Welfare Implications of Increased Retailer Participation in SNAP*

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November 20, 2025

Abstract

Governments often rely on private vendors to deliver in-kind benefits, yet little is known about how vendor participation affects markets and welfare. We study a sharp rise in retailer participation in the Supplemental Nutrition Assistance Program (SNAP) during the Great Recession, driven largely by non-grocer formats. Linking administrative, retail, and household data, we find that sales increased 6% and variety 4% at adopting stores, with no price effects and only modest spillovers to local competitors. A revealed-preference framework shows that, while consumers value adoption at some chains, overall welfare gains for SNAP households were modest—equivalent to a 1.8% reduction in travel costs—with little effect on non-SNAP households.

*Corresponding author: kmeckel@ucsd.edu. Fahad Algifari, Nathaniel Bechhofer, Cindy Feng, Andre Gray, and Nhat-Ha Pham provided excellent research assistance. Jessie Handbury thanks the Research Sponsors' Program of the Wharton Zell-Lurie Real Estate Center and the Baker Retailing Center for generous financial support. This research was supported in part by the extramural research program of the US Department of Agriculture, Economic Research Service, cooperative Agreement Number 58-4000-0-0058. *Disclaimers: (1) The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA, FTC, or U.S. Government determination or policy. The views expressed in this article are those of the author and do not necessarily reflect those of the Federal Trade Commission or any individual Commissioner. (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

Safety net programs in the United States often rely on private vendors to deliver in-kind benefits. Because vendors operate in competitive markets and serve both program participants and other consumers, their participation decisions can shape access, market competition, and the incidence of program transfers. Despite the central role of vendors in these programs, we know relatively little about how increased vendor participation affects market outcomes and household welfare.

We study a sharp rise in retailer participation in the Supplemental Nutrition Assistance Program (SNAP, or "food stamps") during the Great Recession. SNAP is the largest U.S. nutrition assistance program, providing more than $100 billion annually in benefits redeemable at authorized stores. Between 2007 and 2012, against the backdrop of the Great Recession and benefit increases legislated under the 2009 American Recovery and Reinvestment Act (ARRA), the number of participating retailers rose by 67 percent. Most new adopters during this period were non-traditional food retailers—dollar stores, club stores, drugstores, convenience stores, and mass merchandisers—whose entry broadened both the scale and composition of outlets competing for SNAP customers, potentially inducing adjustments to retail prices and variety that affect recipients and non-recipients alike.

To analyze these changes, we link several nationally representative datasets: administrative records on all SNAP-authorized retailers, a census of U.S. food outlets, a large household purchasing panel, and product-level transaction data from a broad set of retailers that account for the majority of food spending by SNAP-eligible households. To our knowledge, this is the first effort to merge SNAP administrative store data to detailed retailer and household records. These new linkages make it possible to distinguish store openings from SNAP authorizations and to infer competitor exposure from observed shopping patterns (as recommended in Ellickson, Grieco, and Khvastunov (2020)).

Our analysis proceeds in three steps. First, we document stylized facts that characterize the 2008–2012 adoption wave. Second, we estimate the causal effects of adoption on store outcomes——sales, prices, and product variety——both for adopting outlets and their competitors. Finally, we apply a revealed preference framework to assess how SNAP adoptions benefited SNAP and non-SNAP households.

We first present a set of stylized facts about the 2008–2012 adoption wave. Adoption was concentrated in non-traditional formats, which moved from partial to near-universal participation over this period, largely through the decisions of nine large national chains. As a result, SNAP households saw meaningful improvements in access: the average distance to the nearest SNAP-accepting store fell by 16 percent, with the largest declines following ARRA's benefit increase. At the same time, the share of a typical store's competitors accepting SNAP rose from roughly 85 percent in 2008 to nearly 100 percent by 2011, increasing competition in the market for SNAP customers. Finally, we show that SNAP purchases at adopting stores rose sharply after authorization, becoming the largest source of food sales at dollar stores. Together, these facts suggest that adoption induced important shifts in both household and retailer behavior, motivating the causal analysis that follows.

We estimate the causal effects of adoption on store outcomes using a generalized event study design (Schmidheiny and Siegloch 2023) that exploits both the discrete timing of individual store adoptions and the continuous growth in competitor participation. This approach allows us to trace dynamic adjustments in sales, prices, and variety at adopting outlets and to measure spillover effects on nearby competitors. We find that adoption increases food sales by about 6 percent and product variety by about 4 percent, with larger effects in dollar and mass-merchandise formats. We detect little evidence that adopting stores increased prices: our estimates allow us to rule out price increases over 0.6 percent. Competitors of new adopters experienced modest sales declines and did not systematically adjust prices or variety. We also test whether these competitive effects operate at the chain level rather than the outlet level, but find little evidence of such responses.

The increase in food sales could be entirely driven by SNAP households, who benefit from being able to use their SNAP benefits in lieu of cash in adopting stores. It could also reflect non-SNAP households drawn to expanded product variety. To test whether adoption made stores more appealing to both groups—and to quantify the welfare effects of the adoption wave—we estimate a model of retail demand. In this framework, SNAP and non-SNAP households can assign a chain-specific premium (or discount) to SNAP stores relative to non-SNAP stores. We estimate this valuation gap with chain-by-SNAP acceptance fixed effects, which capture discontinuous breaks in store preferences at the time of adoption. To avoid conflating secular adjustments in chain popularity with the impact of SNAP adoption, our demand specification controls for linear trends in chain demand. Consistent with our reduced-form findings of limited competitive responses, only the adopting store sees a break in preferences at the adoption date.

The demand estimates show that the average SNAP-eligible consumer prefers to shop at stores accepting SNAP benefits. The "SNAP-authorization premium" is highest in three chains, a dollar store, a club store, and a mass merchandiser. We estimate that SNAP adoption by these chains yielded welfare gains to SNAP households equivalent to each chain's nearest store moving 40-70% closer. SNAP-ineligible households also prefer dollar, drug, and mass merchandiser stores after SNAP adoption, but their preference adjustments are mostly small and statistically insignificant except for a single dollar store chain where adoption is equivalent to their nearest store moving 54% closer.

Collectively, our welfare analysis shows that SNAP adoptions modestly improved shopping options for SNAP households, with nearly all experiencing at least some gain. On average, the 2008–2012 adoption wave raised expected consumer surplus for SNAP households by the equivalent of a 1.8 percent reduction in travel costs. For most households, however, the aggregate effects are small because non-traditional adopters are valued less than grocery stores, which had almost universally accepted SNAP before 2008. The largest gains came in areas where access to SNAP stores was otherwise limited and, for over 20% of SNAP-eligible households, adoption delivered larger welfare gains than new store entry. For SNAP-ineligible households, adoption had little impact: small positive responses at some chains were offset by declines at others, leaving average effects near zero.

Although the welfare effects we document are modest, our findings highlight vendor participation as an important mechanism through which expansions in benefit generosity can translate into household welfare. The sharp rise in retailer participation following the 2009 legislated benefit increases suggests that higher program spending induced many stores to incur the fixed, upfront costs associated with participation. Our paper analyzes the extent to which growth in vendor participation amplified the associated welfare gains, increasing the value of all benefit dollars, not just those added. In this way, program expansions can generate multiplier effects that enhance the overall efficacy of nutrition assistance.

Our analysis contributes to several strands of the economics literature. Most closely related is emerging work on how nutrition assistance programs shape retail grocery markets—specifically, how program design affects retailer participation, pricing, and consumer welfare. These studies are of policy interest given the rapid expansion of food assistance spending in recent decades and current proposals to modify the size and scope of SNAP. Recent work has examined the effects of benefit issuance timing on grocery sales and pricing (Goldin, Homonoff, and Meckel 2022); the introduction of SNAP in the 1970s and its effects on local retail markets (Bitler, Beatty, and Van Der Werf 2019); and state-level variation in program size and food pricing (Leung and Seo 2022). Related research has studied retail responses to other food assistance programs, including the National School Lunch Program (Handbury and Moshary 2021) and WIC (Meckel 2020; Meckel, Rossin-Slater, and Uniat 2021; Ambrozek 2025). We contribute to this literature by providing the first comprehensive analysis of the welfare effects of expanded retailer participation in SNAP.[1][2]

More broadly, our study is related to several papers analyzing the effects of the SNAP program on food purchasing behavior of low-income households. Prior work shows that SNAP participation raises food spending and that beneficiaries have higher marginal propensities to

1. Concurrent work analyzes the chain-wide adoption of SNAP by a dollar store chain in 2004, prior to our study period, and finds increases in SNAP adoption among competitor stores (Li et al. 2025).

2. 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) and Cunha, De Giorgi, and Jayachandran (2019)).

consume food out of benefits than out of cash (Hoynes and Schanzenbach 2009; Beatty and Tuttle 2015; Hastings and Shapiro 2018). With monthly benefit issuance, recipients exhibit a well-documented "benefit cycle," spending heavily just after receipt and cutting back later in the month (Wilde and Ranney 2000; Shapiro 2005; Hastings and Washington 2010; Damon, King, and Laibtag 2013; Goldin, Homonoff, and Meckel 2022). Our findings suggest that which stores participate in SNAP impacts where people buy food.[3]

Our study is also related to work on the changing food retail landscape, which emphasizes the entry of non-traditional outlets such as mass merchandisers, club stores, dollar stores, and drugstores (USDA-ERS 2021; Courtemanche and Carden 2014; Bauner and Wang 2019). Brecko, Ellickson, and Haviv (2025) study how retailers across different formats compete with distinct pricing strategies, product assortment, and store locations. We show non-traditional retailers competing for lower-income customers by adopting SNAP benefits. Our welfare analysis complements recent work demonstrating that dollar-store expansion lowers shopping costs in underserved areas (Cao et al. 2024).[4]

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 food assistance program in the United States. Eligibility is determined primarily by income: households must have gross income below 130 percent of the federal poverty line and must also satisfy net

3. 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.

4. Caoui, Hollenbeck, and Osborne (2023) show that dollar stores displace grocery stores in rural markets. By contrast, we find that grocery stores see a small (1-2%) decline in food sales when a nearby retailer adopts SNAP, but do not adjust inventory or prices.

income and asset limits. In 2009, during our sample period, SNAP provided $73 billion (2024 dollars) in benefits to an average of 33 million people per month, about 11 percent of the U.S. population. By 2024, annual benefits had risen to $94 billion, reaching 42 million people, or roughly 12 percent of the population (USDA-FNS 2024).

The private food retail sector plays an integral role in SNAP. Households receive monthly lump-sum benefits redeemable at USDA-authorized stores for nearly all grocery items, with exclusions limited to alcoholic beverages and hot or prepared foods. These purchases represent a substantial share of the grocery market, accounting for an estimated 8 percent of all food-at-home spending in the United States.[5]

The distribution of authorized retailers across local markets may shape beneficiary welfare by influencing both the accessibility of benefits and the variety of store formats and products available. Authorization may also alter retailers' strategic choices—affecting revenues, pricing, stocking, and competitive dynamics—with possible spillovers to non-program customers. This study investigates these potential effects of retailer authorization.

2.1 Retailer Authorization and Adoption Costs

Understanding the requirements and costs of authorization is key to explaining why some retailers choose not to participate. Participation in SNAP requires authorization from the USDA Food and Nutrition Service (FNS), which processes store-level applications on a rolling basis and typically issues a decision within 45 days. While the application process itself imposes little direct cost, two requirements may limit participation: (1) stocking perishable staple foods and (2) installing technology to accept Electronic Benefit Transfer (EBT) payments.

To satisfy the stocking requirement, stores must (a) carry a minimum variety of staple foods across four categories—bread/cereals, meat/poultry/fish, dairy, and fruits/vegetables—with a portion of these items required to be perishable, OR (b) derive more than 50% of

5. Source: Center on Budget and Policy Priorities (CBPP), "SNAP Boosts Retailers and Local Economies," available at https://www.cbpp.org/research/snap-boosts-retailers-and-local-economies.

gross sales from staple foods.[6] Perishable goods are defined as those that spoil within two weeks at room temperature. In grocery and superstores, these items are typically sold fresh in perimeter departments (produce, milk, meat, bakery) or in refrigerator or freezers in the aisles. In non-grocer retailers such as dollar stores, perishable goods are generally frozen or refrigerated rather than fresh, in which case compliance may require adding cold storage—– entailing investments in refrigerators or freezers, or reallocating existing chilled space from other products (e.g., beverages, frozen desserts).

The second major cost is EBT implementation. Since 2004, SNAP benefits have been issued exclusively via EBT cards, requiring retailers to install compatible hardware and software and to pay ongoing transaction-processing fees.[7] EBT systems are procured through third-party vendors. Large chains sometimes secure volume discounts from these vendors, but face additional costs to integrate the EBT systems with their proprietary checkout systems. Additional smaller costs include employee training to ensure compliance with SNAP regulations and installing USDA-provided signage.

Because participation primarily involves fixed, upfront costs with relatively low ongoing expenses, we expect most stores to remain in the program once authorized. Non-participation should be more likely among stores with limited food sales, narrow product variety, or few SNAP customers, where the expected sales gains do not offset the costs of meeting inventory requirements and installing EBT.

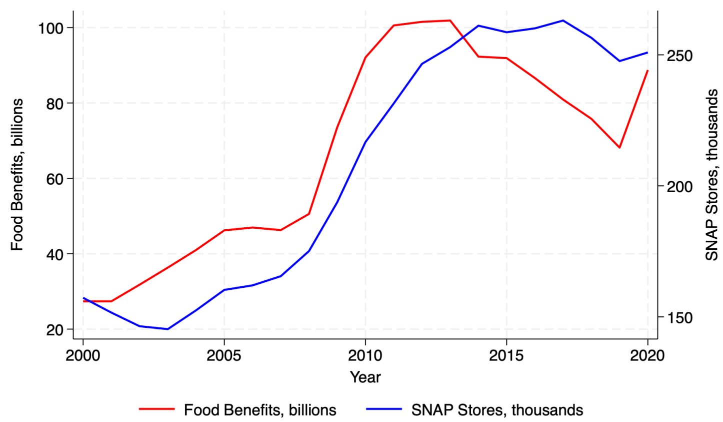
2.2 Wave of Adoptions during the Great Recession

Figure 1 plots counts of SNAP-authorized stores alongside total program benefit expenditures. SNAP spending rose sharply in the late 2000s, driven by rising poverty rates and changes in eligibility thresholds—which together expanded household eligibility—as well as

6. The second criterion is most relevant for specialty retailers (e.g., butcher shops), which account for less than 5% of SNAP sales during our sample period. See https://www.fns.usda.gov/snap/retailer-eligibility-clarification-of-criterion.

7. When a beneficiary shops at a SNAP-authorized retail store, their EBT account is debited for the cost of eligible food items, and the store is reimbursed. See https://www.fns.usda.gov/snap/ebt.

Figure 1: Total SNAP Stores and SNAP Benefits



Retailer counts are from FNS Benefit Redemption Division Annual Reports and represent the number of authorized retailers as of September 1. Food benefits reflect total SNAP benefit outlays (excluding administrative and other program costs) and are reported in FNS's SNAP Participation and Costs annual summary. Dollar amounts are expressed in 2024 dollars (January 2024), calculated using the BLS CPI Inflation Calculator (https://www.bls.gov/data/inflation_calculator.htm.

legislated benefit increases during the Great Recession.[8] The resulting growth in SNAP food sales increased the potential revenue from participation, strengthening incentives for retailers to join the program.

