competitors is associated with a 0.5% decrease in retailer food sales. Recall that a 1 std. dev. increase is approximately an 11pp increase in the sales share of nearby competitors that have adopted SNAP (the average share is 80%). The decrease in sales to precede the increase in SNAP adoption by 1-2 months, possibly reflecting the anticipatory shift in inventory that we observe at adopting stores in Figure 10(c)-(d). Differencing from the sales level 4-6 months prior to competitor SNAP adoption, the full impact of a 1 std. dev. increase in the SNAP competitor share is 0.75%. Figure 11 shows that grocery stores see the largest declines in sales.

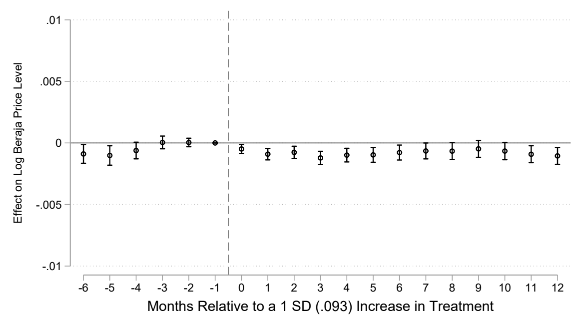
Figure 10(b) shows a very small drop in prices after competitor SNAP adoption, that

Figure 10: Event Study Estimates of Indirect Effect of SNAP Adoption by Nearby Competitors: All Channels

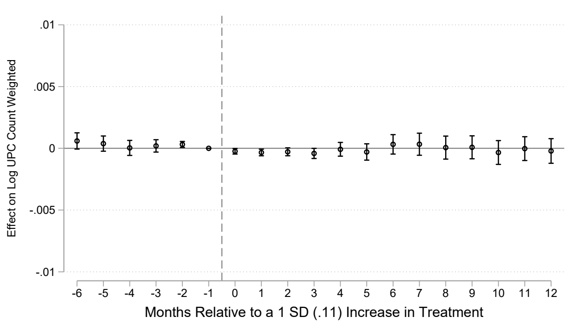
(a) Sales



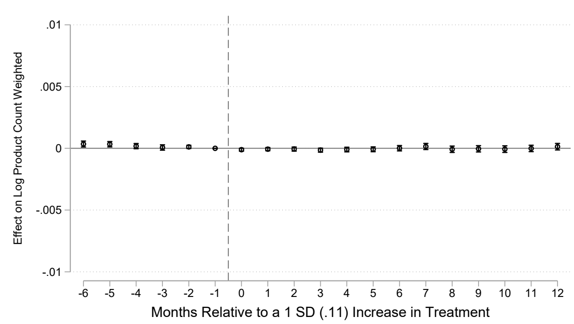
(b) Prices



(c) Weighted UPC Count

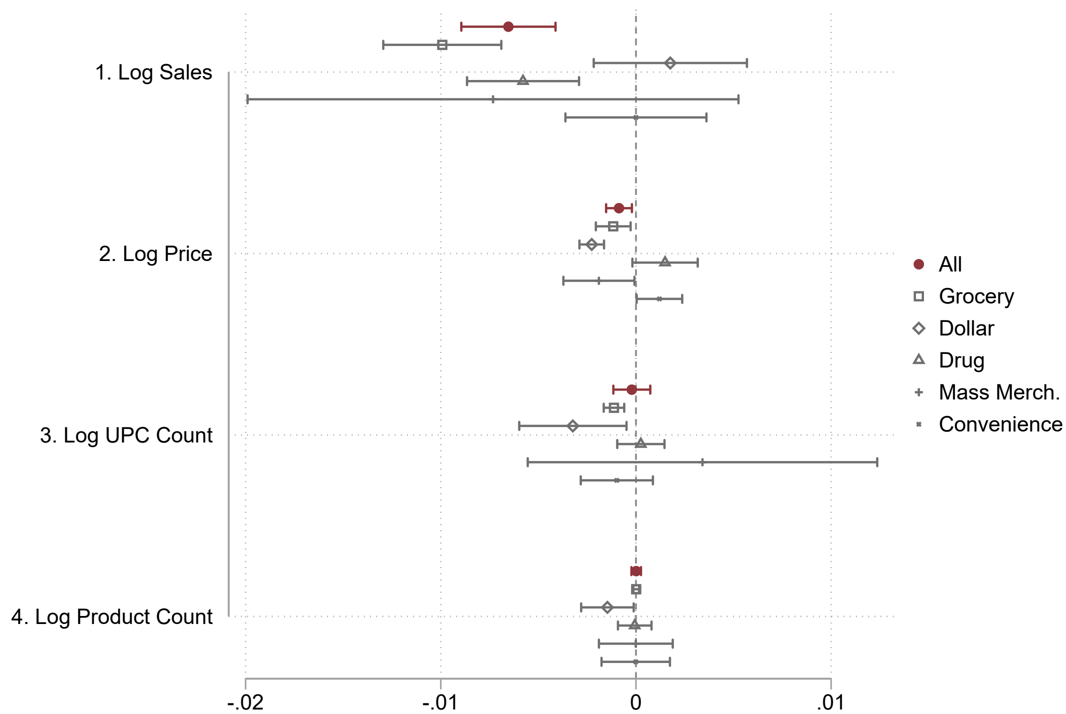


(d) Weighted Product Count



Notes: Difference-in-differences event study estimates of SNAP adoption by nearby competitors for all channels combined, studying effects on four outcomes: total store sales, prices as measured by a singular price index, and product variety as measured by national sales-weighted UPC and product counts. Estimates reflect the effects of a 1 std. dev. increase in the market share-weighted rate of SNAP acceptance among a store's local competitors.

Figure 11: Difference-in-Differences Estimates of Indirect Effect of SNAP Adoption by Nearby Competitors by Channel



Notes: Notes: Pre-post differences-in-differences estimates of the indirect effect of SNAP adoption by nearby competitors on four outcomes: total store sales, prices as measured by a singular price index, and product variety as measured by national sales-weighted UPC and product counts. Estimates reflect the effects of a 1 std. dev. increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. Effects are estimated separately for all channels and by each individual store channel.

is indistinguishable from the prices 4-6 months prior to competitor SNAP adoption. Figure 10(c)-(d) show no adjustment in product variety in response to an increase in local market SNAP adoption rates. In sum, we do not find evidence that the increases in SNAP adoption during our sample period led to changes in prices or product inventory among competitor retailers.

5.2.3 Chain-Level Responses

It is possible that chains make uniform pricing decisions that apply across all of their outlets. These chain-level pricing decisions would not be detected by our specifications above. To test for such responses, we add chain-level averages of our store-level treatment variables to our main specification equation (1). The results, in Appendix A.7, show no evidence of store pricing co-moving with chain-level adoption or of price or variety responses to chain-level exposure to SNAP adoption.

6 Welfare

In this section we use a simple model of retail demand to measure the causal effect of SNAP adoption on household welfare.

6.1 Simple Model of Retail Demand

On each purchase occasion t, consumer i of type $k \in \{SNAP, Non-SNAP\}$ selects which store s to shop from to maximize indirect utility:

$$V_{i,s,t} = \delta_{s,t}^{k(i)} + \tau_{r(s)}^{k(i)} \ln dist_{l(i,t),s} + \varepsilon_{i,s,t}$$

where $\delta_{s,t}^{k}$ is type k's perception of the price-assortment-amenity mix offered by store s at time t; $\tau_{r(s)}^{k}$ is type k's time-invariant distance elasticity specific to store s's channel $r(s)$; $dist_{l(i,t),s}$ is the distance between i's residential location at time t $l(i,t)$ and store s; and $\varepsilon_{i,s,t}$ is an iid draw from a type 1 extreme value distribution.

For tractability, we assume that perceived quality $\delta_{s,t}^{k}$ is common within chain, but varies with SNAP acceptance. Specifically, a store's perceived quality is equal to a chain-specific perceived quality plus a chain-specific demand shifter that switches on when a store accepts SNAP (i.e., $SNAP_{s,t} = 1$):

$$\delta^k_{s,t} = \delta^k_{ch(s)} + \delta^{k,SNAP}_{ch(s)} SNAP_{s,t}$$

We measure the utility of a type k consumer with the inclusive value of retail opportunities in the set of stores S_l within 15 miles of location l:

$$IV^k_{l,t} = \sum_{s \in S_{l,t}} \exp\left(\delta^k_{ch(s)} + \delta^{k,SNAP}_{ch(s)} SNAP_{s,t} + \tau^k_{r(s)} \ln dist_{l,s}\right) \tag{2}$$

The overall change in welfare from 2008 to 2012 is $IV^k_{l,2012} - IV^k_{l,2008}$.

We attribute changes in welfare to store SNAP adoption by looking at changes in utility holding the choice set $S(l)$ and chain-specific perceived qualities $\delta^k_{s,t}$ fixed at their 2008 levels:

$$IV^k_{l,2012CF} - IV^k_{l,2008} = \sum_{s \in S_{l,2008} | \underbrace{SNAP_{s,2012} - SNAP_{s,2008} = 1}_{\text{0 for non-adopters}}} \exp \delta^{k,SNAP}_{ch(s)} \exp\left(\delta^k_{ch(s),2008} + \tau \ln dist_{l,s}\right) \tag{3}$$

Therefore, the impact of each SNAP adoption on welfare is the change in the perceived quality of that store attributable to SNAP adoption mediated by how far the store is away from the consumer. We abstract from any changes in store quality not attributable to shifts in SNAP acceptance. Under this assumption, incumbent stores that do not adopt SNAP between 2008 and 2012 are differenced out.

6.2 Parameter Estimation

We estimate distance elasticity τ and perceived quality δ parameters using a Poisson pseudo-maximum-likelihood estimator (PPMLE, Silva and Tenreyro (2006)).

The estimating equation is:

$$Y_{i,s,t} = \delta^{k(i)}_{ch(s)} + \delta^{k(i),SNAP}_{ch(s)} SNAP_{s,t} + \tau^{k(i)}_{r(s)} \ln dist_{is} + \rho_i + \gamma^{k(i)}_t + \epsilon_{i,s,t}$$

where Y_{ict} denotes household i's expenditure at (or, for robustness, trips to) store s in quarter t; $\delta^{k}_{ch(s)}$ is the perceived quality of chain $ch(s)$; $\delta^{k,SNAP}_{ch(s)}$ is a chain-specific quality shifter for when store s accepts SNAP (i.e., $SNAP_{s,t} = 1$); $\ln dist_{is}$ is the log distance from the census block centroid of household i to store s; and ρ_i and γ^k_t are household and quarter fixed effects, respectively. We estimate demand separately for households who are SNAP-eligible ($k(i) = 1$) and those who are ineligible ($k(i) = 0$).

We estimate this equation using the purchases reported in the Circana household panel. This estimation sample is less restricted than store analysis above, allowing us to identify preferences for 54 of the top 100 chains, including all chains that adopted SNAP en masse over our sample period (including the club stores excluded from our store analysis). We assume that households visit the nearest outlet of a chain for tractability.

Table 1 shows the channel-specific distance elasticities for SNAP ineligible and SNAP eligible household expenditure. There are no statistically significant differences in the distance elasticities between SNAP-eligible and ineligible households, consistent with other work that finds no income gradient in distance elasticities (Cao et al. 2024). Both sets of households are more willing-to-travel to club, dollar, and mass merchandisers than to drug and grocery stores.

Figure 12 shows the chain preference parameter estimates for each of non-traditional retail chains that participate in the Circana Store Panel and had waves of adoptions between 2008 and 2012. The blue circles represent the preferences for stores of the chain when they do

Table 1: Distance Elasticity Estimates

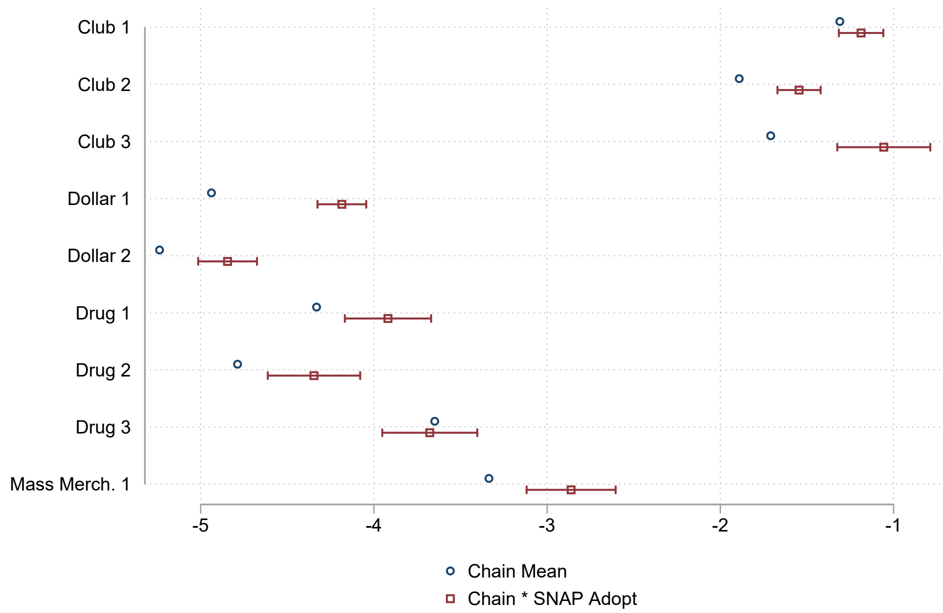
	(1) All	(2) SNAP Eligible	(3) SNAP Ineligible
Log Distance * Grocery	-0.914***	-0.912***	-0.914***
	(0.005)	(0.023)	(0.006)
Log Distance * Drug	-0.841***	-0.894***	-0.837***
	(0.007)	(0.026)	(0.008)
Log Distance * Mass Merch.	-0.693***	-0.671***	-0.694***
	(0.007)	(0.036)	(0.008)
Log Distance * Dollar	-0.760***	-0.710***	-0.758***
	(0.010)	(0.031)	(0.010)
Log Distance * Club	-0.756***	-0.692***	-0.758***
	(0.009)	(0.045)	(0.009)
SNAP Adopt	0.115***	0.293***	0.109***
	(0.007)	(0.037)	(0.007)
Dep. Var. Mean	34.76	32.21	34.94
Dep. Var. Std. Dev.	121.8	117.36	122.11
Household Count	188,517	16,922	172,012
Chain Count	54	54	54
Observations	16,412,613	1,090,973	15,321,610

Notes: Estimated with PPML for different subsets of households using household-chain-quarter data for 2008-2012. Chain is represented by the characteristics of the nearest store in that chain to the household's block. "SNAP Adopt" is an indicator for whether or not that nearest store in the chain in a given quarter accepts SNAP benefits, and is not estimated separately by chain in this specification. SNAP Eligible households have a household income below 130% of the Federal Poverty Line. Estimation includes household, chain, and quarter fixed effects. Clustering is at the block level.

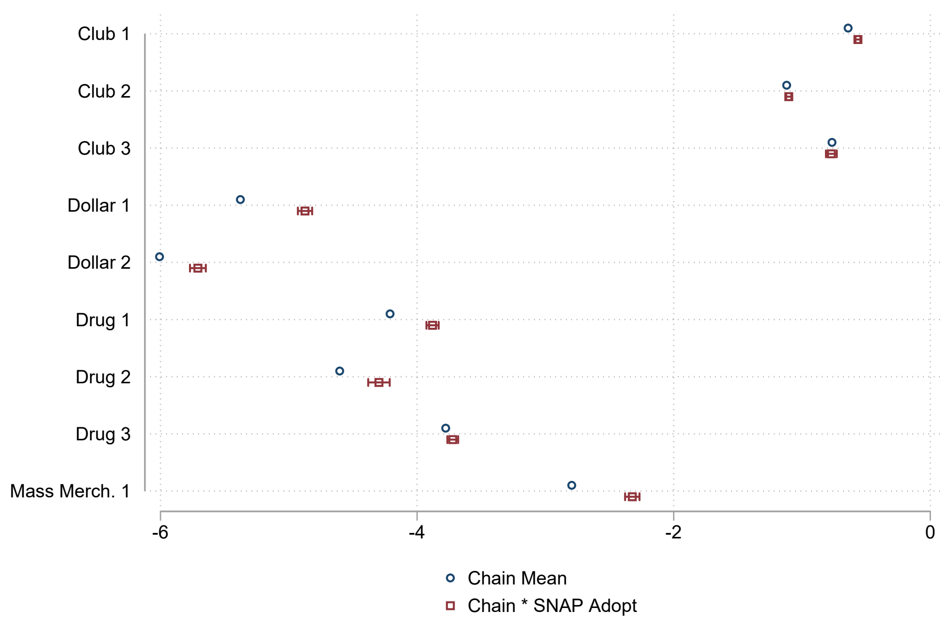
not accept SNAP benefits (δ^k_{ch}), while the red diamonds reflect the preferences for stores of the chain that do accept SNAP benefits ($\delta^{k,SNAP}_{ch}$). SNAP eligible households prefer stores from all but one chain when they accept SNAP benefits. SNAP ineligible households prefer dollar, two drug, and a mass merchandiser chain when they accept SNAP benefits, but to not prefer SNAP-accepting stores of any of the club chains. This could reflect that the club chains are less likely to add new varieties after adopting SNAP (since they were all likely to carry a range of food products before SNAP adoption).

Figure 12: Chain Preferences

SNAP Eligible Households



SNAP Ineligible Households



Notes: Estimated with PPML using expenditure as the dependent variable for two different subsets of households using household-chain-quarter data for 2008-2012. SNAP Eligible households have a household income below 130% of the Federal Poverty Line. Estimation includes household, chain, and quarter fixed effects. The "Chain Mean" points are the chain fixed effects, normalized to the fixed effect estimated for the largest traditional grocery chain in our data. "SNAP Adopt" is an indicator for whether or not the nearest store in the chain in a given quarter accepts SNAP benefits, and the by-chain coefficient for SNAP Adopt with 95% confidence intervals are shown.

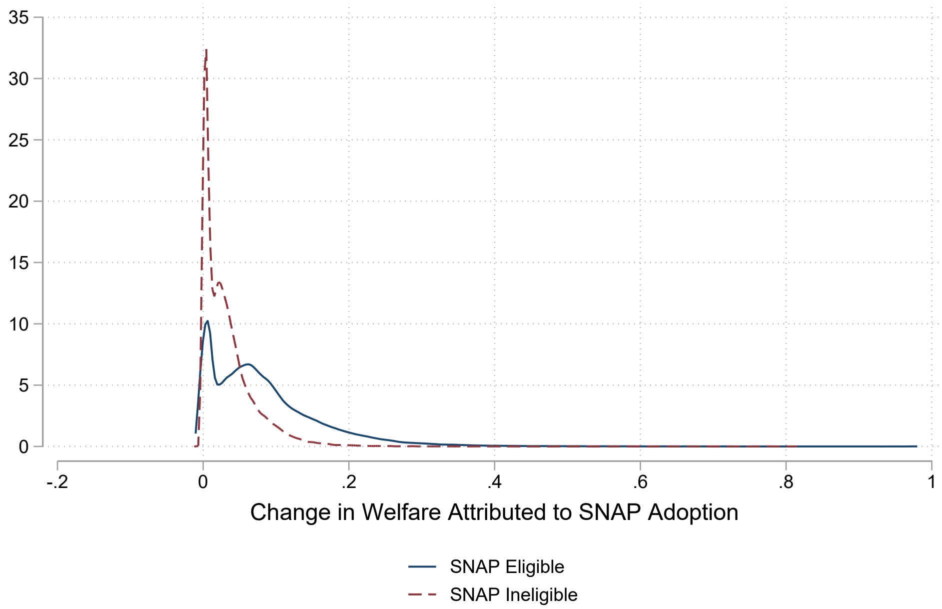
6.3 Welfare Results

We use equation (3), along with the parameter estimates presented above and the records of SNAP adoptions from the FNS data, to calculate the change in a welfare-relevant metric — shopping costs — induced by store SNAP adoptions. Figure 13 shows the distribution of changes in welfare attributed to SNAP adoption between 2008 and 2012 across different household residential zip codes. The median adjustment for SNAP eligible households is a 6.7% reduction in shopping costs, compared to 2.3% for SNAP ineligible households.

There is sizeable variation in the benefits of SNAP adoption across zip codes. Figure 14 shows how the welfare adjustments attributable to SNAP adoption compare to the adjustments induced by both SNAP adoptions and store entry, equation (2). The zip codes that did not experience much utility improvement from store entry did see benefits from SNAP adoption: chains adopting SNAP improved access to food retail in areas that did not benefit from store entry.

Table 2 shows the welfare changes attributable to SNAP adoptions (columns 1 and 2) and both SNAP adoptions and entries (columns 3 and 4) of different types of retailers. Unsurprisingly, there are no benefits from SNAP adoptions of grocery stores, which almost universally accepted SNAP in 2008. SNAP adoptions contribute substantively to the welfare benefits from changes in store offerings by non-traditional food retailers. Across all retail types, over a third of the overall welfare gains from changes in retail options for SNAP-eligible households is attributable to SNAP adoption.

Figure 13: Distribution of Changes in Welfare Attributed to SNAP Adoption



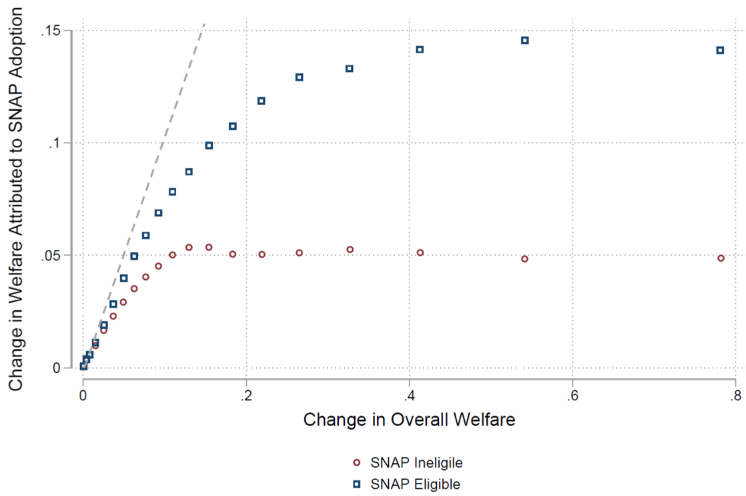
Notes: Changes are for 2008 to 2012. Changes attributed to SNAP adoption only consider SNAP adoption events between 2008 to 2012 for pre-existing store locations. Distribution across census blocks where consumer panelists live (are not nationally representative) weighted by census block group population. Extreme values are binned.