Retailer participation expanded markedly during this period, rising from roughly 150,000 authorized stores in 2000 to 250,000 in 2012.[9] A particularly large increase occurred in 2009, coinciding with legislated benefit increases. Benefit expenditures declined during the economic recovery from 2013 to 2019, but retailer participation remained elevated, consistent with the fixed-cost nature of adoption.

This paper examines the causal effects of the 2008–2012 surge in retailer participation 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. The next section describes these data.

8. The American Reinvestment and Recovery Act increased the maximum benefit 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/.

9. See, for example, "More Retailers Say Yes to Food Stamps," ABC News, July 28, 2009.

3 Data

We combine several data sources to characterize the local food retail environment and the responses of shoppers and retailers to SNAP adoption. These include proprietary retail panels from NielsenIQ and Circana, together with administrative SNAP redemption records from USDA-FNS. All datasets cover the period 2008–2012.

NielsenIQ's TDLinx is an establishment-level dataset that provides comprehensive coverage of U.S. retail food outlets. For each store, the data report the store name, geocoded address, parent company, opening date, and market channel. See Cho et al. (2019) for a detailed description.

USDA's FNS Store Tracking and Redemption System (STARS) contains administrative information on all SNAP-authorized retailers. For each store, STARS reports the name, geocoded address, market channel, and a unique identifier. Store attributes are self-reported to FNS and verified periodically through audits. The data also include monthly EBT redemptions—the total value of SNAP benefits spent at each store. We define a store's SNAP adoption date as the first month in which it records positive (non-zero) EBT redemptions.

The Circana Omnimarket Core Outlets data provide weekly, product-level transaction records for a panel of approximately 44,000 food stores, covering about 51% of grocery food sales in the US.[10] For each transaction, we observe the price, number of units sold, and the value of any discounts or coupons.[11] Store-level variables include the store name, geocoded address, parent company, and a unique identifier.

The Circana Consumer Panel is drawn from the National Consumer Panel, a household survey panel that tracks food purchases for roughly 120,000 households per year. The panel is designed to be representative both nationally and within individual markets. Households record all food purchases from any outlet using an in-home barcode scanner and receive points

10. Our data include point-of-sale (POS) transactions representing all food products except perimeter fresh produce, fresh meat, deli and baked goods.

11. Price is measured as the sales-weighted average retail transaction price, calculated by dividing the total dollar sales of a product by the total units sold. This average includes both regularly-priced and promoted sales.

redeemable for prizes as incentives. Participants also provide demographic information, including income, household size, and census block group of residence. Although demographics are collected annually, we observe them only for 2012, the final year of our sample. Thus, all demographic measures are time-invariant in our analysis.

For each shopping trip, we observe the trip date, store name, and total expenditure. For each food product purchased, we observe the unit price, quantity, and any discounts applied. Circana validates reported prices using scanner data it collects independently from retail chains. See Muth et al. (2016) for additional detail on the Circana outlet and consumer panel data.

3.1 Analysis Samples

We combine our data sources in two analysis samples, which we refer to as the "Household Store Choice Dataset" and the "Retailer Panel." We use the first to analyze how nearby retailer SNAP adoption affects household purchasing behavior. We use the second to study how retailers respond to their own SNAP adoption and adoptions by their competitors. This section describes how these datasets are constructed.

3.1.1 Household Store Choice Dataset

A central focus of our analysis is how the shopping behavior of SNAP and non-SNAP households responds to SNAP adoption by nearby retailers. To study this, we merge the Circana Consumer Panel with TDLinx retailer-level data and USDA's STARS retailer authorization records (see Appendix A.3 for full details).

The Consumer Panel provides detailed information on shopping trips, expenditures, and household demographics. Because SNAP participation is not directly observed, we infer eligibility using household income (reported in brackets) and family size, applying the federal gross income test.[12] As household demographics are observed only in 2012 and income is bracketed, this measure is a noisy indicator of SNAP eligibility.

12. Household income is reported in $5,000-$10,000 brackets; we impute income using the upper bound of the bracket to avoid misclassifying SNAP-eligible households as ineligible.

Roughly 6% of households in our data are imputed to be SNAP-eligible, compared to an actual national participation rate of about 14% in 2012.[13] This gap is consistent with prior evidence that the Consumer Panel, though designed to be nationally representative, tends to undersample low-income households (Lusk and Brooks 2011).

For analysis, we collapse the Consumer Panel to the household–quarter–chain level and construct two outcomes: total expenditures and total shopping trips. We then aggregate across all households and quarters to compute total expenditure by chain over the 2008–2012 period. Based on this aggregation, we identify the top 100 chains and restrict the analysis dataset to these chains, as doing so increases the tractability of our computations. These top 100 chains account for roughly 80% of SNAP-eligible food spending in the Consumer Panel during this period.

We next characterize the retail environment for Consumer Panel households. We start with the TDLinx data, restricted to the same top 100 chains, and link stores to administrative records on SNAP participation from STARS. This new linkage, described in Appendix A.5, is based on geocoded address, name, and opening/closing dates, and allows us to observe whether and when TDLinx stores began accepting SNAP. Because TDLinx records store opening dates, we can distinguish between SNAP adoption at the time of store opening (which may independently affect shopper behavior) and adoption by existing stores. To ensure consistency across datasets, we retain only those TDLinx chains that can be reliably linked to STARS, which reduces the number of chains from 100 to 54.

Finally, we use the centroid of each household's census block group to identify all stores in these chains within a 15-mile radius, which we define as the household's food retail environment. The Consumer Panel does not report the specific 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 and ignore visits further than 15 miles from a household's census block group.

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

3.1.2 Retailer Panel

Our second analysis sample is a monthly panel of retailers, used to examine how a store's sales, prices, and product offerings change when it adopts SNAP, as well as how its competitors respond. We begin with the Core Outlets retailer panel; of our top 100 chains, 38 appear in this dataset. Core Outlets excludes club retailers—a format that began accepting SNAP during this period—so we cannot analyze how their sales, pricing, or product variety respond to SNAP adoption.

We link the Core Outlets retailer panel to the STARS administrative records at the store level, using geocoded location, store name, and operating dates, as described in Appendix A.5. This new linkage allows us to observe the month in which each store adopts SNAP, and to calculate the share of its food sales (from Core Outlets) paid for with EBT (from STARS).

We then construct monthly outcomes for each retailer: total food sales, total EBT sales, a price index of food products, and two measures of food product variety. 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.6.

Our measures of variety include weighted store-level UPC and product counts. While UPCs are the most disaggregated product unit, "products" are groups of items aggregated one level above UPC in the Circana data. Each UPC or product is weighted based on its share of national sales in 2012, so that the index is more responsive to price fluctuations in frequently-purchased products.

Finally, we define each store's competitors using shopping patterns from the Household Store Choice dataset following a revealed preference approach. The Circana household data are too sparse to identify competitors directly for each store in the Retailer Panel. Instead, we use our Household Store Choice dataset to model household demand for stores in top 54 chains in the household's choice set as a function of channel-specific distance and chain effects. From this model, we predict expenditure weights for households residing in the same census block as the focal store, assuming these households are representative of the store's broader customer base. We then use the predicted weights to calculate, for each month, the expenditure-weighted share of a store's competitors that accept SNAP. Appendix A.7 provides details.

4 Stylized Facts

Before turning to the causal analysis, we first document three descriptive facts using our analysis samples: (1) the increase in SNAP adoption among non-grocer food retailers between 2008 and 2012, (2) the resulting change in household access to SNAP stores, and (3) the evolution of EBT payments after a retailer begins accepting SNAP.

4.1 Patterns of SNAP Adoptions, 2008-2012

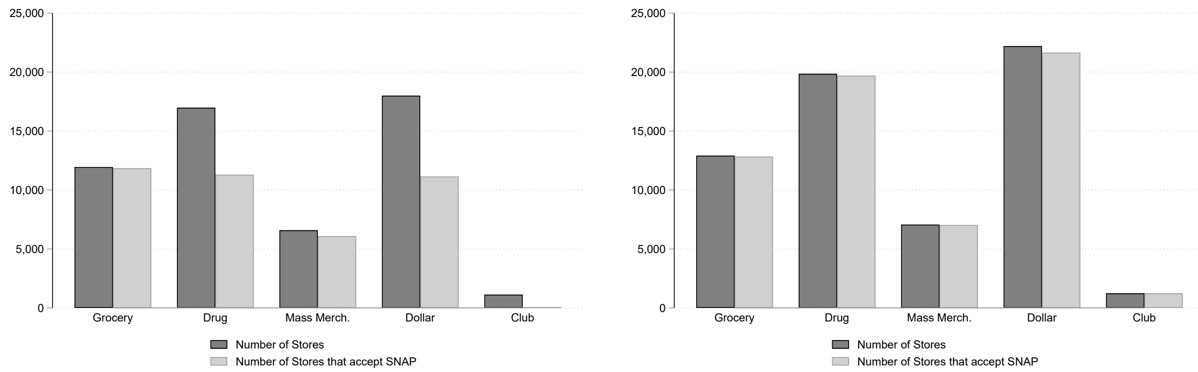
We begin with the retail environment dataset described above, which links administrative records on SNAP stores to a census of food outlets. Figure 2 shows the number of food stores in 2008 and 2012 by retail channel and SNAP participation status. For each channel, light gray bars show the total number of stores, and dark gray bars show the number participating in SNAP. Panel A shows that, in 2008, nearly all grocery stores and most mass merchandisers already participated, whereas only about two-thirds of drug and dollar stores did, and none of the club stores in our sample did.

Between 2008 and 2012, drug and dollar chains expanded, increasing their store counts, while other channels remained comparatively stable. Over the same period, SNAP participation shares in all non-grocer channels rose sharply, reaching near-universal participation by 2012.

These results are consistent with the predictions in Section 2. Retailers with limited food

Figure 2: Store Count by Channel and SNAP Adoption Status

(a) 2008 (b) 2012

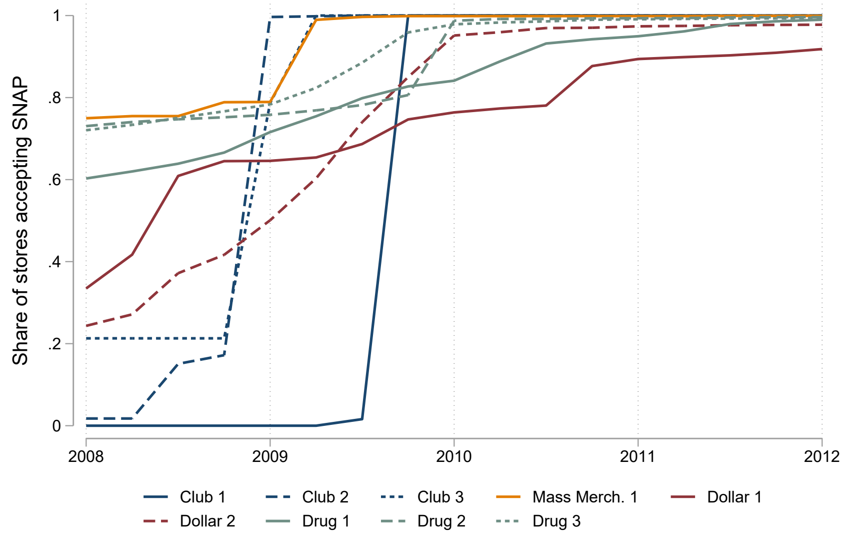


Notes: Total store counts are from NielsenIQ's TDLinx; counts of SNAP-authorized stores are from USDA-FNS STARS. The sample is limited to retailers we are able to link across the two sources, covering 54 of the top 100 chains by household expenditure.

offerings or with higher-income clientele were initially less likely to participate in SNAP. In particular, drug, dollar, mass-merchandiser, and club store formats historically carried a large share of non-food goods and club stores further required paid memberships and catered to higher-income shoppers. By contrast, grocery stores—–offering a broad selection of foods and serving customers across the income distribution—–were already nearly universal SNAP participants in 2008. The legislated benefit expansion under the ARRA in 2009 likely increased the incentive for marginal stores to adopt, spurring the wave of non-grocery adoptions observed during this period.

The increase in SNAP acceptance outside the grocery channel is driven in large part by nine national chains. Figure 3 plots adoption timing for stores in these nine anonymized chains. Some chains adopted in a single wave (Club 1–3; Mass Merchandiser 1; Drug 2), while others rolled out adoption more gradually (Dollar 1, Dollar 2, Drug 1, Drug 3). In what follows, we exploit both store- and chain-level variation in adoption timing for identification.

Figure 3: SNAP Adoption by Chain



Notes: This figure plots the share of stores authorized to accept SNAP within each chain over time, from 2008 to 2012, for nine anonymized chains. Total store counts are drawn from Nielsen TDLinx, and counts of SNAP-authorized stores are drawn from FNS STARS. The sample is restricted to stores that can be linked across the two data sources.

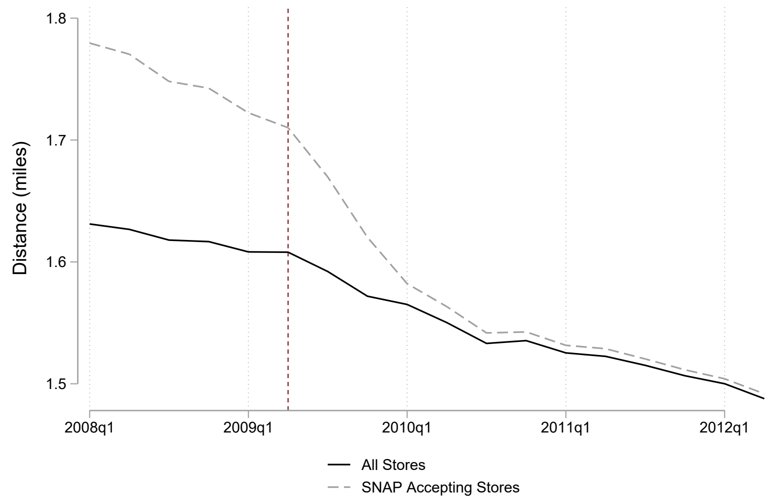
4.2 Changes in Household Access to SNAP Stores

We next examine how store SNAP adoptions changed household access to food benefits. Using the Household Store Choice dataset, Figure 4 plots two series for households over time: the average distance to the nearest SNAP store and the average distance to the nearest food store of any kind. The first measure will decrease either when new SNAP stores open or when existing stores begin accepting SNAP, while the second falls only when new stores open. Plotting both series allows us to separate changes in general store access from changes in access to stores that accept benefits.

From 2008 to 2012, the average distance to the nearest food store declined from 1.63 to 1.49 miles (an 8.6% decrease), reflecting the expansion of drug and dollar formats shown in Figure 2. Over the same period, the average distance to the nearest SNAP-authorized store fell more sharply—from 1.78 to 1.49 miles (a 16.3% decrease)—with the steepest decline occurring after the legislated benefit increase in 2009Q2.

These reductions represent meaningful declines in the minimum travel distance to SNAP-

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



Notes: This figure plots the mean distance for consumer panel households to the nearest store location in the Household Store Choice Dataset. 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. The nearest distance is based only on stores in top 54 chains and excludes households with no chain within 15 miles.