Table 2: Changes in Welfare from SNAP Adoption By Channel

	Mean Welfare Change Attributed to SNAP		Mean Overall Change in Welfare		Share of Overall Gain From SNAP	
	SNAP	Non-SNAP	SNAP	Non-SNAP	SNAP	Non-SNAP
All	6.68%	3.32%	19.4%	15.0%	34.4%	22.1%
Grocery	0.00%	0.00%	6.4%	6.5%	0.0%	0.0%
Drug	0.36%	0.45%	1.3%	1.3%	27.7%	34.1%
Mass Merchandiser	0.42%	0.80%	2.3%	2.9%	18.3%	27.4%
Dollar	0.66%	0.25%	1.5%	0.6%	44.6%	39.1%
Club	5.24%	1.82%	7.9%	3.6%	65.9%	50.6%

Notes: Changes are for 2008 to 2012. Changes attributed to SNAP adoption only consider SNAP adoption events between 2008 to 2012 for pre-existing store locations. Overall changes are driven by SNAP adoption and store entry between 2008 and 2012. Includes data for census blocks where consumer panelists live (are not nationally representative) weighted by census block group population.

Figure 14: Welfare Effects of SNAP Adoption Relative to Overall Changes in Welfare



Notes: Changes are for 2008 to 2012. Changes attributed to SNAP adoption only consider SNAP adoption events between 2008 to 2012 for pre-existing store locations. Overall changes are driven by SNAP adoption and store entry between 2008 and 2012. Includes data for census blocks where consumer panelists live (are not nationally representative) weighted by census block group population.

7 Conclusion

In this paper, we examine the effects on households and stores of a dramatic increase in food store participation in the SNAP program. We ask how this wave of SNAP adoptions affected retail customers in three ways. First, we characterize the set of stores that start accepting SNAP, and study how access costs (proxied by distance) changed for SNAP recipients. Second, we estimate the causal effects of SNAP adoption on sales, prices and inventory for both the adopting stores and their competitors. Finally, we ask how welfare changed for SNAP and non-SNAP households.

We find that the wave of SNAP adoptions reduced the distance to the nearest SNAP store for recipients by 16%, driven by non-traditional food retailers such as drug, dollar, club, and mass merchandisers. New adopters added new products and saw 5% increases in sales. In response to these SNAP store adoptions, nearby incumbents saw 1-2% lower sales, explained entirely by reductions in SNAP receipts, but did not respond to the competition for SNAP customers by adjusting prices or variety at the store or chain level.

We then estimate estimate a retail demand model motivated by the reduced-form results to quantify the welfare impacts of these SNAP adoptions on recipients and non-recipients, separately. The demand estimates show that the average consumer prefers to shop at a store accepting SNAP benefits but consumers eligible for SNAP have approximately twice the preference for SNAP-accepting retailers. We estimate that the wave of SNAP adoptions between 2008 and 2012 reduced shopping costs for SNAP-eligible households by around 7%, and for SNAP-ineligible households less than 3%.

Given our evidence, we conclude that there is an important interplay between SNAP and private markets in which vendors operate. These spillovers are important considerations when evaluating policies that impact program generosity and/or vendor participation.

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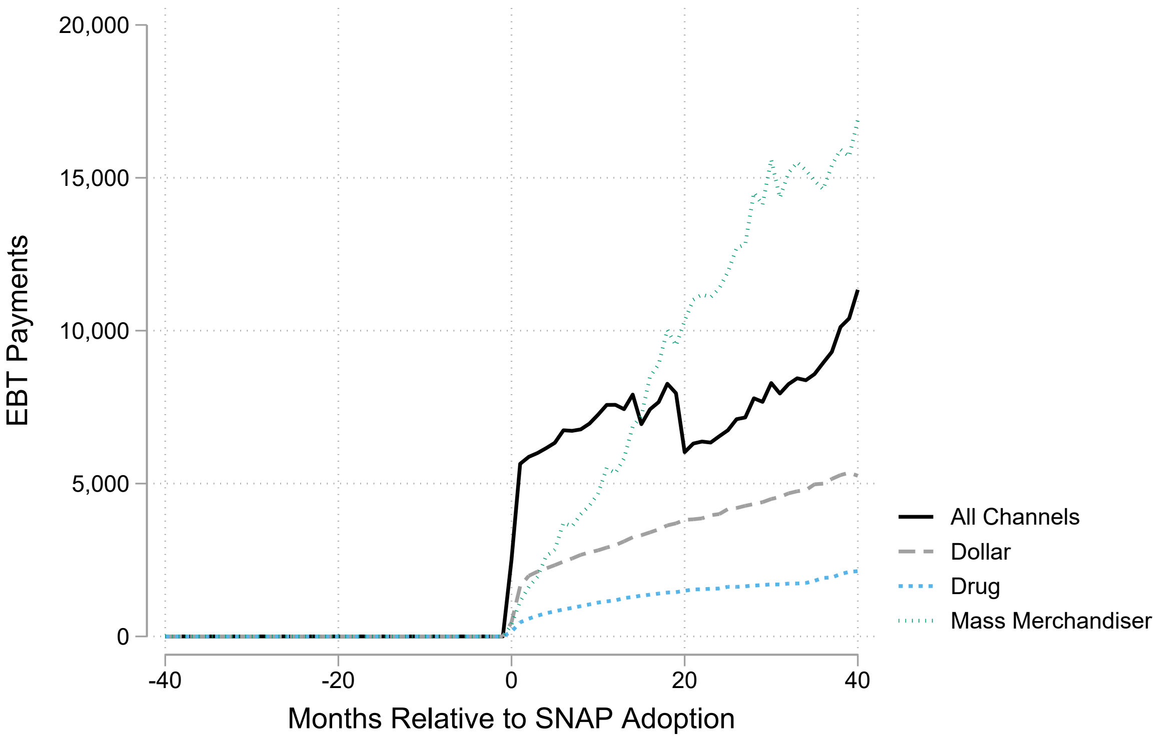
A.1 Appendix Figures

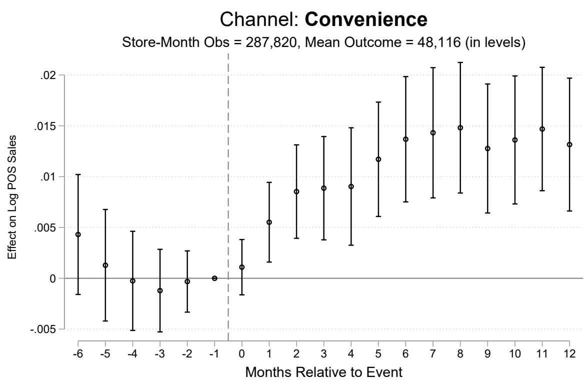
Figure A.1: EBT Mean Sales Before and After SNAP Authorization



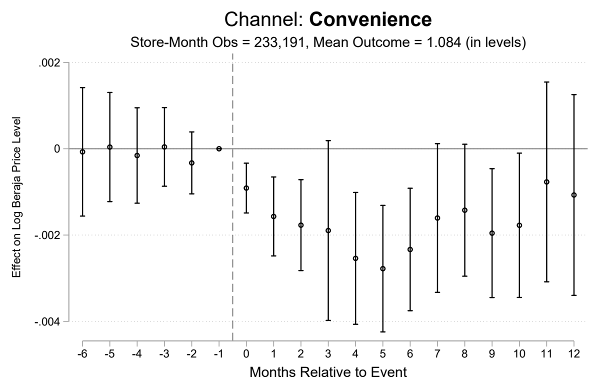
Horizontal line represents mean value for always-accepters.

Figure A.2: Own Store Results: Convenience

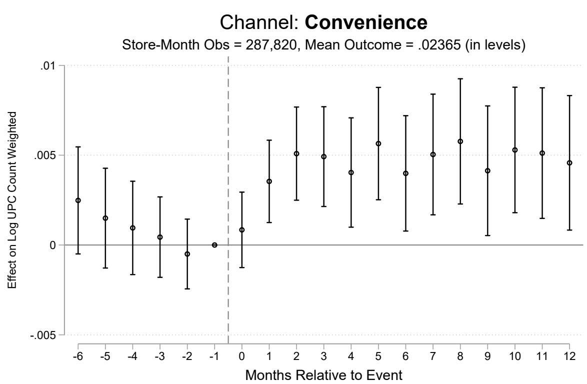
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

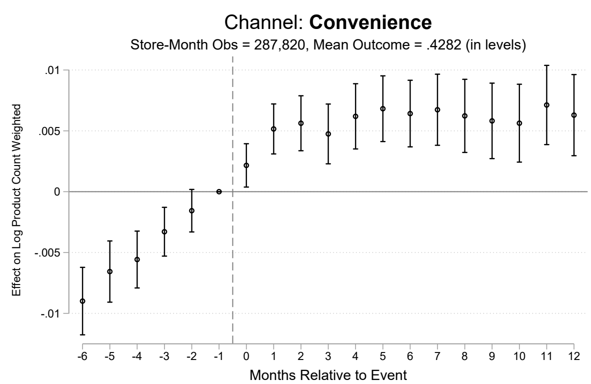
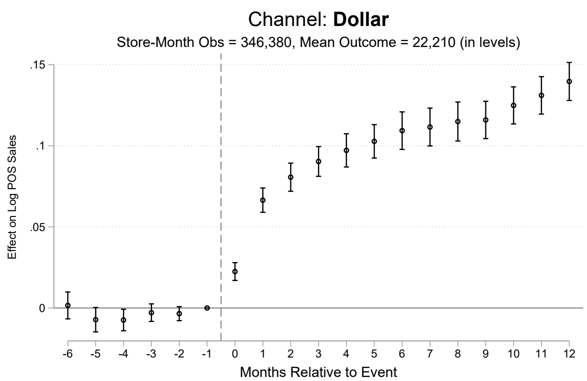
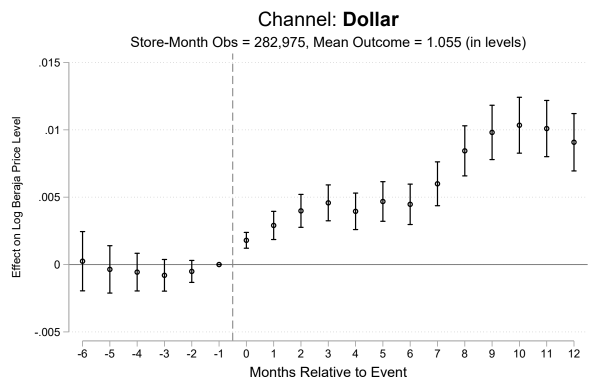