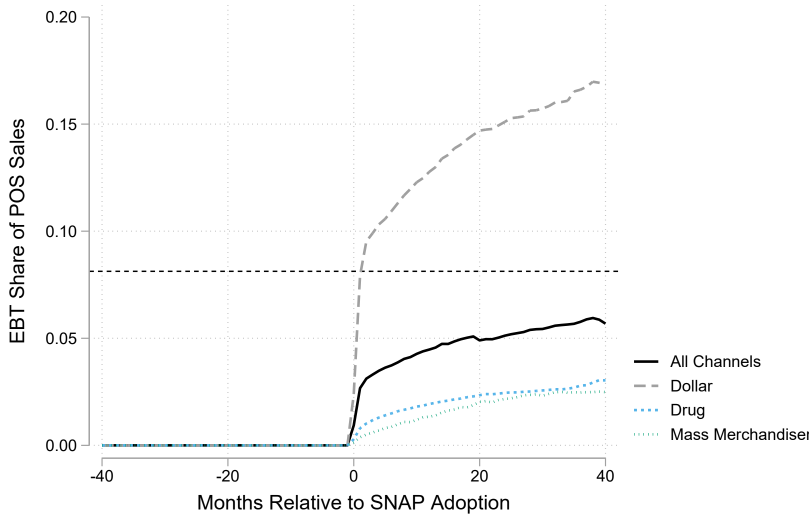
authorized retailers for SNAP-eligible households, potentially lowering shopping burdens and generating welfare gains. Below, we examine the extent of these gains.

4.3 Evolution of EBT payments after SNAP Adoption

Lastly, we use our novel linkage of store-level sales (Circana Core Outlets) to administrative records on SNAP authorization (FNS STARS) to provide the first evidence on how EBT payments evolve after a store adopts SNAP. Figure 5 plots monthly EBT payments as a share of food sales by months since adoption (Figure A.1 shows the corresponding EBT totals). Across channels, EBT shares rise sharply at adoption and remain elevated for at least 40 months, with some gradual increase over time. This continued growth likely reflects adjustment frictions: consumers learn about newly accepting stores and adjust shopping habits, while stores may adapt their assortment and pricing in response to new demand.

On average across adopters, EBT accounts for about 5 percent of food sales after authorization. The share is substantially higher for dollar stores (around 15 percent) and lower for mass merchandisers and drug stores (about 2.5 percent). This heterogeneity reflects dif-

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



Notes: This figure plots average monthly EBT payments as a share of point-of-sale food sales, relative to the month of SNAP adoption. The sample includes all adopting stores in the Retailer Panel, which links Circana Omnimarket Core Outlets to FNS STARS. The horizontal line shows the mean for stores that always accept SNAP in the Retailer Panel.

ferences in overall food sales volumes across formats, as well as differences in the shopping patterns of SNAP households across channels.

These patterns suggest that SNAP is likely an important revenue source for adopting stores, but the effect on overall sales depends on whether SNAP purchases substitute for, or add to, pre-existing non-SNAP spending at these outlets. If SNAP meaningfully increases revenue, retailers may respond by adjusting their competitive strategies—–pricing and product assortment—–in ways that affect both SNAP and non-SNAP households.

5 The Causal Effects of SNAP Adoption on Retailer Outcomes

We now turn to the causal effects of SNAP adoption on retailer outcomes. Higher sales for adopting retailers (and potentially lower sales for their competitors) could reflect shifts in customer traffic or spending, but could also arise as a result of changes to pricing or product variety. To disentangle these channels, we next examine pricing and product variety directly. Changes in these outcomes would indicate that, beyond improving proximity, SNAP adoption also alters other store amenities in ways that could affect SNAP shoppers, with potential spillovers to non-SNAP shoppers as well. The household welfare analysis later in the paper uses a revealed-preference framework to quantify how much shoppers value these store-level changes brought about by the wave of SNAP adoptions.

5.1 Identification Strategy

We use an event study approach to estimate how store outcomes evolve after SNAP adoption. As shown in our analysis of EBT payments, customer spending tends to adjust gradually after stores begin accepting SNAP, motivating a dynamic specification. We also examine outcomes in the months before adoption to check for any pre-existing trends that could confound our estimates.

In our setting, an "event" is a change in SNAP adoption——either the month a store itself becomes authorized or a change in the share of its competitors that accept SNAP. The first is a discrete change ("turning on" in a single month), while the second is a continuous measure that can vary in intensity over time. To jointly estimate the effects of both types, we apply the generalized event study approach of Schmidheiny and Siegloch (2023), which accommodates repeating treatments of varying intensities.

Formally, for store i in month t we estimate the following by weighted OLS:

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

where $Y_{i,t}$ is log sales, log EBT, log price, or log variety, and weights are the store's mean monthly sales over the full sample period. ℓ indicates the number of months relative to period t. $\text{StoreAdopt}_{i,t-\ell}$ is an indicator for whether store i adopted SNAP ℓ months before t. $\text{CompetitorsAdopt}_{i,t-\ell}$ denotes the month-to-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, binning observations outside this window.

The model includes store fixed effects (μ_i) and normalizes the coefficients for $\ell = -1$ to zero, so all other event study coefficients measure deviations from the month immediately preceding adoption, within the same store. County-by-month ($\theta_{cty(i),t}$) and channel-by-month ($\gamma_{ch(i),t}$) fixed effects control for local and channel-specific shocks. Standard errors are clustered at the census block level, which is also the level at which competitor adoption is defined.

The event study graphs plot the estimated coefficients on the leads and lags of each treatment variable. For the discrete store-adoption measure, we plot the lead and lag coefficients directly. For the continuous competitor-adoption measure, we plot the estimated change in the outcome associated with a one–standard deviation change in treatment. These figures are interpreted analogously to standard event studies.

Identification requires that, conditional on controls, counterfactual trends in outcomes are uncorrelated with treatment intensity. Although this assumption cannot be tested directly, the pre-adoption lead coefficients offer evidence on whether divergent trends existed prior to adoption.

To illustrate the variation that identifies our estimates——and the extent to which it is spread over time——we plot monthly changes in SNAP adoption in Figures A.2 and A.3. Figure A.2 shows the number of store adoptions per month from 2008–2012 in our retailer panel. Adoption peaks in early 2010, with over 1,000 stores adopting in January, but continues at roughly 100 per month through 2011–2012. Figure A.3 shows the corresponding change in competitor adoption, which rises steadily from just over 85% in early 2008 to nearly 100% by early 2011. This spread in adoption timing helps ensure that our event study design is not driven by a single period, allowing us to control flexibly for time-specific shocks.

5.2 Results

5.2.1 Effects on Own Store Outcomes

We first examine how SNAP adoption affects a retailer's own food sales, as well as its pricing and product variety. Figure 6 plots the event study estimates $\beta_{1\ell}$ from Eq. (1) for each outcome using the full retailer sample,[14] while Figure A.4 reports effect estimates 10-12

14. Table A.1 provides the corresponding point estimates.

months after SNAP adoption (with 95% confidence intervals), separately by retailer channel. Dollar stores experience the largest sales increases, while convenience stores experience the smallest.

Panel (a) of Figure 6 shows a sharp increase in food sales one month after adoption, followed by more moderate growth over the first year. Sales level off at roughly 6% above their pre-adoption level between 9 and 12 months post-adoption. In contrast, the pre-adoption coefficients are small ($|\beta_{1\ell}| < 0.02$) and lack a consistent sign, supporting our identifying assumption that adoption timing is unrelated to pre-existing sales trends.

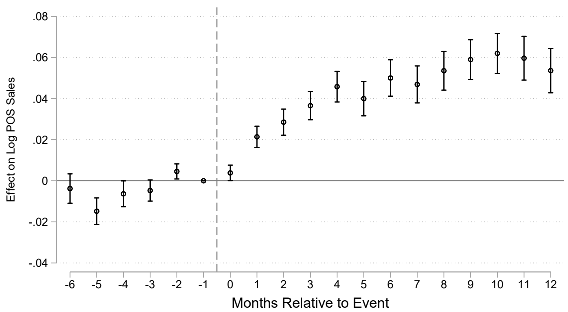
The increases in food sales observed at SNAP-adopting outlets are relatively large and may reflect changes in store offerings—such as product variety and prices—as well as the fact that SNAP customers can now use their benefits at these stores. To investigate these potential channels, we next examine how prices and product variety change following SNAP adoption.

In Figure 6(b), we find little evidence of price changes following SNAP adoption. Event study estimates of store price indexes around adoption are small and show no consistent trend. All but one post-adoption coefficient are statistically indistinguishable from zero, and even the largest estimate—eight months after adoption—has a 95% confidence interval that rules out price increases above 0.6%. Channel-specific estimates in Figure A.4 are similarly small, all below 1 percent, in sharp contrast to the large heterogeneity observed in sales effects.

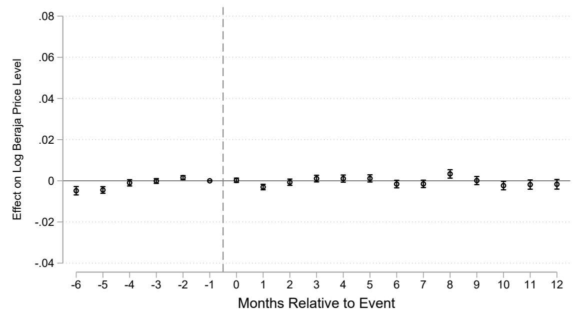
We next examine product variety. Figures 6(c)–(d) show clear increases in both the variety of UPCs and product categories offered after SNAP adoption. One year post-adoption, the national-sales–weighted UPC count is 4% higher than at adoption. Over one-quarter of this increase comes from new product categories, consistent with the requirement that SNAP-authorized retailers stock products across a range of food categories. The larger increase in UPC variety relative to category variety indicates that new products are concentrated within a few categories. Channel-level estimates in Figure A.4 show the largest increases in dollar

Figure 6: Impact of Store SNAP Adoption on Store Outcomes: Event Study Estimates

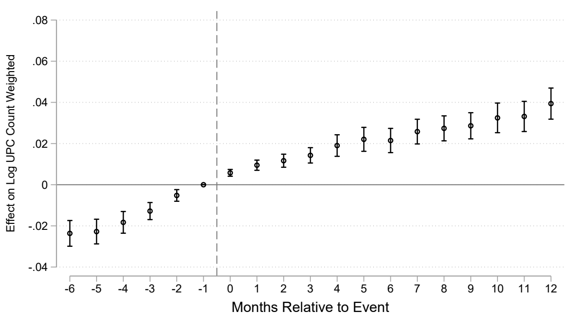
(a) Sales



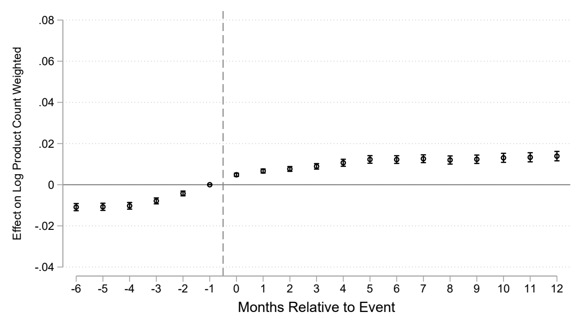
(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count



Notes: These figures plot event study estimates of $\beta_{1\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{1\ell}$ measures the effect of SNAP adoption on a store's sales, pricing, and product variety relative to event time $\ell = -1$. The specification is estimated using the Retailer Panel dataset. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

stores (12.0%) and mass merchandisers (16.7%), the same channels with the largest increases in sales.

Figure 6(c)-(d) also shows an increasing pre-trend in both measures of product variety beginning about 3 months before SNAP adoption. This result is consistent with stores increasing inventory to meet stocking requirements before they can begin accepting benefits. We find no evidence of a broader pre-trend: inventory coefficients for months –6 to –3 are similar in magnitude and statistically indistinguishable from one another, suggesting that the inventory build-up around adoption is unlikely to be driven by unrelated trends.

Including this pre-adoption "stock-up" period, variety increases at SNAP-adopting retailers amount to a 6% 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

We next examine how SNAP adoption by a retailer affects food sales, pricing, and product variety among its competitors ($\beta_{2\ell}$ from Eq.1). Figure 7 presents the event study estimates for each outcome.[15] Figure A.5 reports the corresponding coefficients and 95% confidence intervals for the effect 10-12 months after SNAP adoption by retailer channel.

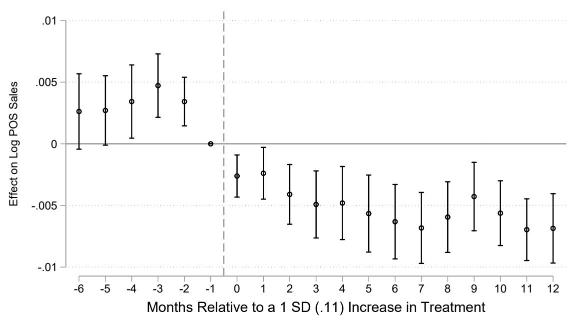
Figure 7(a) reveals a moderate decrease in sales following competitor SNAP adoption. A one–standard deviation increase in the market share-weighted share of local competitors accepting SNAP—–about an 11 percentage point increase from an average of 80%—–is associated with a 0.5% drop in sales. Given that the average store faces around 10 competitors, the treatment corresponds roughly to the entry of one additional SNAP-accepting retailer.

This decline begins one to two months before competitor adoption, potentially reflecting the anticipatory shift in inventory that we observe at adopting stores in Figure 7(c)-(d). Compared to the sales level four to six months before competitor adoption, the total effect is roughly –0.75%. By channel (Figure A.5), grocery stores experience the largest sales

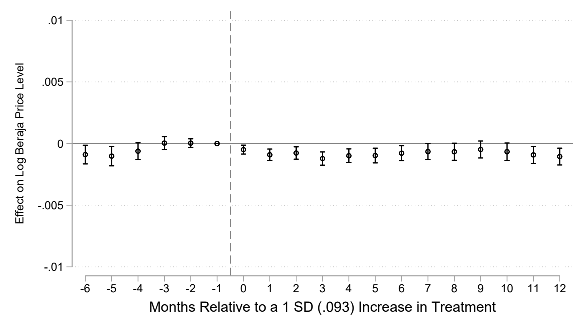
15. Appendix Table A.1 reports the corresponding point estimates.

Figure 7: Impact of Competitor Store SNAP Adoption on Store Outcomes: Event Study Estimates

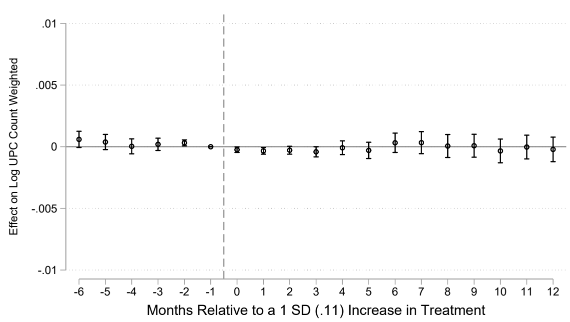
(a) Sales



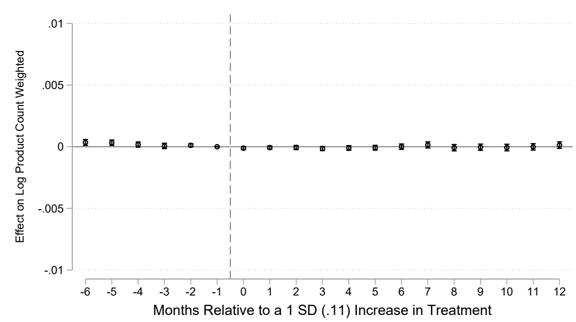
(b) Prices



(c) Weighted UPC Count



(d) Weighted Product Count



Notes: These figures plot event study estimates of $\beta_{2\ell}$ from Equation (1), alongside 95% confidence intervals. The coefficient $\beta_{2\ell}$ measures the effect of competitor store SNAP adoptions on a store's outcomes relative to event time $\ell = -1$, which corresponds to the month before adoption. Estimates are scaled to represent a one-standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, because the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

declines.[16]

Figure 7(b) shows a very small drop in prices in response to competitor SNAP adoption, which is statistically indistinguishable from the level four to six months prior to adoption. Figure 7(c)-(d) indicate no significant adjustments in product variety. Overall, we find little evidence that increases in SNAP adoption during our study period led competitors to change prices or product assortments.

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 captured by our specifications thus far. 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.8, show no evidence that store prices co-move with chain-level adoption, nor any evidence of price responses to chain-level adoption among competitors.

6 Welfare

Our analysis thus far shows that the 2008–2012 wave of non-grocer SNAP adoptions (i) reduced the distance to SNAP-accepting retailers, (ii) increased adopter revenues and product variety without affecting prices, and (iii) modestly reduced competitor sales, again without price or variety effects. From a revealed-preference perspective, the reallocation of shopper expenditures toward adopting stores suggests potential gains in consumer welfare. In this section, we use a simple model of retail demand to estimate the causal effects of SNAP adoption on the welfare of both SNAP and non-SNAP households.

16. To isolate competitive effects on stores that were already SNAP-authorized, we repeat the analysis restricting the sample to retailers that accepted SNAP throughout the study period (17,196 of the 29,228 retailers in the main sample). Results, reported in Appendix Table A.1, show a similar sales decline: relative to 4–6 months before competitor adoption, sales are about 0.7% lower 10 months after. For EBT sales specifically, the decline is about 0.8%.

6.1 Simple Model of Retail Demand

On each purchase occasion o in quarter t, consumer i of type $k \in \{\text{SNAP-eligible, SNAP-ineligible}\}$ residing in location $l(i,t)$ selects which store s to shop from to maximize indirect utility:

$$V_{i,s,t,o} = \delta_{s,t}^{k(i)} + \tau_{r(s)}^{k(i)} \ln dist_{l(i,t),s} + \varepsilon_{i,s,t,o}^{k(i)} \tag{2}$$

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 for channel $r(s)$; $dist_{l(i,t),s}$ is the distance between consumer i's residential location and store s at time t; and $\varepsilon_{i,s,t,o}^{k}$ is an iid draw from a standard type-I extreme value distribution, representing the idiosyncratic component of a household's preferences over stores at each purchase occasion.

For tractability, we assume that perceived quality $\delta_{s,t}^{k}$ is composed of the following additive components:

$$\delta_{s,t}^{k} = \delta_{ch(s),g(s)}^{k,0} + \delta_{ch(s)}^{k,1} t + \delta_{ch(s)}^{k,SNAP}\,\text{PostAdopt}_{s,t} \tag{3}$$

where $\delta_{ch(s),g(s)}^{k,0}$ is a baseline quality level, allowed to vary with g, an indicator for whether the store either always accepted SNAP during the sample (2008-2012) or adopted SNAP during this period. $\delta_{ch(s)}^{k,1} t$ is a linear time trend in quality, common across all stores in a chain. $\text{PostAdopt}_{s,t}$ indicates whether store s accepts SNAP at time t, and its coefficient, $\delta_{ch(s)}^{k,SNAP}$, is a chain-specific demand shifter that we use to measure how type-k households value SNAP acceptance in chain $ch(s)$.

These assumptions amount to a simplified version of a differences-in-differences framework within each chain, where the treatment is SNAP adoption. Within a chain, stores in a treatment group versus a comparison group can offer different levels of utility, but are assumed to share a common linear trend over time. Deviations from this trend for treated stores are attributable to the effects of SNAP adoption.

In Section 5, we found no systematic evidence of competitive responses (e.g., price or variety changes) when nearby stores adopt SNAP. Accordingly, our preferred specification rationalizes any loss in sales to a nearby SNAP-adopter as arising solely from the adopter's change in quality and does not allow for competitive responses by exposed stores.

We measure the impact of SNAP adoptions on expected consumer surplus per purchase occasion using inclusive values. In the model above, a type-k consumer's inclusive value over the retail opportunities across the set of stores S_l within 15 miles of location l in quarter t is:

$$IV_{l,t}^{k} = \Gamma + \log\left(\sum_{s\in S_{l,t}} \exp\left(\delta_{s,t}^{k} + \tau_{r(s)}^{k} \ln dist_{l,s}\right)\right) \tag{4}$$

where Γ is the Euler-Mascheroni constant, which cancels out when differences are taken. The inclusive value is the expected maximum utility offered by the set of store choices a consumer has, and takes this convenient form due to the distributional assumption on $\varepsilon_{i,s,t,o}^{k}$.

The overall change in expected consumer surplus from 2008 to 2012 is $IV_{l,t(2012Q2)}^{k} - IV_{l,t(2008Q1)}^{k}$. We are interested in the components of this change attributable to SNAP adoption, rather than changes in store quality or store entries. To that end, we consider two counterfactual changes in inclusive value. The first counterfactual ignores all store entries that occur between 2008 and 2012:

$$IV_{l,t(2012Q2)}^{k,\text{No Entry}} = \Gamma + \log\left(\sum_{s\in S_{l,t(2008Q1)}} \exp\left(\delta_{s,t(2012Q2)}^{k} + \tau_{r(s)}^{k} \ln dist_{l(t(2008Q1)),s}\right)\right) \tag{5}$$

Note that entry affects both the choice set and the distance to the nearest store in a chain from a given location. The second counterfactual ignores both the store entries and the SNAP adoptions that occur between 2008 and 2012:

$$IV_{l,t(2012Q2)}^{k,\text{No Entry, No Adopt}} = \Gamma + \log\left(\sum_{s\in S_{l,t(2008Q1)}} \exp\left(\delta_{s,t(2012Q2)}^{k,\text{No Adopt}} + \tau_{r(s)}^{k} \ln dist_{l(t(2008Q1)),s}\right)\right) \tag{6}$$

$$\delta_{s,t(2012Q2)}^{k,\text{No Adopt}} = \delta_{ch(s),g(s)}^{k,0} + \delta_{ch(s)}^{k,1} t(2012Q2)$$

$IV_{l,t(2012Q2)}^{k,\text{No Entry, No Adopt}}$ reflects the expected consumer surplus from the set of stores available in 2008, given their 2008 SNAP status, assuming that their chain quality had updated to its 2012 level, $\delta_{ch(s)}^{k,1} t(2012Q2)$. This counterfactual reflects the surplus from the 2008 store set, assuming 2008 SNAP status but updated 2012 chain trends.

To measure the welfare impact of SNAP adoptions between 2008 and 2012, we compute $IV_{l,t(2012Q2)}^{k,\text{No Entry}} - IV_{l,t(2012Q2)}^{k,\text{No Entry, No Adopt}}$. To measure the combined welfare impact of both SNAP adoptions and store entries between 2008 and 2012, we compute $IV_{l,t(2012Q2)}^{k} - IV_{l,t(2012Q2)}^{k,\text{No Entry, No Adopt}}$. Both metrics capture the additional expected consumer surplus accruing to households by 2012 due to SNAP adoptions and/or store entries that occurred between 2008 and 2012, assuming that store quality is otherwise at its 2012 level.

6.2 Estimating Equation

We estimate the distance elasticity and perceived quality parameters $\{\tau_s^r, \delta_{ch,g}^{k,0}, \delta_{ch}^{k,1}, \delta_{ch}^{k,SNAP}\}$ using Poisson pseudo maximum likelihood (PPML, Silva and Tenreyro (2006)). Because $\varepsilon_{i,s,t,o}^k$ is assumed to follow a type-I extreme value distribution, the probability $P_{i,s,t}$ that store s offers the highest utility to consumer i at any given purchase occasion in time t has a convenient closed form solution. Our application of PPML in this setting approximates $P_{i,s,t}$ with the observed share of household i's expenditure at store s (or, in robustness checks, the share of trips), given by $\frac{Y_{i,s,t}}{Y_{i,t}}$, with measurement error $\eta_{i,s,t}^k$:

$$\frac{Y_{i,s,t}}{Y_{i,t}} \cdot \frac{1}{\eta_{i,s,t}^k} = P_{i,s,t}^k = \frac{\exp(\delta_{s,t}^k + \tau_{r(s)}^k \ln dist_{l,s})}{\sum_{s \in S_{l,t}} \exp(\delta_{s,t}^k + \tau_{r(s)}^k \ln dist_{l,s})} \tag{7}$$

Rearranging terms and defining $\rho_{it}^k = -\log\left(\sum_{s \in S_{l,t}} \exp(\delta_{s,t}^k + \tau_{r(s)}^k \ln dist_{l,s})\right) + \log(Y_{i,t})$ yields the following PPML estimating equation:

$$Y_{i,s,t} = \exp\left(\delta_{s,t}^k + \tau_{r(s)}^k \ln dist_{l,s} + \rho_{it}^k\right) \eta_{i,s,t}^k \tag{8}$$

where $Y_{i,s,t}$ is household i's expenditure at (or trips to) store s in quarter t; $\delta^k_{s,t}$ is the perceived quality of store s at quarter t; and $\tau^k_{r(s)} \ln dist_{l,s}$ is the store distance adjustment. In practice, ρ^k_{it} is absorbed by household-by-quarter fixed effects.

We estimate demand separately for households who are SNAP-eligible ($k = 1$) and those who are ineligible ($k = 0$), and parameterize store-specific, time-varying perceived quality $\delta^k_{s,t}$ as follows:

$$\delta^k_{s,t} = \delta^{k,0}_{ch(s),g(s)} + \delta^{k,1}_{ch(s)} t + \delta^{k,SNAP}_{ch(s)} \text{PostAdopt}_{s,t} + \sum_{j=-2}^{3} \delta^{k,SNAP}_{ch(s),j} \text{StoreAdopt}_{s,t-j} \tag{9}$$

The first three terms mirror equation (3): $\delta^{k,0}_{ch(s),g(s)}$ is a baseline store quality within chain $ch(s)$, varying by whether a store always accepted SNAP ($g = 0$) or adopted during 2008-2012 ($g = 1$); $\delta^{k,1}_{ch(s)} t$ reflects a linear, chain-specific time trend; and $\delta^{k,SNAP}_{ch(s)}$, is the chain-specific demand shifter identified from adopting stores.

The final term accounts for the transitional dynamics that we observed in product offerings around the SNAP adoption date (see section 5). We want $\delta^{k,SNAP}_{ch(s)}$ to measure how consumers value SNAP acceptance after this adjustment period has occurred. Therefore, we include a set of event-time controls around SNAP adoption: $\text{StoreAdopt}_{s,t-j}$ is an indicator for whether store s in chain $ch(s)$ adopted SNAP j quarters before quarter t. We use $j = -2, ..., 3$ to capture variation from two quarters before adoption to a year after. With these controls, $\delta^{k,SNAP}_{ch(s)}$ acts as a chain-specific demand shifter that switches on when a store adopts SNAP, but ignores the period immediately surrounding the adoption.

This parametric form reflects three empirical patterns observed in our data: (i) absent adoption, store quality evolves approximately linearly over this time period, (ii) SNAP adoption generates a level shift in store quality outside of a 6-quarter transition window, and (iii) the qualities of SNAP adopting stores and always accepting stores evolve on similar trends between 2008 and 2012. Appendix A.9 demonstrate these trends and the extent to which our parametrization captures them.[17]

6.3 Parameter Estimation

We estimate equation (8) using the household purchasing panel and employ the resulting parameter estimates to compute the inclusive values defined in equations (4)-(6). For tractability, we assume households visit the nearest outlet of each chain. To reduce computational burden, we estimate SNAP-ineligible household preferences with a random 20% subsample (though we use all of the available purchase data for SNAP-eligible households).

The estimation identifies two sets of parameters for each household type: the chain-specific distance elasticities $\tau^k_{r(s)}$ and chain preference parameters $\delta^k_{s,t}$. Distance elasticities are identified from the extent to which households favor chains whose nearest outlet is closer to their home. If chains strategically locate nearer to (or further from) households with strong chain preferences, we might overestimate (underestimate) the distance elasticities. We assess the sensitivity of our welfare estimates to such potential biases below.

The store preference parameters are identified from variation in household store choices, conditional on distance. The household panel includes more stores than the store-level panel used in Section 5, allowing us to identify preferences for 54 of the top 100 chains. This set includes all chains that adopted SNAP en masse during our sample period, including club stores excluded from the earlier store-level analysis.

We normalize $\delta^k_{s,t}$ to zero for a large national grocery chain across all time periods.[18] Under this normalization, $\hat{IV}^k_{l,t}$ is interpreted relative to the value of the base chain in each period. Because the base chain's value is unlikely to be truly stable over time, a differencing of $\hat{IV}^k_{l,t}$ between the beginning and end of our sample will be sensitive to the choice of base chain. Our comparisons of 2012 surplus, $\hat{IV}^k_{l,t(2012Q2)}$, to surplus estimates in counterfactuals

17. Specifically, we estimate how chain preferences vary over time in a more flexible version of (8) that replaces $\delta^k_{s,t}$ from equation (9) with a finer set of fixed effects, and compare the two sets of time-varying preference estimates.

18. An alternative would be to normalize this chain's $\delta^k_{s,t}$ to zero in a single period, and allow preferences for that chain to grow linearly over time. This approach is not feasible, however, because of collinearity between the linear trends and the household-by-quarter fixed effects $\rho_{i,t}$. Our estimation strategy relies on these $\rho_{i,t}$ fixed effects to account for the denominators of the store choice probabilities and expenditure shares.

that remove entries and/or SNAP adoptions, are invariant to the choice of base chain.

6.4 Estimation Results

Table 1 reports channel-specific distance elasticities for SNAP-eligible and SNAP-ineligible households, estimated from equation (8) using expenditure as the dependent variable. The coefficients are statistically indistinguishable across the two groups, consistent with other work that finds no income gradient in distance elasticities (Cao et al. 2024). Both SNAP-eligible and SNAP-ineligible households are less distance elastic with respect to club, dollar, and mass merchandise stores than grocery or drug stores.

Table 1: Distance Elasticity Parameter Estimates

	SNAP-eligible (1)	SNAP-ineligible (2)
Log Distance × Grocery	-0.918	-0.911
	(0.023)	(0.015)
Log Distance × Drug	-0.896	-0.865
	(0.027)	(0.020)
Log Distance × Mass Merch.	-0.678	-0.689
	(0.037)	(0.020)
Log Distance × Dollar	-0.708	-0.694
	(0.032)	(0.029)
Log Distance × Club	-0.697	-0.727
	(0.045)	(0.024)
Pseudo R^2	0.619	0.594
Chain Count	54	54
Household Count	16,783	25,722
Observations	1,086,512	2,274,844

Notes: This table reports channel-specific distance elasticities, $\tau^k_{r(s)}$, with standard errors estimated using PPML, following Equation (8), with household expenditure as the dependent variable. Specifications are estimated separately for SNAP-eligible and SNAP-ineligible households. SNAP-eligible households are defined as those that have a household income below 130% of the Federal Poverty Line. The estimation uses the Household Store Choice Dataset, which contains household–chain–quarter observations for 2008–2012. The estimation sample includes the full set of SNAP-eligible households and a 20% random sample of SNAP-ineligible households. The specification includes household-by-quarter fixed effects. Standard errors are clustered at the block group level.

Figure 8 summarizes our estimates of the perceived quality implied by equation (9) at the start (2008Q1) and end (2012Q2) of the sample for non-traditional food chains included in the Circana Store Panel that adopted SNAP between 2008 and 2012. Panel (a) reports estimates for SNAP-eligible households, and Panel (b) for SNAP-ineligible households. Confidence intervals are wider for the SNAP-eligible sample, reflecting their smaller share (less than 10%) of the Household Panel.