Figure A.3: Own Store Results: Dollar

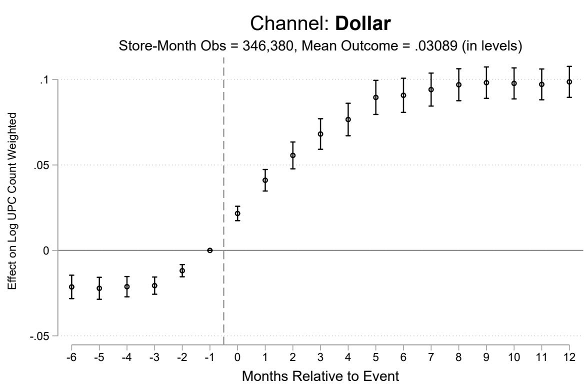
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

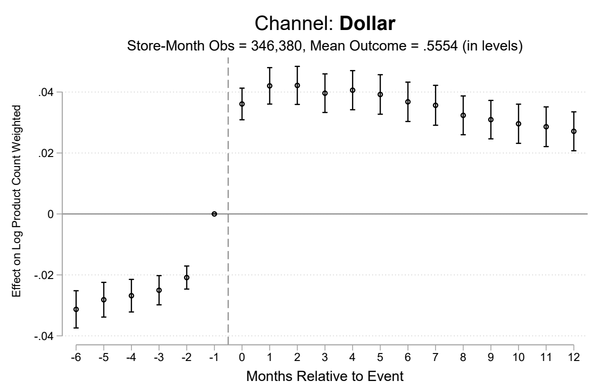
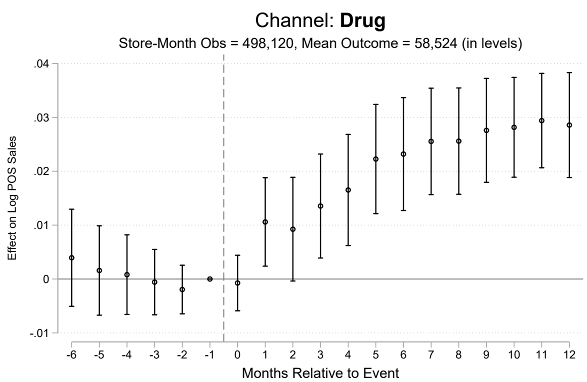
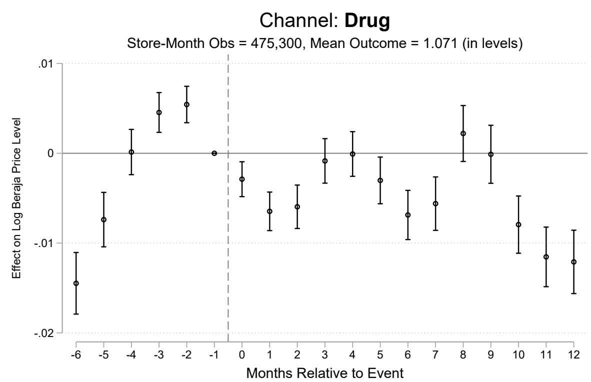


Figure A.4: Own Store Results: Drug

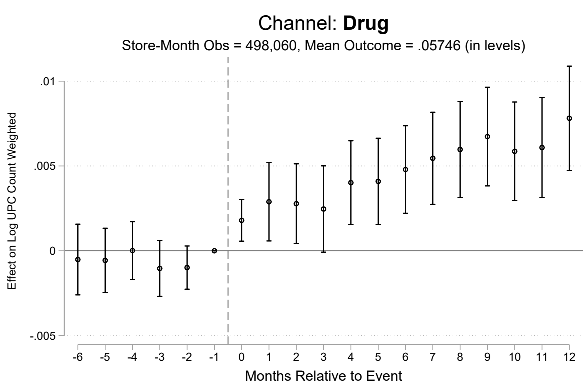
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

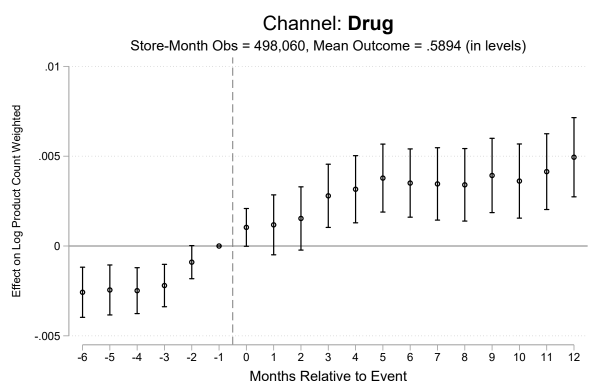
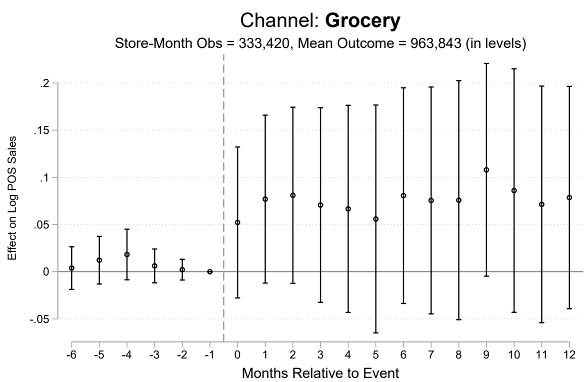
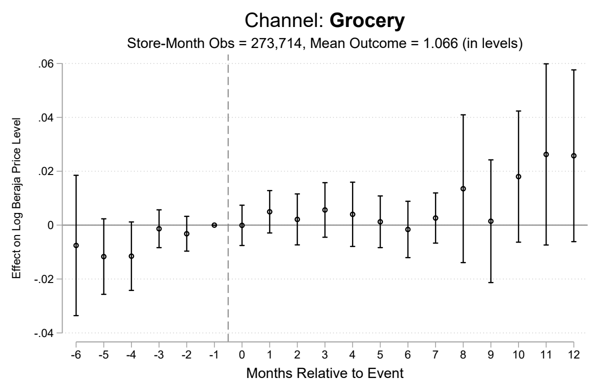


Figure A.5: Own Store Results: Grocery

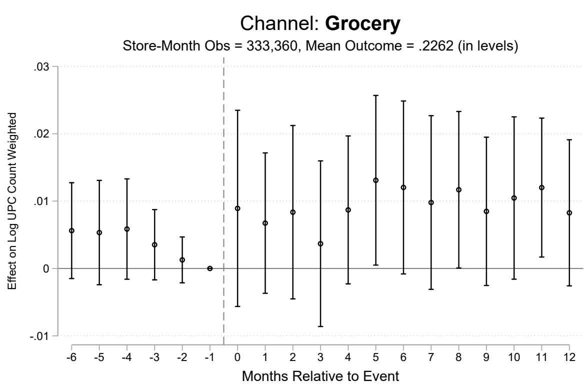
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

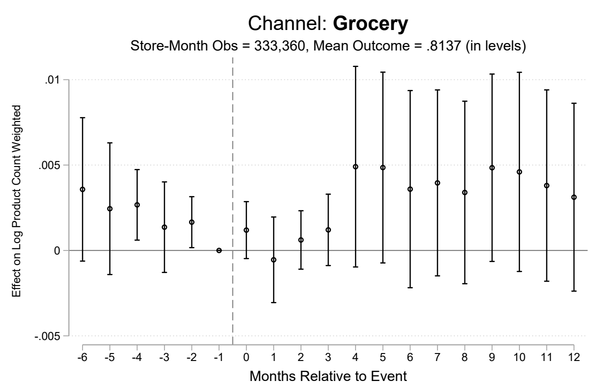
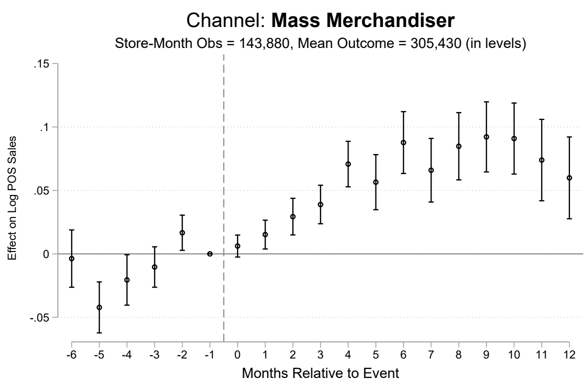
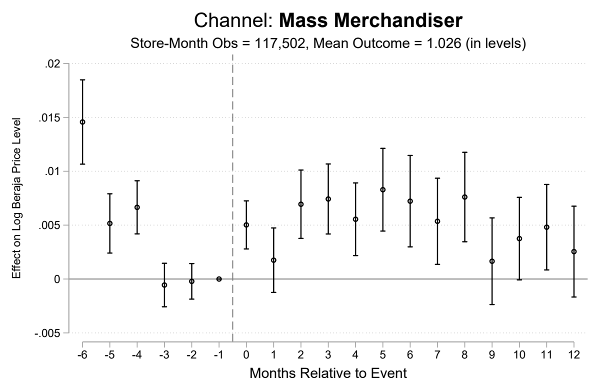


Figure A.6: Own Store Results: Mass Merchandiser

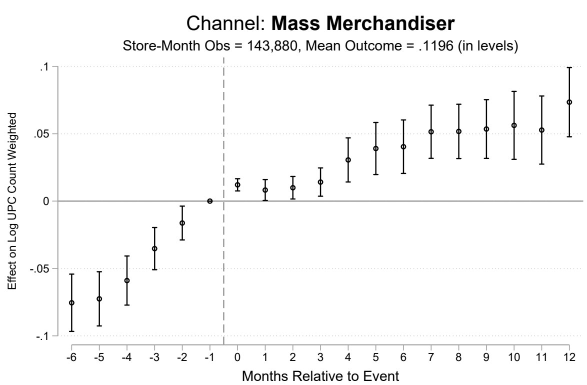
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

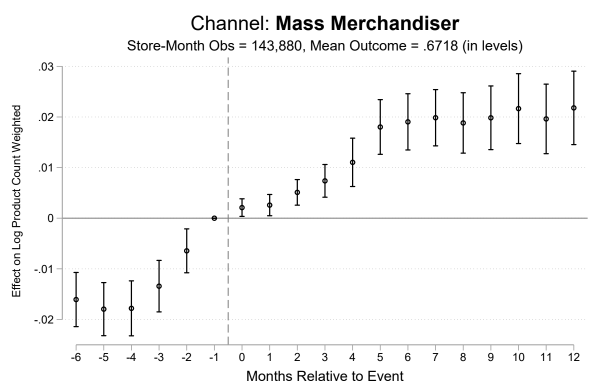
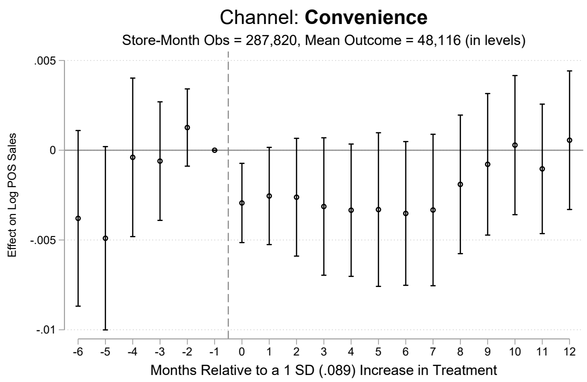
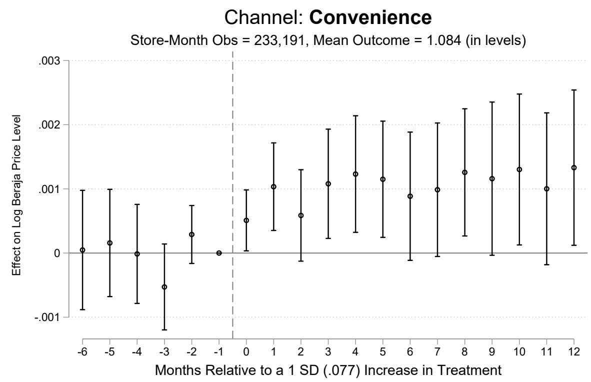