In each plot, grey circles denote mean preferences for SNAP-adopting stores in 2008 ($\delta^{k,0}_{ch,g=1}$). Red diamonds show preferences in 2012 after 2012 ($\delta^{k,0}_{ch,g=1} + \delta^{k,1}_{ch} t(2012Q2) + \delta^{k,SNAP}_{ch}$). The blue squares show counterfactual preferences for those stores had they not accepted SNAP, i.e., accounting only for chain-specific trends ($\delta^{k,0}_{ch,g=1} + \delta^{k,1}_{ch} t(2012Q2)$).

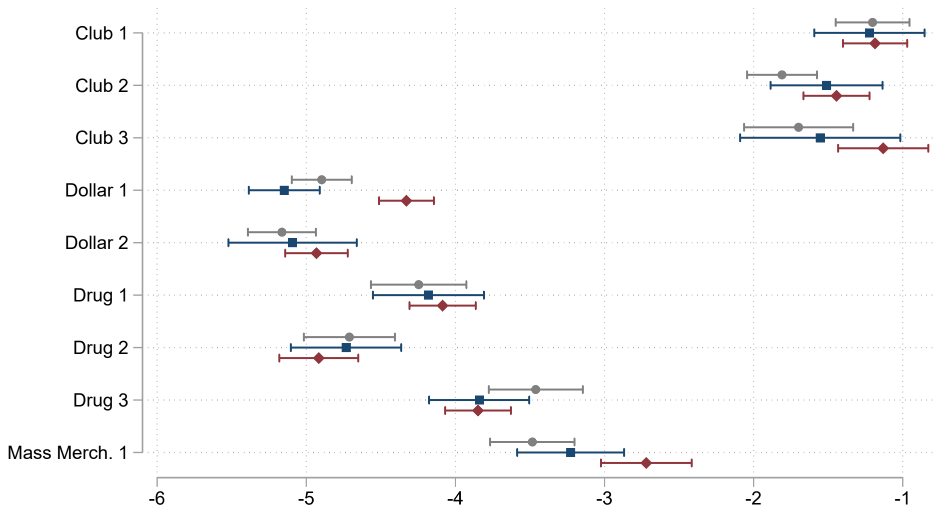
All of the preference estimates are negative, indicating that none of the non-traditional food chains that adopted SNAP over this period were preferred to the base grocery chain. The most preferred among them are the three warehouse club chains, followed by the mass merchandiser, then drugstores, and finally the dollar store chains.

The impact of SNAP adoption is captured by the gap between the blue squares and the red diamonds. Panel (a) shows that SNAP-eligible households at least weakly prefer all retailers once they accept SNAP benefits, with the exception of one drug chain. We estimate a statistically significant increase in preferences for Dollar Chain 1 and the mass merchandiser following SNAP adoption. Normalizing by the corresponding channel-specific distance elasticities, these increases imply that a SNAP-eligible household is willing to travel 69% farther to Dollar Chain 1 stores and 53% farther to the mass merchandiser once the stores adopted SNAP.

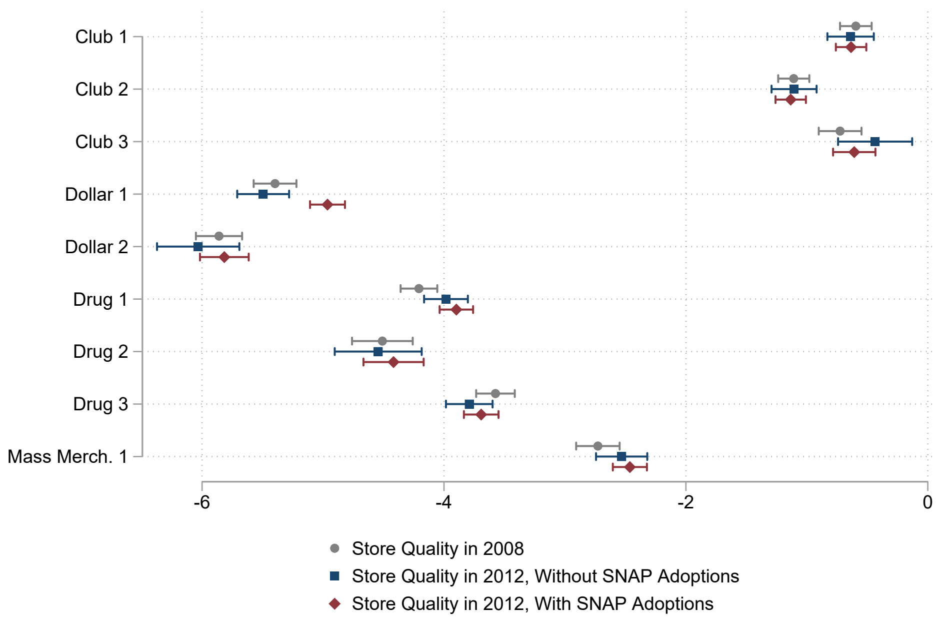
Among SNAP-ineligible households (Panel b), we estimate a similar increase in preferences for Dollar Chain 1 after SNAP adoption, but not for the mass merchandiser, which may have had less scope to expand food offerings given its existing assortment prior to adoption.

Figure 8: Chain Preference Parameter Estimates at Sample End-Points

(a) SNAP Eligible Households



(b) SNAP Ineligible Households



Notes: These figures plot point estimates of perceived store quality for SNAP-adopting stores for nine chains with a wave of SNAP adoptions between 2008 and 2012, along with 95% confidence intervals. The preference estimates are linear combinations of parameters estimated with PPML following equation 8 with expenditure as the dependent variable, for SNAP-eligible and SNAP-ineligible households separately, with standard errors clustered at the block group level. Parameters are normalized relative to the perceived store quality of the largest traditional grocery chain in our data. Panel (a) shows the preference estimates of SNAP-eligible households, while Panel (b) shows preferences of SNAP-ineligible households. The grey circles represent the mean preferences for SNAP-adopting stores in 2008 ($\delta^{k,0}_{ch,g=1}$), while the red diamonds reflect the preferences for those stores after they had adopted SNAP in 2012 ($\delta^{k,0}_{ch,g=1} + \delta^{k,1}_{ch} t(2012Q2) + \delta^{k,SNAP}_{ch}$). The blue squares reflect the preferences for those stores had they not accepted SNAP, that is, accounting only for the change in preferences attributable to chain trends ($\delta^{k,0}_{ch,g=1} + \delta^{k,1}_{ch} t(2012Q2)$). Uses the Household Store Choice Dataset, including all SNAP-eligible households, and a random 20% subsample of SNAP-ineligible households. This data contains household-chain-quarter level observations for 2008-2012. SNAP-eligible households have a household income below 130% of the Federal Poverty Line.

6.5 Welfare Results

We measure the welfare impact of SNAP adoptions as the difference in inclusive values between two counterfactuals. The first, $\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)}$ (equation (5)), measures expected consumer surplus from the set of stores present in 2008, allowing store qualities to evolve with chain trends and SNAP adoption. The second, $\hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$ (equation (6)), measures expected consumer surplus from the same 2008 store set, allowing qualities to evolve with chain trends but *not* SNAP adoption. We also compare these results to the combined effect of SNAP adoption and store entry, given by the difference between the inclusive value in 2012, $\hat{IV}^{k}_{l,t(2012Q2)}$ (equation (4)), and the inclusive value in the same period not allowing for SNAP adoption or entry, $\hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$).

Table 2 reports these estimates. Columns 1 and 4 show the average change in consumer surplus attributable to SNAP adoptions, while columns 2 and 5 report the combined effect of adoption and entry. Averages are calculated across census block groups, weighted by the estimated SNAP-eligible or SNAP-ineligible population, and scaled into standard deviations in average expected consumer surplus in 2012.

The first row summarizes aggregate effects across all stores. For SNAP-eligible households, SNAP adoption increased expected consumer surplus by 0.014 standard deviations, accounting for more than 20 percent of the overall gain from adoption and entry combined. For SNAP-ineligible households, adoption led to a small decline in expected consumer surplus (–0.003 standard deviations), reflecting weaker preferences for some chains after adoption. For example, in Figure 8 Panel (b), the red diamonds (post-adoption) lie to the left of the blue squares (counterfactual without adoption) for Clubs 2 and 3.

The remaining rows decompose results by retailer type. Not surprisingly, there are no welfare gains from grocery stores, which had almost universally adopted SNAP by 2008. Instead, the welfare impact of SNAP adoption arises almost entirely from non-traditional food retailers. For two of the three club chains and the mass merchandiser, adoption contributed more to SNAP-eligible household welfare than did new store entry over the period.

Table 2: Average Changes in Welfare from SNAP Adoption By Channel

	SNAP-eligible			SNAP-ineligible		
	SNAP (1)	SNAP + Entry (2)	SNAP Share (3)	SNAP (4)	SNAP + Entry (5)	SNAP Share (6)
Welfare Impact	0.014	0.069	21%	-0.003	0.053	-5%
Channel/Chain Impacts:						
Club	0.009	0.013	68%	-0.006	0.001	-465%
Club 1	0.001	0.003	40%	0.000	0.004	5%
Club 2	0.002	0.003	84%	-0.001	-0.001	239%
Club 3	0.005	0.007	73%	-0.005	-0.003	188%
Dollar	0.003	0.009	37%	0.002	0.004	38%
Dollar 1	0.002	0.003	65%	0.001	0.001	57%
Dollar 2	0.002	0.003	67%	0.001	0.001	77%
Drug	0.000	0.004	0%	0.001	0.005	18%
Drug 1	0.000	0.002	17%	0.000	0.002	12%
Drug 2	0.000	0.000	179%	0.000	0.000	84%
Drug 3	0.000	0.002	-3%	0.000	0.003	15%
Grocery	0.000	0.027	0%	0.000	0.031	0%
Mass Merchandiser	0.002	0.014	14%	0.000	0.011	4%
Mass Merchandiser 1	0.002	0.003	73%	0.000	0.002	22%

Notes: Units are standard deviations of welfare for the given population nationally in 2012, expressed in utils using inclusive values following equation (4). The table reports average household changes in welfare attributed to either SNAP adoption ($\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$) or SNAP adoption and store entry combined ($\hat{IV}^{k}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$), based on adoptions and entries that occurred between 2008 and 2012. Inclusive values are first calculated at the census block group level, then averaged nationally, weighting by the population of SNAP-eligible or SNAP-ineligible households. Columns (3) and (6) report the ratio of Column (1) by (2) and Column (4) by (5), respectively. Impacts are reported separately for SNAP-eligible and SNAP-ineligible households. Estimates are reported for overall population, then disaggregated by channel for all 54 chains in the Household Store Choice Dataset, and further disaggregated by chain for nine chains with a wave of SNAP adoptions between 2008 and 2012. The underlying parameters are estimated using PPML following equation (8), with household expenditure as the dependent variable. Specifications are estimated separately for SNAP-eligible and SNAP-ineligible households. The estimation sample is drawn from the Household Store Choice Dataset, including all SNAP-eligible households, and a random 20% subsample of SNAP-ineligible households. SNAP-eligible households are defined as those with household income below 130% of the Federal Poverty Line.

Appendix Table A.3 probes the sensitivity of these welfare impacts to deviations in the distance elasticities as estimated in Table 1. Multiplying all distance elasticities by 2 produces slightly smaller impacts of SNAP adoptions, at 0.009 standard deviations for SNAP-eligible households and 0 for SNAP-ineligible households. Dividing distance elasticities by 2 produces larger magnitudes, at 0.018 standard deviations for SNAP-eligible households, and -0.004 for SNAP-ineligible households. Restricting these distance elasticity adjustments to only club stores produces roughly similar results, showing that the club channel largely mediates this sensitivity.

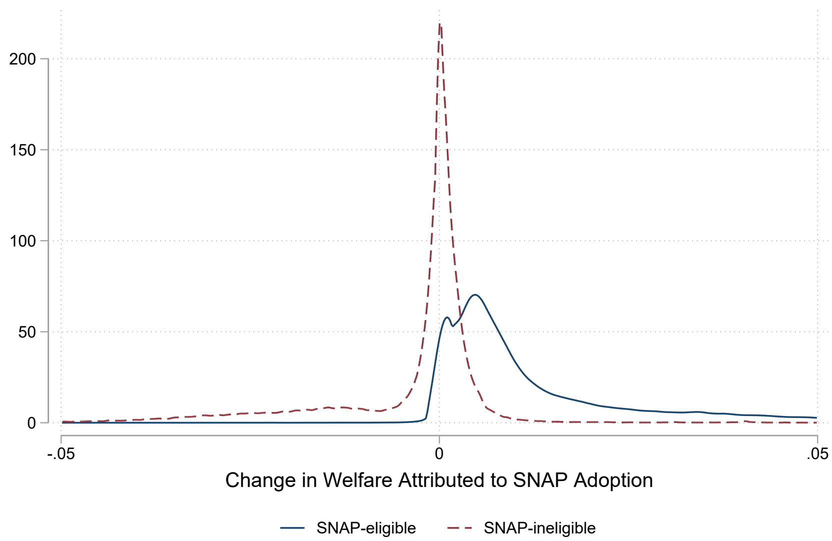
Appendix Table A.4 replicates Table 2 using trips instead of expenditure as the dependent variable in equation (8). Trips may correlate less well to the quantities of products purchased, but they avoid potential issues of expenditure changes being driven by price changes instead of quantity changes. While the null price results in Figure 6 largely preclude these concerns for SNAP adoption, the Retailer Panel used does not contain club stores, and so cannot speak to the largest driver of our welfare results. Nevertheless, using trips in Appendix Table A.4, SNAP impacts are only slightly lower for SNAP-eligible households, at 0.012 standard deviations. For SNAP-eligible households, the expected consumer surplus impact becomes 0. Combined with the sensitivity results of Appendix Table A.3, our findings of moderate gains for SNAP-eligible households appear robust, whereas the very small losses we detect for SNAP-ineligible households can fade to 0.

Figure 9 Panel (a) shows the distribution of estimated changes in expected consumer surplus that we attribute to SNAP adoption between 2008 and 2012 ($\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$) across population-weighted census block groups. Almost all SNAP-eligible households benefit from SNAP adoptions. The change in consumer surplus for SNAP-ineligible households, meanwhile, is evenly distributed around zero.

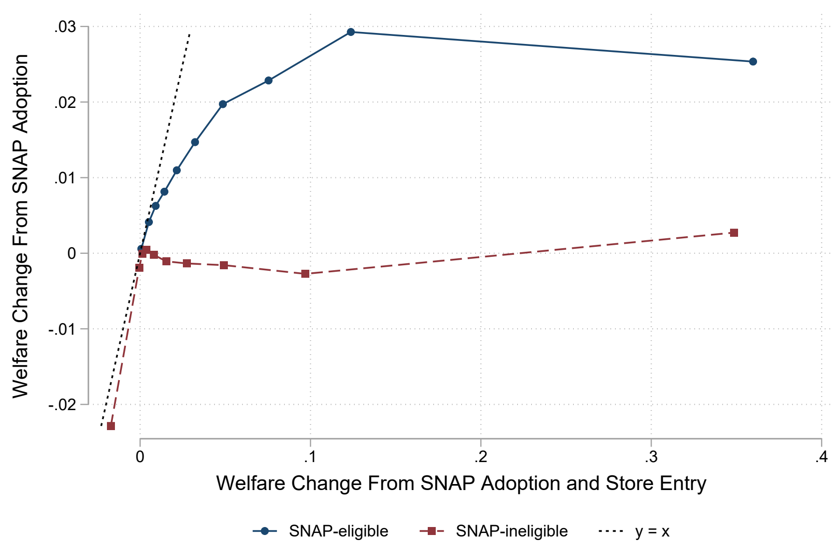
We next examine heterogeneity in welfare effects. Figure 9 Panel (b) compares the change in consumer surplus from SNAP adoption alone ($\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$) with the change from adoption plus entry ($\hat{IV}^{k}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$), binned into deciles of

Figure 9: Distributions of Household Welfare Changes

(a) Distribution of Changes in Welfare Attributed to SNAP Adoption



(b) Welfare Changes from SNAP Adoption Relative to Adoption and Store Entry



Notes: Panel (a) plots kernel density estimates of the distribution of changes in welfare attributed to SNAP adoption for adoptions that occurred between 2008 and 2012, defined as $(I\hat{V}^{k,\text{No Entry}}_{l,t(2012Q2)} - I\hat{V}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)})$, for SNAP-eligible and SNAP-ineligible populations separately, across population-weighted census block groups nationally. Panel (b) plots binscatters of these welfare changes versus against the combined effect of SNAP adoption and store entry over the same period, defined as $(I\hat{V}^{k}_{l,t(2012Q2)} - I\hat{V}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)})$. The binscatters are constructed using 10 deciles of the combined effect and show the average values of both variables within each group. For reference, Panel (b) also includes a 45-degree line denoted "$y = x$". Units are measured in standard deviations of welfare for the given population nationally in 2012, expressed in utils using inclusive values following equation (4). The underlying parameters are estimated using PPML following equation (8), with household expenditure as the dependent variable. Specifications are estimated separately for SNAP-eligible and SNAP-ineligible households separately. The sample is drawn from the Household Store Choice Dataset and includes all SNAP-eligible households and a random 20% subsample of SNAP-ineligible households. SNAP-eligible households are defined as those with household income below 130% of the Federal Poverty Line.

the latter.

For SNAP-eligible households (blue line), block groups with little welfare improvement from entry did benefit from adoption: SNAP adoption expanded access in areas that did not benefit from store entry. By contrast, in block groups with large welfare gains from entry, the effect of adoption flattens, consistent with the fact that many highly valued food retailers had already adopted SNAP before 2008.

For SNAP-ineligible households (red line), the bottom two deciles of block groups experience declines in consumer surplus almost entirely driven by adoption, as shown by the dashed red line tracking the 45-degree line below zero. For most other block groups, gains in consumer surplus are explained almost entirely by entry, with adoption contributing little beyond it.

Discussion Overall, we find that SNAP-eligible households benefited from the adoption of SNAP by non-traditional food retailers between 2008 and 2012. In many areas, these adoptions served as a substitute for new store entry, expanding access where entry was limited. Almost all SNAP-eligible households experience at least modest benefits from the 2008-2012 wave of SNAP adoption. The average welfare gain is equivalent to approximately a 1.8% reduction in travel costs to all stores, with some variation across census block groups in different retail environments.[19] The benefits are greatest in block groups proximate to stores from the three chains with the highest SNAP premiums (Dollar 1, Club 3, and the mass merchandiser) and far from others. The upper tail of the gains are still modest, however, with only 5% of SNAP-eligible households living in block groups with gains greater than an equivalent 6.2% reduction in travel costs to all stores, because the non-traditional retailers that adopt SNAP are undervalued relative to grocery stores, which already accepted SNAP at the beginning of our sample period.

19. $-1.8\% = \exp\left(\frac{0.014 \times 1.174}{-0.918}\right) - 1$, where 0.014 is the SNAP welfare impact from Column (1) of Table 2 in standard deviations of welfare in 2012, 1.174 is that standard deviation in terms of standard deviations of $\varepsilon^k_{i,s,t,o}$, and -0.918 is the distance elasticity estimate for grocery stores from Column (1) of Table 1. Since grocery stores have the largest distance elasticity estimate, this calculation represents a conservative lower bound on the equivalent distance reduction to all stores.

For SNAP-ineligible households, the results are more muted. While our event study evidence suggested that adoption could have benefited them through broader product assortments, the revealed-preference demand estimates indicate that adoption did not, on average, raise the perceived quality of adopting stores. Consequently, SNAP-ineligible households were largely unaffected by adoption.

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 product variety 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 percent, driven by non-traditional food retailers such as drug, dollar, club, and mass merchandisers. New adopters expanded product offerings and experienced sales increases of about 6 percent, with wide variation across formats. Nearby incumbents saw modest sales declines of roughly 0.5 percent but did not respond to the new competition by adjusting prices or variety.

We then estimate a retail demand model motivated by these stylized facts and event study results. The analysis shows that consumers, on average, prefer stores that accept SNAP, with stronger preferences among SNAP-eligible households. The welfare consequences of adoption were positive but modest overall: on average, the 2008–2012 adoption wave raised expected consumer surplus for SNAP-eligible households by the equivalent of a 1.8 percent reduction in travel costs, with nearly all SNAP households experiencing at least some gain. The largest benefits accrued in areas with limited access prior to adoption, where gains from adoption sometimes exceeded those from new store entry. For SNAP-ineligible households, effects were negligible——small positive responses at some chains offset by small losses at others.

Taken together, our evidence points to an important interplay between public programs and private vendors. Beyond their direct transfer effects, expansions in SNAP may also influence the structure of local food markets by altering vendor participation. These spillovers suggest that policies affecting program generosity and vendor incentives could indirectly shape household welfare.

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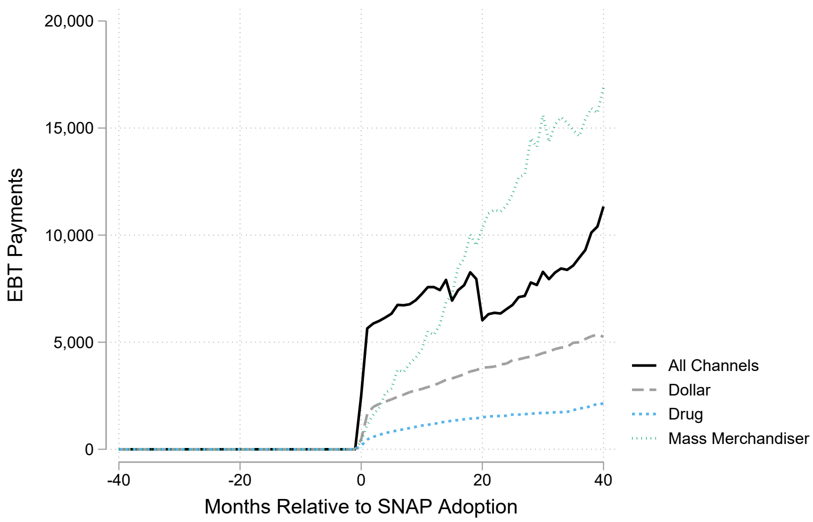
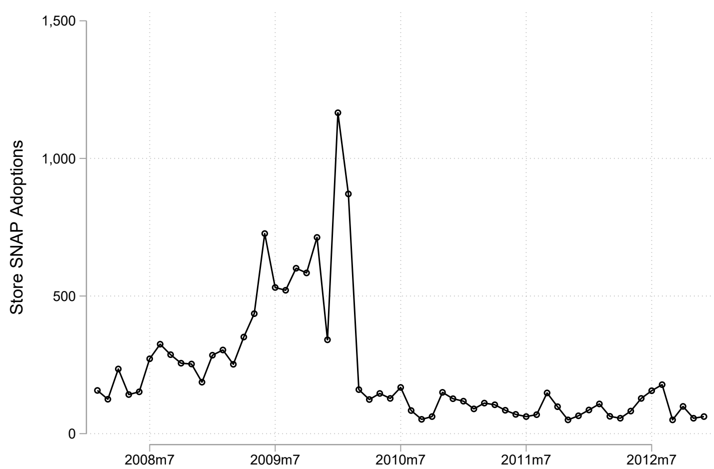
A.1 Appendix Figures

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



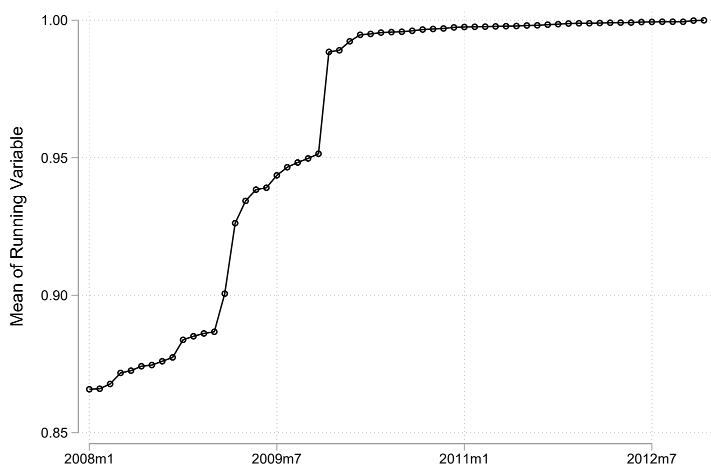
Notes: This figure plots the mean monthly EBT payments relative to the month the store adopted SNAP. The sample includes all SNAP adopting stores in the Retailer Panel, which links Circana Omnimarket Core Outlet data to FNS STARS data.

Figure A.2: SNAP Adoptions Over Time



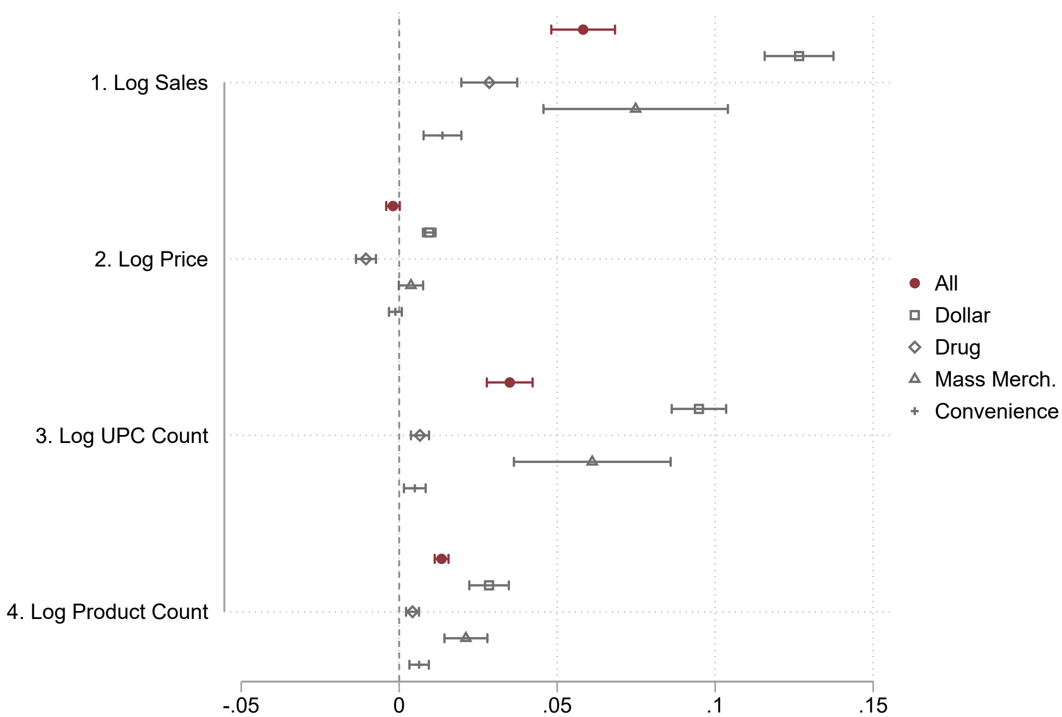
Notes: This figure plots the number of stores in the Retailer Panel which start accepting SNAP in the given month. The Retailer Panel links Circana Omnimarket Core Outlet data to FNS STARS data to detect SNAP adoptions.

Figure A.3: Mean Store Local Market SNAP Adoption



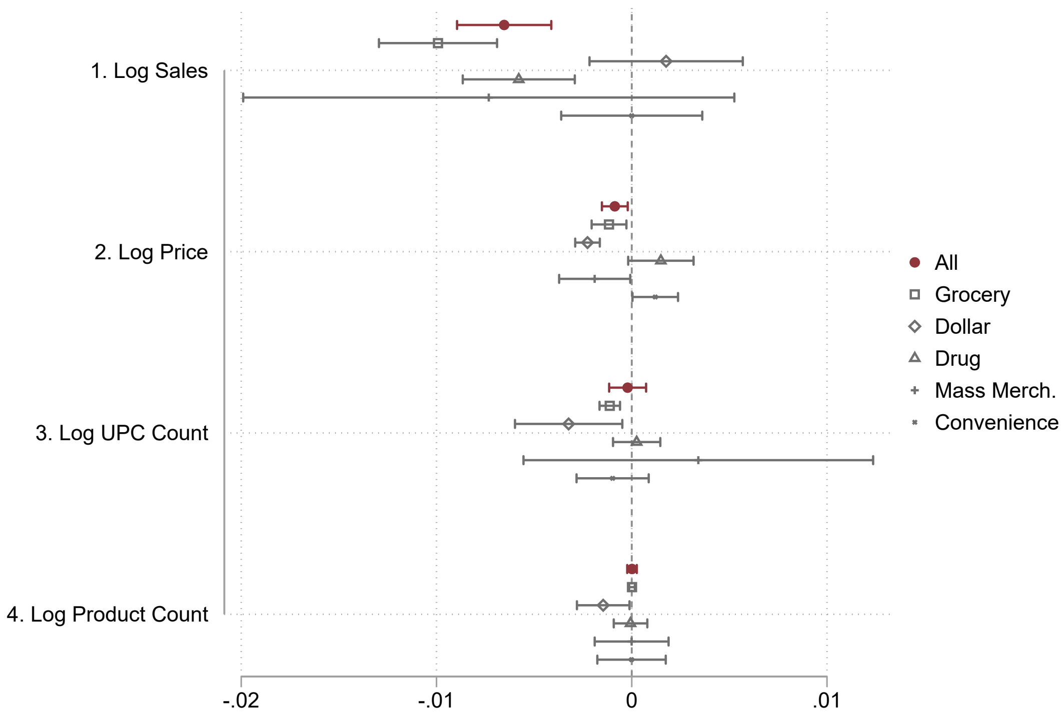
Notes: This figure plots the average value of the market share-weighted rate of SNAP acceptance among a store's local competitors in the Retailer Panel for the given month. Calculation details are in Appendix A.7. The Retailer Panel links Circana Omnimarket Core Outlet data to FNS STARS data to detect SNAP adoptions.