Figure A.7: Indirect Results: Convenience

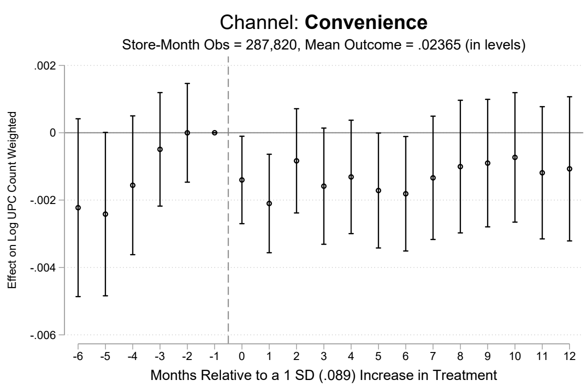
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

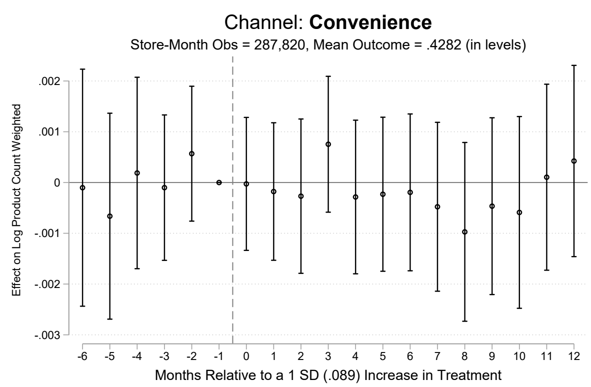
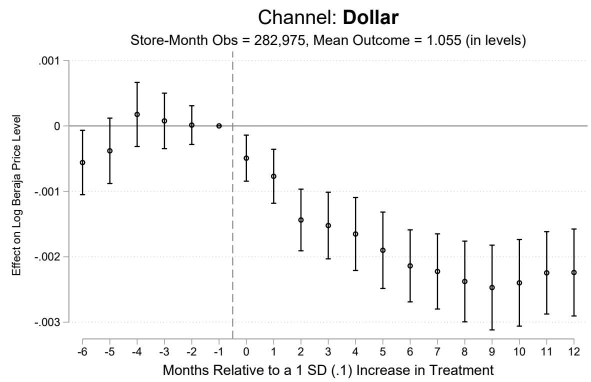


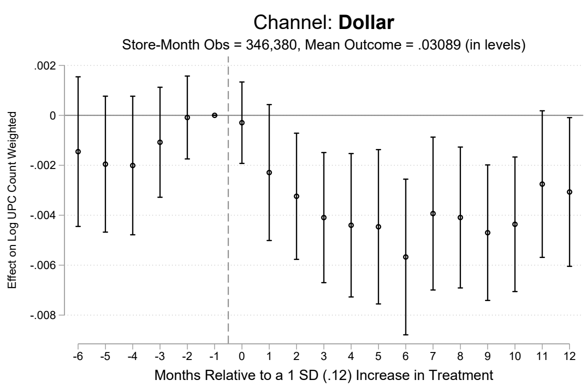
Figure A.8: Indirect Results: Dollar

(a) Sales

(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

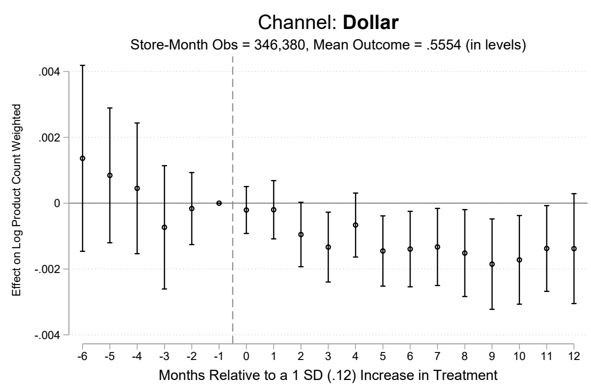
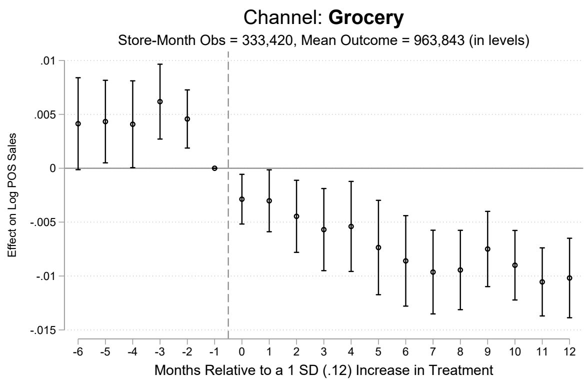
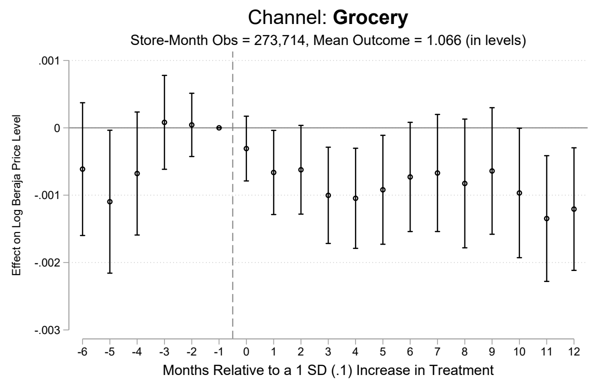


Figure A.9: Indirect Results: Grocery

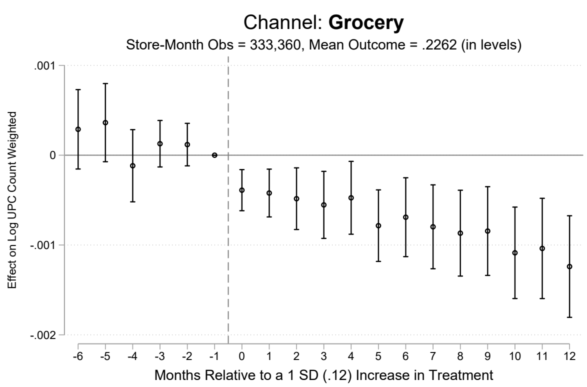
(a) Sales



(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count

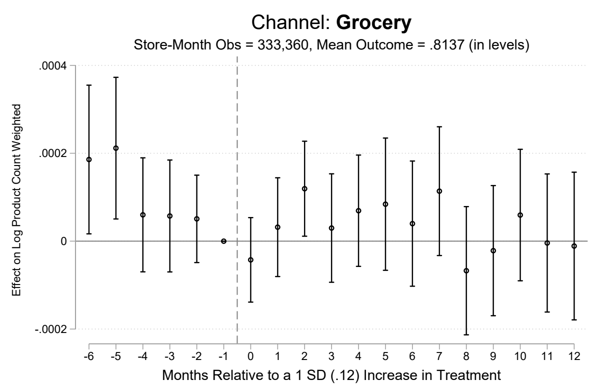
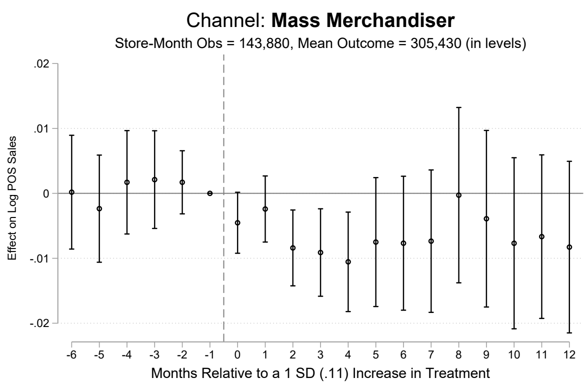
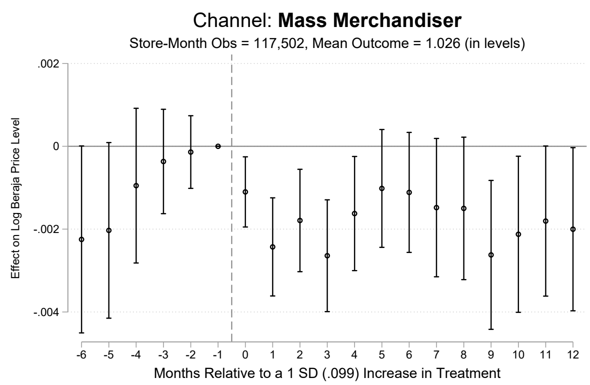


Figure A.10: Indirect Results: Mass Merchandiser

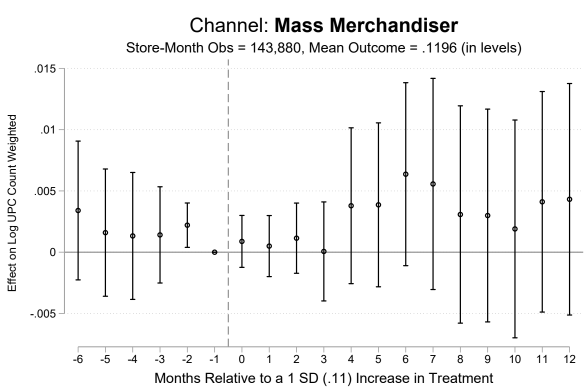
(a) Sales



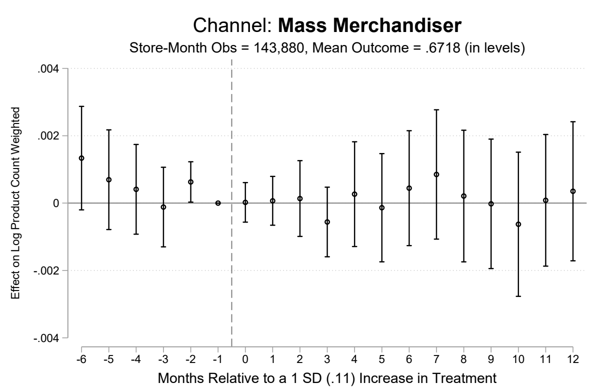
(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count



A.2 Appendix Tables

Table A.1: Table Version of Event Study of Main results (Store Analysis Appendix Table 1)