Figure A.4: Impact of Store SNAP Adoption on Store Outcomes: Estimates by Channel



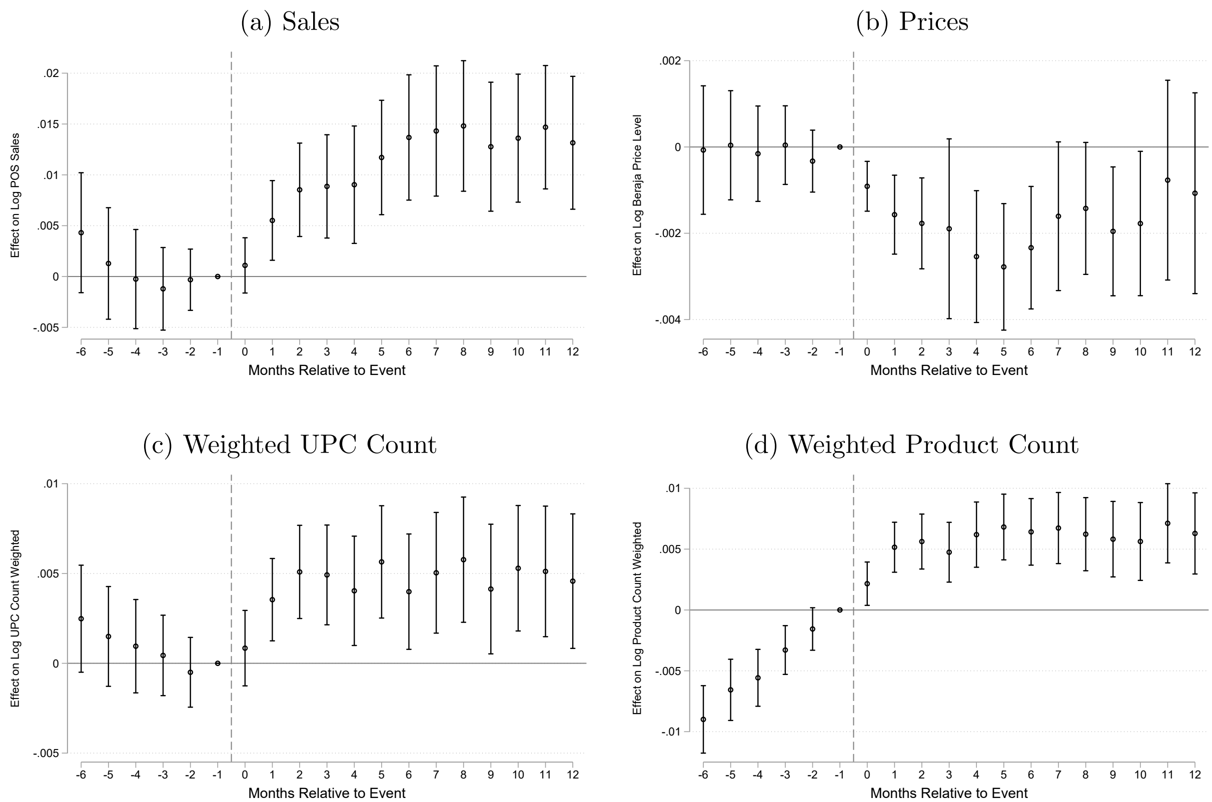
Notes: This figure reports estimates with 95% confidence intervals of the effects of SNAP adoption 10-12 months after SNAP adoption occurs, relative to one month prior to adoption. Effects are estimated in a version of Equation (1) which pools together certain months relative to adoption. Channel-specific estimates are obtained by restricting the sample to one channel at a time. The estimation sample is from the Retailer Panel data, where sales are total store (POS) sales, prices are measured by a singular price index, and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.5: Impact of Competitor Store SNAP Adoption on Store Outcomes: Estimates by Channel



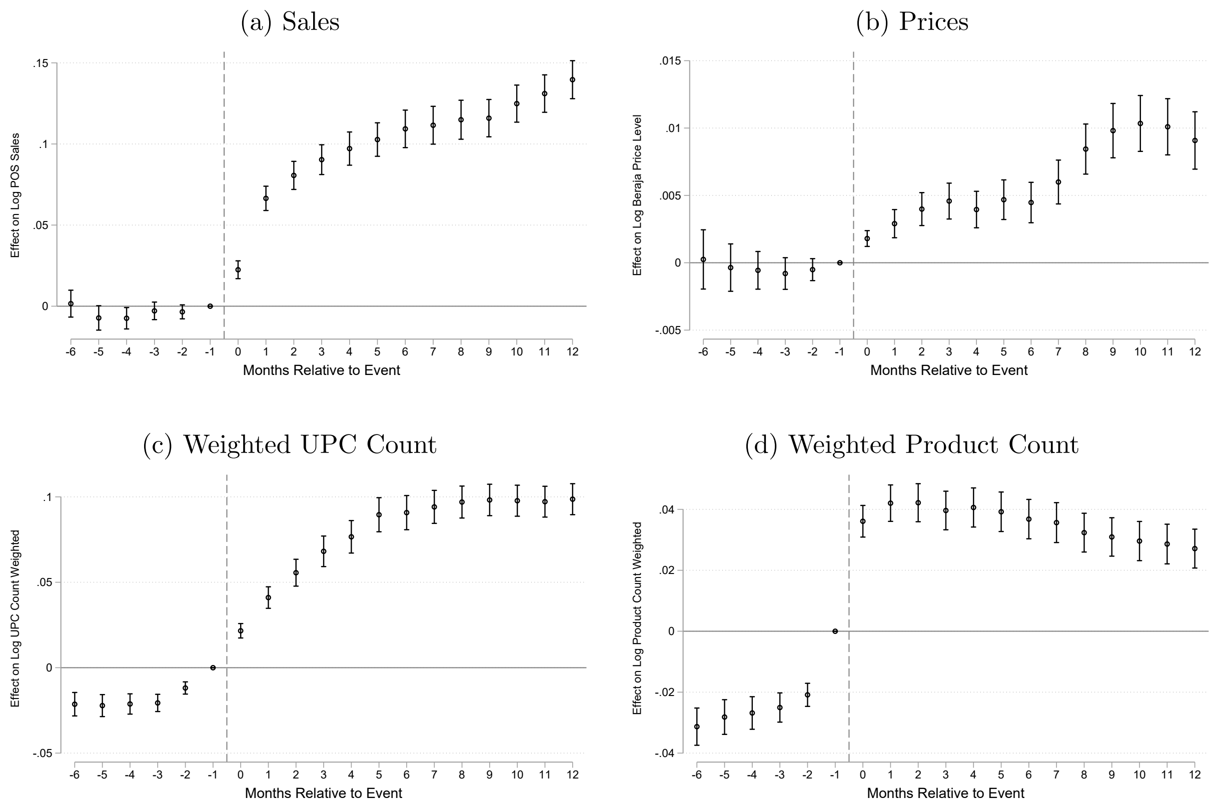
Notes: This figure reports estimates with 98% confidence intervals of the effects of competitor store SNAP adoptions on store outcomes 10-12 months after competitors adopt SNAP, relative to one month prior to the competitors' adoption. Effects are estimated in a version of Equation (1) which pools together certain months relative to adoption. Channel-specific estimates are obtained by restricting the sample to one channel at a time. Estimates are scaled to reflect a 1 standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, since the price index is not defined for the first year of the study period. The estimation sample is from the Retailer Panel data, where sales are total store (POS) sales, prices are measured by a singular price index, and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.6: Impact of Store SNAP Adoption on Store Outcomes for Convenience Stores: Event Study Estimates



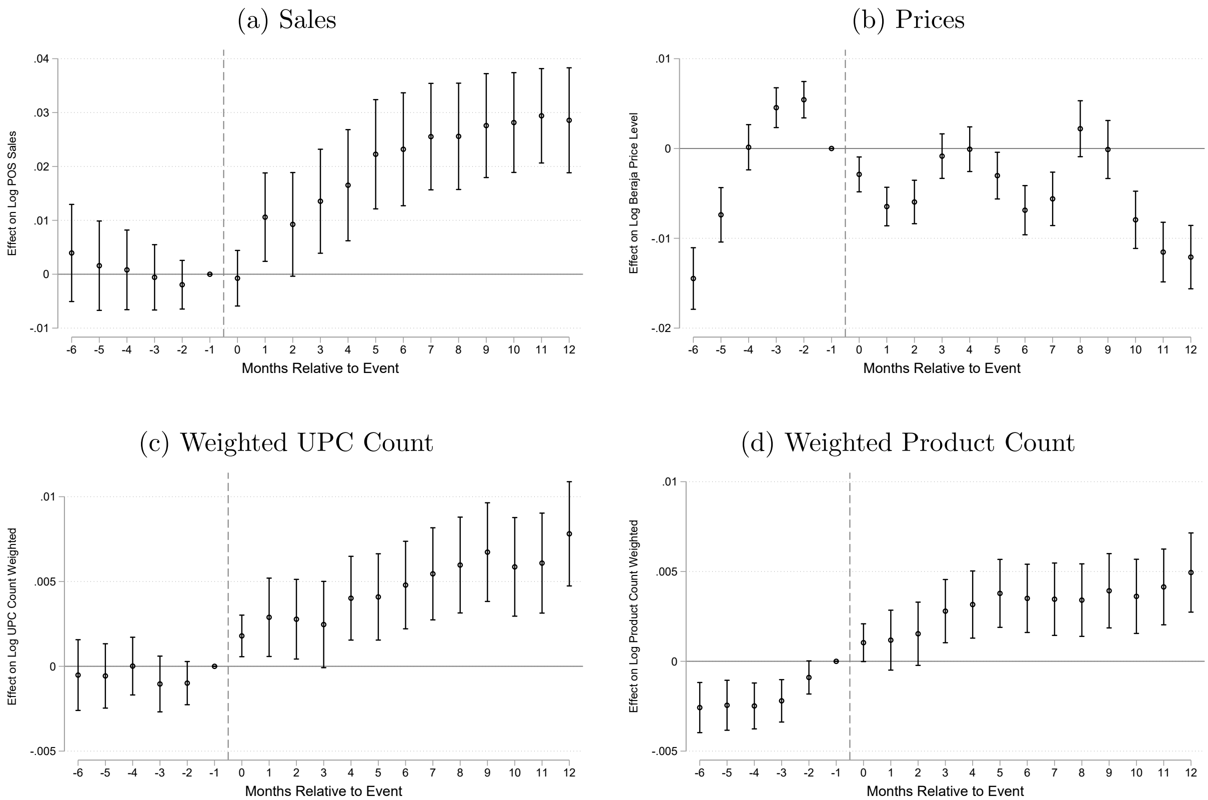
Notes: These figures plot event study estimates of $\beta_{1\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{1\ell}$ measures the effect of SNAP adoption on a store's sales, pricing, and product variety relative to event time $\ell = -1$. The specification is estimated using the Retailer Panel dataset, including stores from the convenience channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.7: Impact of Store SNAP Adoption on Store Outcomes for Dollar Stores: Event Study Estimates



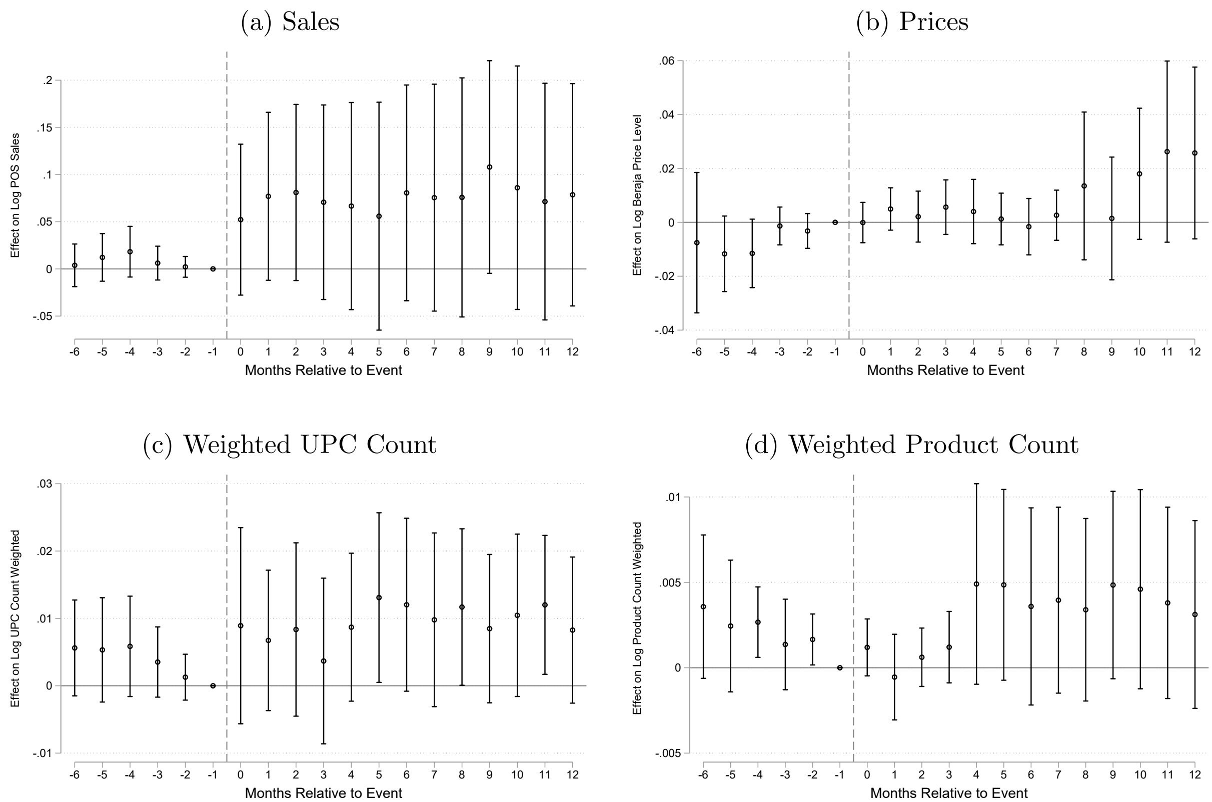
Notes: These figures plot event study estimates of $\beta_{1\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{1\ell}$ measures the effect of SNAP adoption on a store's sales, pricing, and product variety relative to event time $\ell = -1$. The specification is estimated using the Retailer Panel dataset, including stores from the dollar channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.8: Impact of Store SNAP Adoption on Store Outcomes for Drug Stores: Event Study Estimates



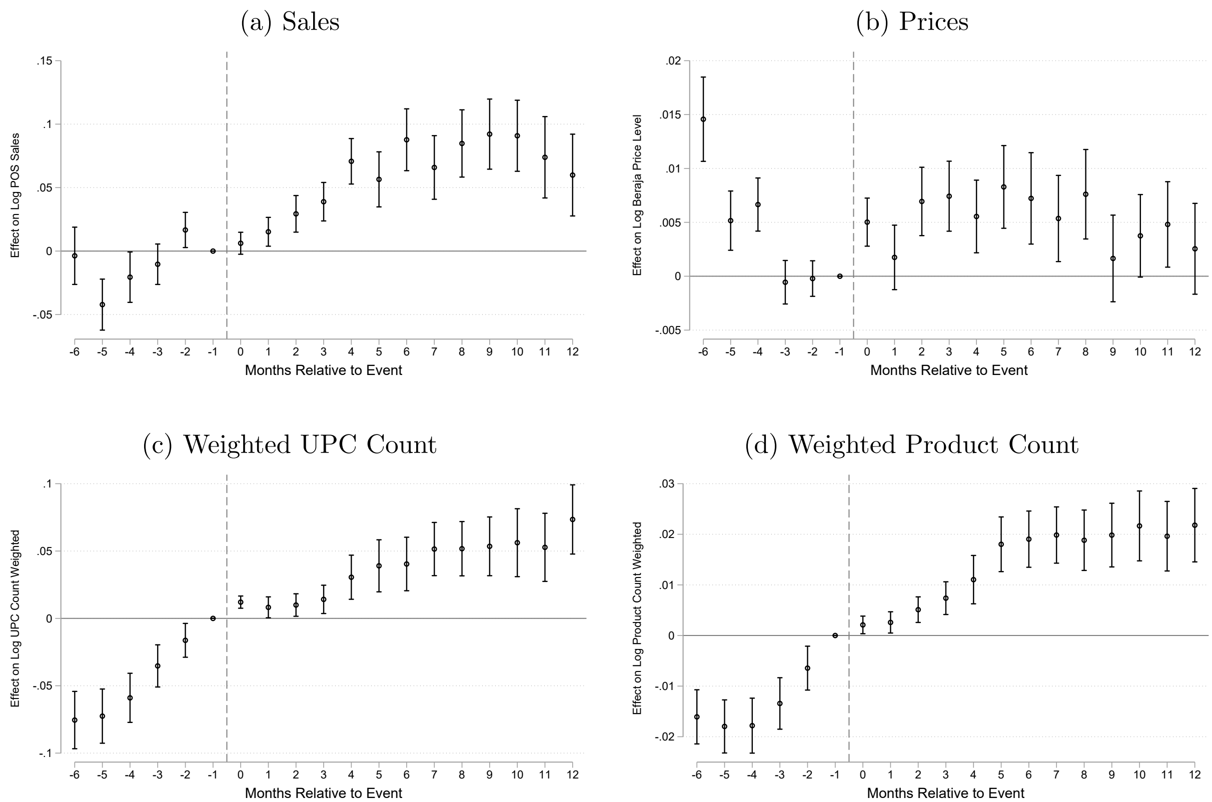
Notes: These figures plot event study estimates of $\beta_{1\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{1\ell}$ measures the effect of SNAP adoption on a store's sales, pricing, and product variety relative to event time $\ell = -1$. The specification is estimated using the Retailer Panel dataset, including stores from the drug channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.9: Impact of Store SNAP Adoption on Store Outcomes for Grocery Stores: Event Study Estimates