	(1)	(2)	(3)	(4)
	Log Sales	Log P UPC	Log UPC	Log Prod
Own: 7+ Months Pre	0.008**	–0.007***	–0.019***	–0.014***
	(0.003)	(0.002)	(0.002)	(0.001)
Own: 4–6 Months Pre	–0.008***	–0.003***	–0.022***	–0.011***
	(0.003)	(0.001)	(0.003)	(0.001)
Own: 2–3 Months Pre	–0.000	0.001	–0.009***	–0.006***
	(0.002)	(0.000)	(0.002)	(0.001)
Own: 0–3 Months Post	0.022***	–0.001	0.010***	0.007***
	(0.003)	(0.001)	(0.001)	(0.000)
Own: 4–6 Months Post	0.045***	0.000	0.021***	0.012***
	(0.004)	(0.001)	(0.003)	(0.001)
Own: 7–9 Months Post	0.053***	0.001	0.027***	0.012***
	(0.005)	(0.001)	(0.003)	(0.001)
Own: 10–12 Months Post	0.058***	–0.002*	0.035***	0.013***
	(0.005)	(0.001)	(0.004)	(0.001)
Own: 13+ Months Post	0.119***	0.000	0.082***	0.022***
	(0.007)	(0.002)	(0.005)	(0.001)
Competitor: 7+ Months Pre	0.002	–0.000	0.001**	0.000**
	(0.002)	(0.000)	(0.001)	(0.000)
Competitor: 4–6 Months Pre	0.003**	–0.001**	0.000	0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 2–3 Months Pre	0.004***	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 0–3 Months Post	–0.004***	–0.001***	–0.000**	–0.000*
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 4–6 Months Post	–0.006***	–0.001***	–0.000	–0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 7–9 Months Post	–0.006***	–0.001*	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 10–12 Months Post	–0.007***	–0.001**	–0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 13+ Months Post	–0.011***	–0.001	0.000	–0.000
	(0.002)	(0.000)	(0.001)	(0.000)
N	1,753,680	1,499,890	1,753,560	1,753,560
Stores	29,228	30,610	29,226	29,226
Std Error Clustering	Block	Block	Block	Block
Num. of Clusters	27,164	28,290	27,163	27,163
R-squared	0.994	0.886	0.996	0.991
Outcome Mean	11.277	0.060	–2.866	–0.539

Table A.2: Main DID with Pre-Trend Sensitivity (Store Analysis Appendix Table 2)

	(1)	(2)	(3)	(4)
	Log Sales	Log P UPC	Log UPC	Log Prod
Own: Post	0.080***	0.005***	0.074***	0.030***
	(0.006)	(0.002)	(0.004)	(0.001)
Own: 1–3 Months Pre	–0.007***	0.006***	0.012***	0.009***
	(0.003)	(0.001)	(0.002)	(0.001)
Competitor: Post	–0.011***	–0.000	–0.001	–0.000***
	(0.002)	(0.000)	(0.001)	(0.000)
Competitor: 1–3 Months Pre	0.001	0.001*	–0.001	–0.000**
	(0.001)	(0.000)	(0.000)	(0.000)
N	1,753,680	1,499,890	1,753,560	1,753,560
Stores	29,228	30,610	29,226	29,226
Std Error Clustering	Block	Block	Block	Block
Num. of Clusters	27,164	28,290	27,163	27,163
R-squared	0.994	0.886	0.996	0.991
Outcome Mean	11.277	0.060	–2.866	–0.539

Table A.3: Main DID for EBT and Sales on Always Adopters (Store Analysis Appendix Table 4)

	(1)	(2)
	Log Sales	Log EBT Sales
Competitor: Post	–0.012***	–0.005
	(0.002)	(0.004)
N	1,031,760	966,480
Stores	17,196	16,108
Std Error Clustering	Block	Block
Num. of Clusters	16,445	15,455
R-squared	0.992	0.990
Outcome Mean	11.855	8.710

Table A.4: Main DID for EBT and Sales on Always Adopters Event Study Version (Store Analysis Appendix Table 4B)

	(1)	(2)
	Log Sales	Log EBT Sales
Competitor: 7+ Months Pre	0.002	–0.009**
	(0.002)	(0.004)
Competitor: 4–6 Months Pre	0.003**	–0.001
	(0.001)	(0.002)
Competitor: 2–3 Months Pre	0.005***	0.003*
	(0.001)	(0.002)
Competitor: 0–3 Months Post	–0.004***	–0.005***
	(0.001)	(0.001)
Competitor: 4–6 Months Post	–0.006***	–0.006***
	(0.002)	(0.002)
Competitor: 7–9 Months Post	–0.006***	–0.007***
	(0.001)	(0.002)
Competitor: 10–12 Months Post	–0.007***	–0.008***
	(0.001)	(0.002)
Competitor: 13+ Months Post	–0.012***	–0.013***
	(0.002)	(0.004)
N	1,031,760	966,480
Stores	17,196	16,108
Std Error Clustering	Block	Block
Num. of Clusters	16,445	15,455
R-squared	0.992	0.990
Outcome Mean	11.855	8.710

Table A.5: Main DID for All Channels: Sales (Store Analysis Appendix Table 5)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Grocery	Dollar	Drug	Mass Merch.	Convenience
Own: Post	0.081***	0.041	0.142***	0.039***	0.142***	0.014***
	(0.006)	(0.058)	(0.007)	(0.005)	(0.013)	(0.003)
Competitor: Post	–0.011***	–0.015***	0.001	–0.003	–0.013*	0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.007)	(0.003)
N	1,753,680	333,420	346,380	498,120	143,880	287,820
Stores	29,228	5,557	5,773	8,302	2,398	4,797
Std Error Clustering	Block	Block	Block	Block	Block	Block
Num. of Clusters	27,164	5,495	5,743	8,200	2,392	4,733
R-squared	0.994	0.977	0.946	0.978	0.984	0.956
Outcome Mean	11.277	13.642	9.907	10.793	12.039	10.673

Table A.6: Main DID for All Channels: Prices UPC (Store Analysis Appendix Table 6)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Grocery	Dollar	Drug	Mass Merch.	Convenience
Own: Post	0.003**	0.044**	–0.000	–0.007***	0.001	–0.003***
	(0.001)	(0.019)	(0.001)	(0.002)	(0.002)	(0.001)
Competitor: Post	–0.000	–0.001**	–0.001***	–0.001	–0.001	0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
N	1,499,890	273,714	282,975	475,300	117,502	233,191
Stores	30,610	5,586	5,775	9,700	2,398	4,759
Std Error Clustering	Block	Block	Block	Block	Block	Block
Num. of Clusters	28,290	5,525	5,745	9,541	2,392	4,696
R-squared	0.886	0.927	0.857	0.799	0.860	0.919
Outcome Mean	0.060	0.061	0.053	0.063	0.021	0.077

Table A.7: Main DID for All Channels: Prices Product Brand (Store Analysis Appendix Table 7)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Grocery	Dollar	Drug	Mass Merch.	Convenience
Own: Post	–0.000	0.033**	0.002	–0.002	–0.007*	–0.004***
	(0.002)	(0.014)	(0.002)	(0.002)	(0.003)	(0.001)
Competitor: Post	–0.001	–0.001	–0.001	–0.001	–0.004**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
N	1,498,763	273,812	282,975	474,908	117,110	232,799
Stores	30,587	5,588	5,775	9,692	2,390	4,751
Std Error Clustering	Block	Block	Block	Block	Block	Block
Num. of Clusters	28,276	5,527	5,745	9,534	2,384	4,689
R-squared	0.872	0.896	0.897	0.766	0.849	0.901
Outcome Mean	0.077	0.081	0.113	0.057	0.045	0.079

Table A.8: Main DID for All Channels: UPC Count (Store Analysis Appendix Table 8)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Grocery	Dollar	Drug	Mass Merch.	Convenience
Own: Post	0.072***	–0.003	0.120***	0.010***	0.167***	0.004*
	(0.004)	(0.007)	(0.005)	(0.002)	(0.011)	(0.002)
Competitor: Post	–0.001	–0.002***	–0.002	0.001	–0.002	–0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.005)	(0.001)
N	1,753,560	333,360	346,380	498,060	143,880	287,820
Stores	29,226	5,556	5,773	8,301	2,398	4,797
Std Error Clustering	Block	Block	Block	Block	Block	Block
Num. of Clusters	27,163	5,495	5,743	8,199	2,392	4,733
R-squared	0.996	0.994	0.987	0.981	0.971	0.974
Outcome Mean	–2.866	–1.510	–3.604	–2.896	–2.253	–3.792

Table A.9: Main DID for All Channels: Product Count (Store Analysis Appendix Table 9)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Grocery	Dollar	Drug	Mass Merch.	Convenience
Own: Post	0.029***	–0.000	0.071***	0.006***	0.043***	0.017***
	(0.001)	(0.003)	(0.005)	(0.001)	(0.003)	(0.002)
Competitor: Post	–0.000***	–0.000***	–0.002	–0.001	–0.002*	–0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
N	1,753,560	333,360	346,380	498,060	143,880	287,820
Stores	29,226	5,556	5,773	8,301	2,398	4,797
Std Error Clustering	Block	Block	Block	Block	Block	Block
Num. of Clusters	27,163	5,495	5,743	8,199	2,392	4,733
R-squared	0.991	0.863	0.886	0.961	0.973	0.945
Outcome Mean	–0.539	–0.206	–0.595	–0.541	–0.427	–0.865

Table A.10: Main DID Results with Chain Control (Cluster at Block Group)

	(1)	(2)	(3)	(4)
	Log Sales	Log P UPC	Log UPC	Log Prod
Own: Post	0.070***	0.001	0.071***	0.028***
	(0.006)	(0.001)	(0.004)	(0.001)
Competitor: Post	–0.010***	–0.000	–0.001	–0.000**
	(0.002)	(0.000)	(0.001)	(0.000)
Own Chain: Post	0.388***	–0.029***	0.091***	0.018***
	(0.020)	(0.005)	(0.012)	(0.005)
Competitor Chain: Post	–0.761***	–0.141***	–0.127***	–0.046***
	(0.051)	(0.013)	(0.026)	(0.006)
N	1,710,300	1,463,875	1,710,180	1,710,180
Stores	28,505	29,875	28,503	28,503
Std Error Clustering	Block	Block	Block	Block
Num. of Clusters	26,563	27,682	26,562	26,562
R-squared	0.994	0.888	0.996	0.989
Outcome Mean	11.245	0.060	–2.875	–0.536

Table A.11: Main DID Results for Chain (Cluster at Chain)

	(1)	(2)	(3)	(4)
	Log Sales	Log P UPC	Log UPC	Log Prod
Own: Post	0.070**	0.001	0.071*	0.028***
	(0.030)	(0.003)	(0.040)	(0.010)
Competitor: Post	–0.095***	–0.003	–0.006	–0.003***
	(0.029)	(0.005)	(0.009)	(0.001)
Own Chain: Post	0.388*	–0.029	0.091	0.018
	(0.209)	(0.031)	(0.147)	(0.034)
Competitor Chain: Post	–0.049***	–0.008**	–0.008	–0.003*
	(0.018)	(0.003)	(0.007)	(0.002)
N	1,710,300	1,463,875	1,710,180	1,710,180
Stores	28,505	29,875	28,503	28,503
Std Error Clustering	Chain	Chain	Chain	Chain
Num. of Clusters	69	69	69	69
R-squared	0.994	0.888	0.996	0.989
Outcome Mean	11.245	0.060	–2.875	–0.536

Table A.12: Event Study Results with Chain Control (Cluster at Block Group)

	(1)	(2)	(3)	(4)
	Log Sales	Log P UPC	Log UPC	Log Prod
Own: 7+ Months Pre	0.010***	0.001	–0.018***	–0.014***
	(0.003)	(0.001)	(0.002)	(0.001)
Own: 4–6 Months Pre	–0.009***	–0.001	–0.023***	–0.010***
	(0.003)	(0.001)	(0.003)	(0.001)
Own: 2–3 Months Pre	0.001	0.000	–0.009***	–0.006***
	(0.002)	(0.000)	(0.002)	(0.001)
Own: 0–3 Months Post	0.020***	–0.000	0.011***	0.007***
	(0.003)	(0.001)	(0.001)	(0.000)
Own: 4–6 Months Post	0.041***	0.000	0.022***	0.011***
	(0.004)	(0.001)	(0.003)	(0.001)
Own: 7–9 Months Post	0.045***	0.000	0.028***	0.011***
	(0.005)	(0.001)	(0.003)	(0.001)
Own: 10–12 Months Post	0.050***	–0.000	0.035***	0.013***
	(0.005)	(0.001)	(0.004)	(0.001)
Own: 13+ Months Post	0.099***	0.003*	0.078***	0.022***
	(0.007)	(0.001)	(0.005)	(0.001)
Competitor: 7+ Months Pre	0.001	–0.001*	0.001*	0.000**
	(0.002)	(0.000)	(0.001)	(0.000)
Competitor: 4–6 Months Pre	0.003**	–0.001***	0.000	0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 2–3 Months Pre	0.004***	–0.000	0.000	0.000**
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 0–3 Months Post	–0.004***	–0.001***	–0.000***	–0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 4–6 Months Post	–0.006***	–0.001***	0.000	–0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 7–9 Months Post	–0.006***	–0.001*	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 10–12 Months Post	–0.006***	–0.001**	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Competitor: 13+ Months Post	–0.010***	–0.001	0.000	–0.000
	(0.002)	(0.000)	(0.001)	(0.000)
Own Chain: 7+ Months Pre	0.136***	–0.050***	–0.070***	–0.006
	(0.019)	(0.006)	(0.010)	(0.005)
Own Chain: 4–6 Months Pre	0.195***	–0.093***	0.073***	–0.041***
	(0.016)	(0.006)	(0.005)	(0.003)
Own Chain: 2–3 Months Pre	0.007	0.049***	–0.000	–0.047***
	(0.011)	(0.004)	(0.004)	(0.003)
Own Chain: 0–3 Months Post	0.167***	–0.012**	–0.033***	–0.029***
	(0.013)	(0.005)	(0.005)	(0.003)
Own Chain: 4–6 Months Post	0.101***	0.018***	–0.128***	0.017***
	(0.017)	(0.005)	(0.009)	(0.004)
Own Chain: 7–9 Months Post	0.350***	0.043***	–0.086***	0.024***
	(0.019)	(0.006)	(0.011)	(0.005)
Own Chain: 10–12 Months Post	0.103***	–0.106***	–0.118***	0.018***
	(0.019)	(0.006)	(0.013)	(0.006)
Own Chain: 13+ Months Post	0.686***	–0.107***	0.123***	–0.004
	(0.030)	(0.007)	(0.013)	(0.005)
Competitor Chain: 7+ Months Pre	0.209***	0.261***	0.071***	0.041***
	(0.039)	(0.028)	(0.015)	(0.005)
Competitor Chain: 4–6 Months Pre	–0.210***	0.054***	–0.039***	0.017***
	(0.036)	(0.020)	(0.009)	(0.004)
Competitor Chain: 2–3 Months Pre	–0.185***	0.016**	–0.029***	0.008***
	(0.022)	(0.008)	(0.006)	(0.002)
Competitor Chain: 0–3 Months Post	–0.146***	0.033***	0.054***	0.010***
	(0.023)	(0.008)	(0.006)	(0.002)
Competitor Chain: 4–6 Months Post	–0.333***	0.040***	0.027*	0.006
	(0.037)	(0.012)	(0.014)	(0.004)
Competitor Chain: 7–9 Months Post	–0.551***	0.060***	–0.083***	–0.000
	(0.041)	(0.014)	(0.020)	(0.005)
Competitor Chain: 10–12 Months Post	–0.633***	–0.024*	–0.150***	–0.008
	(0.040)	(0.014)	(0.021)	(0.005)
Competitor Chain: 13+ Months Post	–0.875***	–0.051***	–0.139***	–0.024***
	(0.055)	(0.016)	(0.029)	(0.007)
N	1,710,300	1,463,875	1,710,180	1,710,180
Stores	28,505	29,875	28,503	28,503
Std Error Clustering	Block	Block	Block	Block
Num. of Clusters	26,563	27,682	26,562	26,562
R-squared	0.994	0.890	0.996	0.989
Outcome Mean	11.245	0.060	–2.875	–0.536

Table A.13: Event Study Results for Chain Treatment (Cluster at Chain)

	(1)	(2)	(3)	(4)
	Log Sales	Log P UPC	Log UPC	Log Prod
Own: 7+ Months Pre	0.010*	0.001	–0.018*	–0.014***
	(0.006)	(0.002)	(0.011)	(0.005)
Own: 4–6 Months Pre	–0.009	–0.001	–0.023	–0.010***
	(0.010)	(0.002)	(0.017)	(0.003)
Own: 2–3 Months Pre	0.001	0.000	–0.009*	–0.006***
	(0.003)	(0.002)	(0.005)	(0.002)
Own: 0–3 Months Post	0.020**	–0.000	0.011***	0.007**
	(0.009)	(0.001)	(0.004)	(0.003)
Own: 4–6 Months Post	0.041**	0.000	0.022**	0.011***
	(0.016)	(0.002)	(0.009)	(0.004)
Own: 7–9 Months Post	0.045***	0.000	0.028**	0.011***
	(0.016)	(0.001)	(0.012)	(0.004)
Own: 10–12 Months Post	0.050***	–0.000	0.035**	0.013***
	(0.017)	(0.001)	(0.015)	(0.005)
Own: 13+ Months Post	0.099**	0.003	0.078*	0.022**
	(0.041)	(0.004)	(0.044)	(0.011)
Competitor: 7+ Months Pre	0.009	–0.007	0.010	0.004*
	(0.021)	(0.005)	(0.008)	(0.002)
Competitor: 4–6 Months Pre	0.027	–0.012***	0.003	0.003**
	(0.019)	(0.004)	(0.003)	(0.001)
Competitor: 2–3 Months Pre	0.040**	–0.000	0.003*	0.001*
	(0.016)	(0.003)	(0.001)	(0.001)
Competitor: 0–3 Months Post	–0.035***	–0.010***	–0.003***	–0.001
	(0.011)	(0.003)	(0.001)	(0.001)
Competitor: 4–6 Months Post	–0.053***	–0.010***	0.001	–0.000
	(0.014)	(0.003)	(0.005)	(0.001)
Competitor: 7–9 Months Post	–0.053***	–0.006	0.003	0.001
	(0.020)	(0.004)	(0.007)	(0.001)
Competitor: 10–12 Months Post	–0.059***	–0.009**	0.000	0.001
	(0.018)	(0.004)	(0.007)	(0.001)
Competitor: 13+ Months Post	–0.097***	–0.007	0.003	–0.001
	(0.031)	(0.006)	(0.012)	(0.002)
Own Chain: 7+ Months Pre	0.136	–0.050	–0.070	–0.006
	(0.102)	(0.037)	(0.146)	(0.038)
Own Chain: 4–6 Months Pre	0.195***	–0.093	0.073	–0.041***
	(0.066)	(0.114)	(0.047)	(0.009)
Own Chain: 2–3 Months Pre	0.007	0.049*	–0.000	–0.047***
	(0.081)	(0.029)	(0.018)	(0.010)
Own Chain: 0–3 Months Post	0.167*	–0.012	–0.033*	–0.029***
	(0.089)	(0.067)	(0.019)	(0.008)
Own Chain: 4–6 Months Post	0.101	0.018	–0.128***	0.017
	(0.083)	(0.083)	(0.043)	(0.017)
Own Chain: 7–9 Months Post	0.350*	0.043	–0.086	0.024
	(0.181)	(0.050)	(0.062)	(0.023)
Own Chain: 10–12 Months Post	0.103	–0.106	–0.118	0.018
	(0.156)	(0.097)	(0.105)	(0.035)
Own Chain: 13+ Months Post	0.686**	–0.107*	0.123	–0.004
	(0.327)	(0.056)	(0.140)	(0.029)
Competitor Chain: 7+ Months Pre	0.014	0.015***	0.005	0.003*
	(0.009)	(0.005)	(0.003)	(0.001)
Competitor Chain: 4–6 Months Pre	–0.014**	0.003	–0.003	0.001
	(0.007)	(0.004)	(0.002)	(0.001)
Competitor Chain: 2–3 Months Pre	–0.012***	0.001	–0.002	0.001
	(0.004)	(0.002)	(0.001)	(0.000)
Competitor Chain: 0–3 Months Post	–0.009**	0.002	0.003***	0.001**
	(0.005)	(0.002)	(0.001)	(0.000)
Competitor Chain: 4–6 Months Post	–0.022***	0.002	0.002	0.000
	(0.006)	(0.003)	(0.003)	(0.001)
Competitor Chain: 7–9 Months Post	–0.036***	0.003	–0.005	–0.000
	(0.008)	(0.003)	(0.006)	(0.002)
Competitor Chain: 10–12 Months Post	–0.041***	–0.001	–0.010	–0.001
	(0.010)	(0.003)	(0.007)	(0.002)
Competitor Chain: 13+ Months Post	–0.057***	–0.003	–0.009	–0.002
	(0.015)	(0.004)	(0.006)	(0.001)
N	1,710,300	1,463,875	1,710,180	1,710,180
Stores	28,505	29,875	28,503	28,503
Std Error Clustering	Chain	Chain	Chain	Chain
Num. of Clusters	69	69	69	69
R-squared	0.994	0.890	0.996	0.989
Outcome Mean	11.245	0.060	–2.875	–0.536

Table A.14: Block-Level Demand Estimation to Predict Expenditure Weights for Competitor SNAP Adoption Metric

	(1)
	Expenditure
Log Distance * Grocery	-0.450***
	(0.005)
Log Distance * Drug	-0.433***
	(0.009)
Log Distance * Mass Merch.	-0.099***
	(0.008)
Log Distance * Dollar	-0.456***
	(0.014)
Log Distance * Club	-0.441***
	(0.010)
Block Count	90268
Chain Count	54
Observations	3,292,267

A.3 Linking Circana Stores with FNS Records on SNAP Stores

To link stores in the Circana database to administrative records on SNAP stores, we take the following steps. First, we generate all possible pairs between Circana stores and SNAP stores that are located within the same state and ZIP code, and calculate the distance between the paired stores. We drop stores that are >10 miles apart. Second, 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 a store name similarity match <0.4 (i.e., the store names are very different). For each store in the remaining pairs, we choose its match as follows. First, we keep all store pairs that are perfect matches on measures (a) through (d). For the remaining stores, we keep pairs with a perfect street address match (only). Among the remaining stores, we keep pairs that are very close in distance (<0.1 miles). Among the remaining stores, we keep pairs that have a very high similarity score for store name and street address. Finally, among the remaining stores, we keep pairs that have the same street number and a similar store name OR the same street number and close distance.

A.4 Beraja Index

The inflation index is an arithmetic Laspeyres index, aggregating first to the product type for each store, and then across products to the store-level. Following Beraja, Hurst, and Ospina (2019), we measure inflation for continuing products: those sold in a given store in every month in both the current and previous calendar year.

The calculation proceeds in two steps. First, for each product module j, we calculate a year-on-year Laspeyres index for each store s. Let i denote a particular product (brand-product type), and $I_{m,s,t-1,t}$ be the set of products sold in store s in module m in years $t-1$ and t. Product-type level inflation from $t-1$ to t in store s is defined as:

$$\frac{P_{s,m,t}}{P_{s,m,t-1}} = \frac{\sum_{i \in I_{m,s,t-1,t}} p_{i,s,t} q_{i,s,t-1}}{\sum_{i \in I_{m,s,t}} p_{i,s,t-1} q_{i,s.t-1}}$$

where $p_{i,s,t}$ is the unit price at which product i is sold in store s in year t and $q_{i,s,t-1}$ is the quantity of product i sold in store s in year $t-1$. We then aggregate across product types sold in store s in years $t-1$ and t ($M_{s,t-1,t}$) using another Laspeyres index:

$$\frac{P_{s,t}}{P_{s,t-1}} = S_{m,s,t-1} \sum_{m \in M_{s,t-1,t}} \left(\frac{P_{s,m,t}}{P_{s,m,t-1}} \right)$$

where $S_{m,s,t-1}$ denotes the expenditure share of module m in store s in year $t-1$. We construct the price level of each store s in month m, $P_{s,m}$, by taking the product of the annual inflation index from January 2008 onwards. The price index takes a value of 1 in January 2008.

A.5 Constructing the Household Store Choice Dataset

The Household Store Choice dataset is constructed from the Circana Consumer Panel, Nielsen TDLinx, and USDA, Food and Nutrition Service Store Tracking and Redemption System (STARS) data. Here we describe the raw data and how it is used to construct our Household Store Choice dataset.

The Circana Consumer Panel contains observations for unique product purchases made by households in the panel at food retailers. Importantly, the panel indicates the retailers' chain names, but not the exact store locations. We assume household trips are made to the nearest retailer of the specified chain. The panel can be linked to additional data including households' characteristics and trip characteristics. Each purchase observation contains the following relevant variables: household id (for data linking), trip id (for data linking), product description, purchase price, purchase quantity. Along with static household characteristics provided by Circana (income, household size, census block), we impute SNAP eligibility status using the gross income test and household size in the relevant years.

TDLinx data contains the following relevant variables for individual retail store-year observations: name, address, latitude and longitude, census blockid, owner (e.g., the company or chain that owns the store), and a store entry date variable which indicates the date on which the store first appears in the TDLinx data. TDLinx is a near census of retail stores in the United States and represents the population of stores in the present study (**?**). TDLinx additionally includes the following variables, which may be used to validate store brands.

The STARS dataset contains the following relevant variables for individual retail store-month observations: name, address, and the EBT sales. STARS is a complete census of SNAP-authorized retail stores in the United States.

Our first data processing step is to identify the "top 100 chain names" in the Circana Consumer Network. The top 100 chain names is the list of chains that collectively have the highest expenditures over the study period in the Circana Consumer Network panel. We identify the top 100 chain names by aggregating the expenditures for 2008 to 2012 across all panelists and selecting the chains with the highest aggregate expenditures. This set of top 100 chain names includes a variety of channel types including grocery, mass and general merchandisers, dollar, drug, club, and convenience stores. In some cases, a chain may have establishments of different types, such as both supercenters and standard general merchandiser formats. In these cases, the stores are categorized as the same chain and combined expenditures are aggregated.

We next identify the "top 100 chains" which is a set of store-year observations with store location information. We select store records in TDLinx that appear between 2008 and 2012. We drop stores whose chain identifier or company ownership code indicates that they are independent. We then identify the chain for each remaining store using the store name and owner name variables, running a series of inspections to confirm chain categorization, and producing a "chain" variable for TDLinx stores that match Circana Consumer Panel chain names. We keep store-year observations where the chain name in TDLinx is included in the list of names of the "top 100 chain names." We call this dataset the "top 100 chains."

We add SNAP authorization information by linking the stores in the top 100 chains to the STARS data. We identify effective SNAP authorization quarter using the quarter in which a store reports positive EBT sales. We additionally check that store locations are consistent between STARS and TDLinx. We restrict the top 100 chain stores to those with at least 70 store locations in the STARS data that are authorized by 2016. We look for consistent chain categorization and store location data between TDLinx and STARS. We restrict the top 100 chains to chains that have widespread SNAP adoption by 2016 by requiring that 80% or more match to the STARS data. This set of restrictions reduces our "top 100 chain names" from 100 to 54. The set of stores that are part of these 54 chains, including their SNAP authorization date, are our "top 54 chains."

Finally, we assemble the dataset, beginning with the Circana Consumer Panel. For a given block where a household lives, we want to create the store choice set. We do this by identifying which of the top 54 chains exist within 15 miles of the household's census block in a given quarter. We assume nearest store location, so choice set does not include multiple establishments of the same chain. We use data from TDLinx included in the top 54 chains to determine which stores are open during which quarters. We then construct a dataset where each observation is at the household-quarter-chain level with the following variables: household id, quarter, chain name, distance to the nearest store location of that chain,[13], expenditures by that household at that chain (may be zero) in that quarter, number of trips made by the household to that chain in the given quarter, and a binary indicator of whether or not the nearest store of the chain was SNAP authorized in the given quarter.

13. Distances are calculated "as the crow flies."

A.6 Constructing Competitor SNAP Adoption Share

When measuring the causal effects of SNAP adoption in Equation 1, we consider the impact of a store's own SNAP adoption ($StoreAdopt_{i,t}$) and the impact of competitor store adoption ($CompetitorsAdopt_{i,t}$) on a store's outcomes. In this equation, $CompetitorsAdopt_{i,t-l}$ is the share of local competing stores within the market in a given month that accept SNAP. We utilize this continuous treatment variable to measure the local retail environment of treatment stores that adopt SNAP during our sample period. The competitive effect reflects the fact that stores could respond as competitors adopt SNAP and their local market becomes more competitive. Similar stores in different areas will have different levels of exposure to these competitive effects depending on what chains exist in their local market.

We construct $CompetitorsAdopt_{i,t}$ by calculating the weighted share of local retail SNAP competitors in the local market of the treatment store. [14] However, measuring the share of competitors in a store's market that accept SNAP is challenging for several reasons. First, defining the market. Traditional methods in the literature to delineate the spatial extent of a retail market have typically set a physical or drive time radius (e.g. 5 miles or 15 minute drive) around the treatment store. Second, the relative importance of stores of differing size and distance. Third, isolating changes in store SNAP participation driven by adoption and not entry or exit. Instead of drawing the market around the treatment store, we based the market around households similar to the approach in Ellickson, Grieco, and Khvastunov (2020). The preference weights help to account for the relative importance of each chain to local SNAP competition based on household preferences (e.g. large mass merchandiser chain vs small drug store chain), which incorporates household utility gain from chain specific attributes and disutility due to distance. These preferences weights provides a way to measure the local retail competitive environment that avoids the "all or nothing" in or out of the market with discrete distance and format cutoff approaches. We estimate household preferences for

14. we note that how markets are defined in this article may or may not reflect relevant antitrust markets or their definition.

each chain with household expenditure share of each SNAP eligible chain that they shop at. We further assume the expenditure shares and consumption patterns of households in the block group for which the treatment store is located in is representative for all households that shop at the treatment store. We also are not creating a store type specific competition measure, same measure for all stores in a block regardless of type. Intuitively, this continuous measure of local SNAP competition around a store is based on the store's consumers revealed preference of all SNAP retailers in their choice set.

To construct $CompetitorsAdopt_{i,t}$, we use the household store choice dataset, which includes data on household demographics, distances to each local chain, the SNAP status of each local retailer, and household expenditure at each chain. For the SNAP market around the household, We limit the chains in the household store choice dataset to chains within 15 miles of the household. [15] Unfortunately, the consumer panel does not have households for every block group that treatment stores are located in. Therefore, we need to predict household expenditure shares based on a modified methodology from Hosken and Tenn (2016). First, we calibrate a demand model by estimating the simple model of retail demand in section 8.1. For block b, chain c, channel r, and quarter t, we regress

$$ln(Y_{bct}) = \tau_r ln(dist_{bc}) + \gamma_c + \epsilon_{bct} \tag{4}$$

with household store choice dataset for the year 2008. This allows the distance elasticity τ_r to vary with channel. We only use data from 2008, which is before the mass store SNAP adoption events, to avoid SNAP adoption from treatment stores influencing the share weights. We calculate the distances from the block centroid to every SNAP adopting retailer within 15 miles of the block population-weighted centroid. We then apply the parameter estimates (distance and chain fixed effects) from the demand model to predict the expenditure

15. The consumer panel only reports the block group of the household, we proxy the household location with the block group centroid

shares for all block groups where stores are located.

We then aggregate the predicted expenditures across all four quarters of 2008 to obtain block-chain predicted expenditure shares. This expenditure share is adjusted into a "leave-out" measure that reflects a given stores competitors by removing the store of interest and adjusting the remaining store expenditure shares accordingly to sum to 100. Using the store SNAP adoption dates, we calculate a monthly measure of the expenditure weighted share of stores that accept SNAP for each block-quarter. We hold composition of stores fixed (no entry or exit) such that the measure only changes within a block over time due to store SNAP adoption events.

A.7 Appendix: Chain-Level Treatment

Firms may not adjust their pricing and inventory decisions at the outlet-level but instead with chain-wide shifts, in response to changes in the share of the chain's stores authorized to accept SNAP and changes in chain-level exposure to SNAP-authorized retailers. To test this hypothesis, we add two terms to our main specification that represent chain-level rates of adoption and exposure to adoption:

$$\begin{aligned} Y_{i,t} = \sum_{\ell} [&\beta_{1\ell}\text{StoreAdopt}_{i,t-\ell} + \beta_{2\ell}\text{CompetitorsAdopt}_{i,t-\ell} + \beta_{3\ell}\text{ChainAdopt}_{i,t-\ell} \\ &+\beta_{4\ell}\text{CompetitorChainsAdopt}_{i,t-\ell}] + \mu_i + \theta_{cty(i),t} + \gamma_{ch(i),t} + \epsilon_{i,t} \end{aligned} \quad . \tag{5}$$

$\text{ChainAdopt}_{i,t-\ell}$ is the month-on-month change in the share of stores in i's chain other than i that accept SNAP ℓ months before month t. $\text{CompetitorsChainsAdopt}_{i,t-\ell}$ is the month-on-month change in the mean share of stores in the competitors' chains that accept SNAP ℓ months before month t. The other terms are defined as in (1).