Notes: These figures plot event study estimates of $\beta_{1\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{1\ell}$ measures the effect of SNAP adoption on a store's sales, pricing, and product variety relative to event time $\ell = -1$. The specification is estimated using the Retailer Panel dataset, including stores from the grocery channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

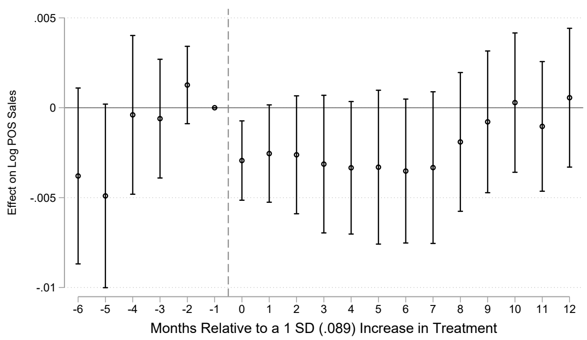
Figure A.10: Impact of Store SNAP Adoption on Store Outcomes for Mass Merchandisers: Event Study Estimates



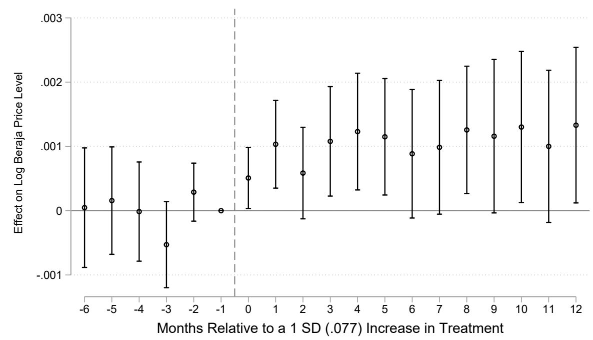
Notes: These figures plot event study estimates of $\beta_{1\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{1\ell}$ measures the effect of SNAP adoption on a store's sales, pricing, and product variety relative to event time $\ell = -1$. The specification is estimated using the Retailer Panel dataset, including stores from the mass merchandiser channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the share of competitors accepting SNAP, as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.11: Impact of Competitor Store SNAP Adoption on Store Outcomes for Convenience Stores: Event Study Estimates

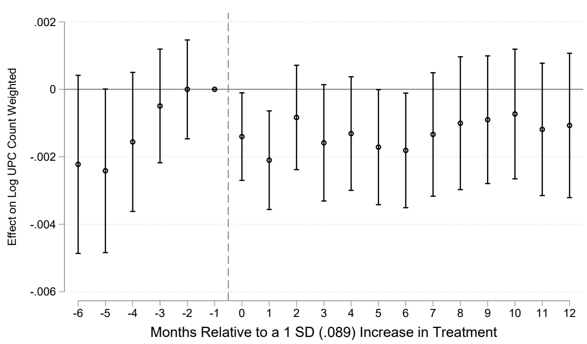
(a) Sales



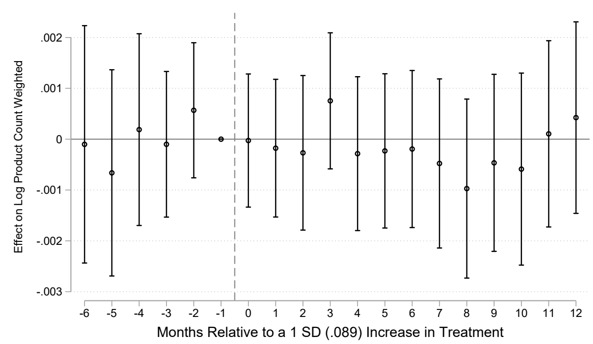
(b) Prices



(c) Weighted UPC Count



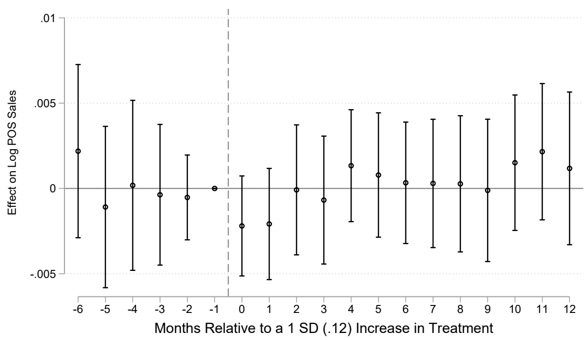
(d) Weighted Product Count



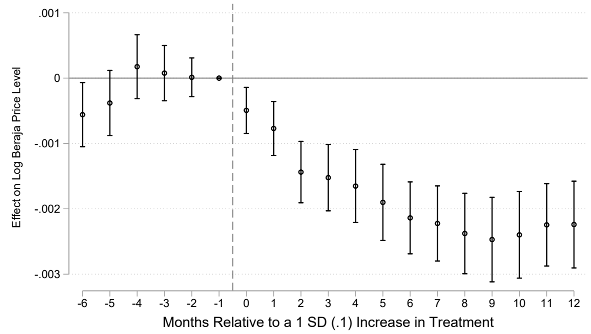
Notes: These figures plot event study estimates of $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{2\ell}$ measures the effect of competitor store SNAP adoptions on a store's outcomes relative to event time $\ell = -1$, which corresponds to the month before adoption. Estimates are scaled to represent a one-standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, because the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data, including stores from the convenience channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.12: Impact of Competitor Store SNAP Adoption on Store Outcomes for Dollar Stores: Event Study Estimates

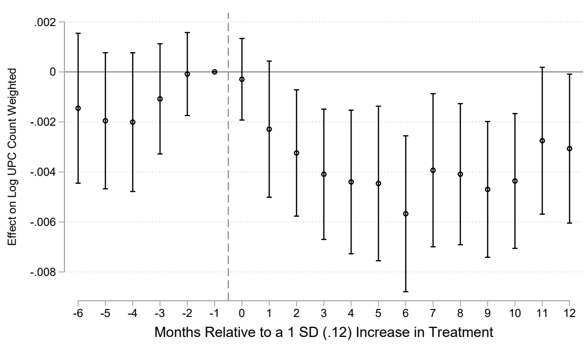
(a) Sales



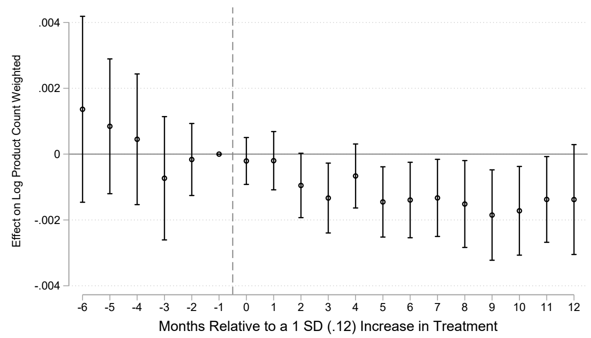
(b) Prices



(c) Weighted UPC Count



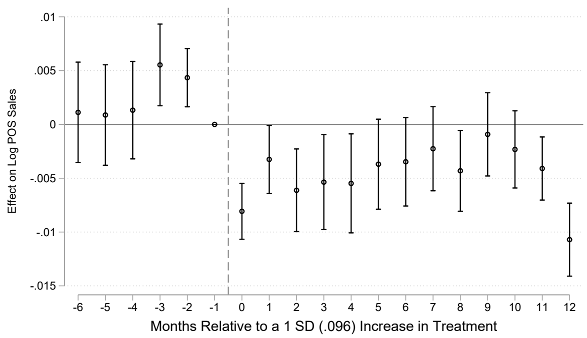
(d) Weighted Product Count



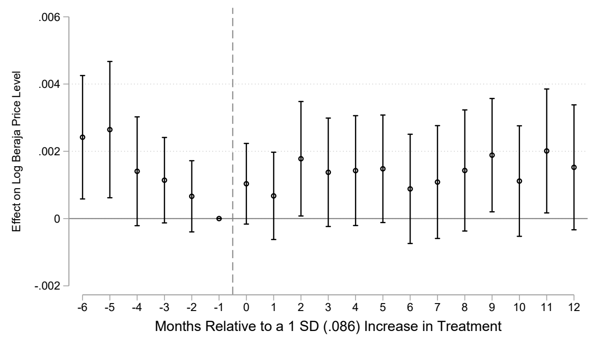
Notes: These figures plot event study estimates of $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{2\ell}$ measures the effect of competitor store SNAP adoptions on a store's outcomes relative to event time $\ell = -1$, which corresponds to the month before adoption. Estimates are scaled to represent a one-standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, because the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data, including stores from the dollar channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.13: Impact of Competitor Store SNAP Adoption on Store Outcomes for Drug Stores: Event Study Estimates

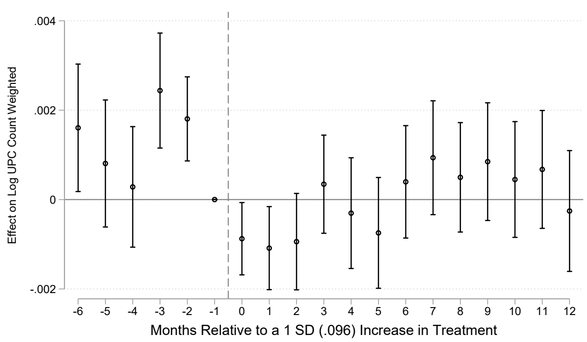
(a) Sales



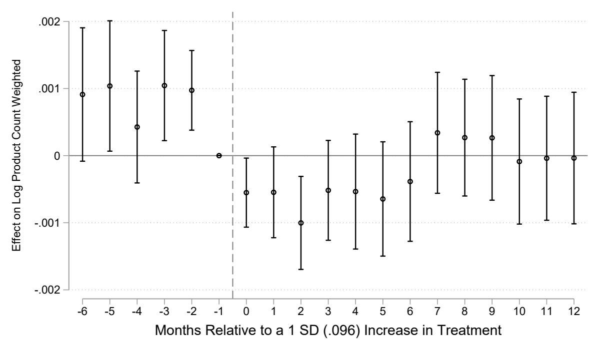
(b) Prices



(c) Weighted UPC Count



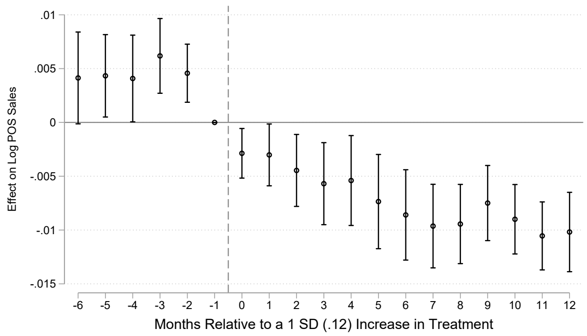
(d) Weighted Product Count



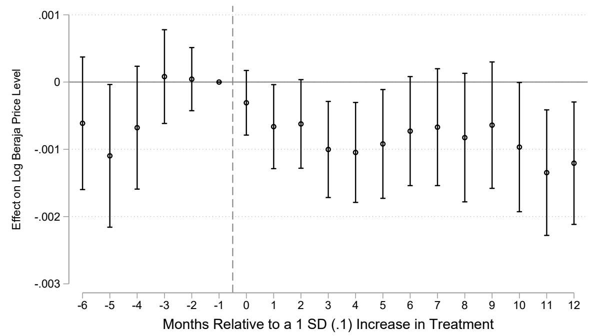
Notes: These figures plot event study estimates of $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{2\ell}$ measures the effect of competitor store SNAP adoptions on a store's outcomes relative to event time $\ell = -1$, which corresponds to the month before adoption. Estimates are scaled to represent a one-standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, because the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data, including stores from the drug channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.14: Impact of Competitor Store SNAP Adoption on Store Outcomes for Grocery Stores: Event Study Estimates

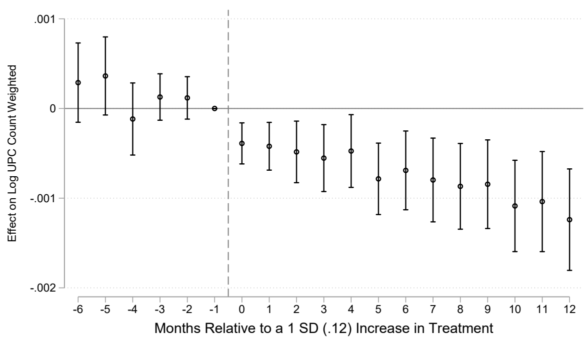
(a) Sales



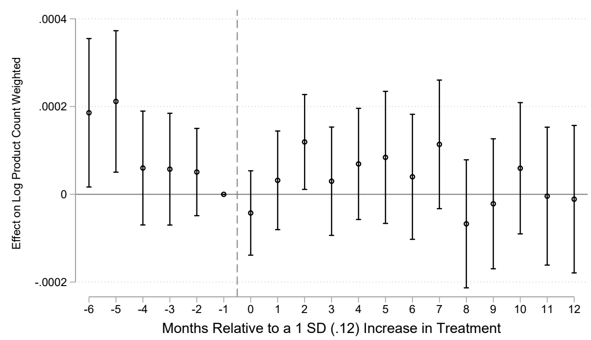
(b) Prices



(c) Weighted UPC Count



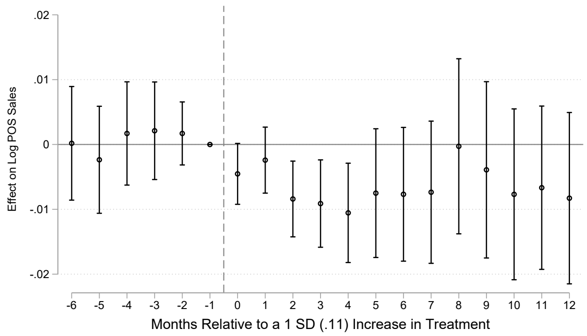
(d) Weighted Product Count



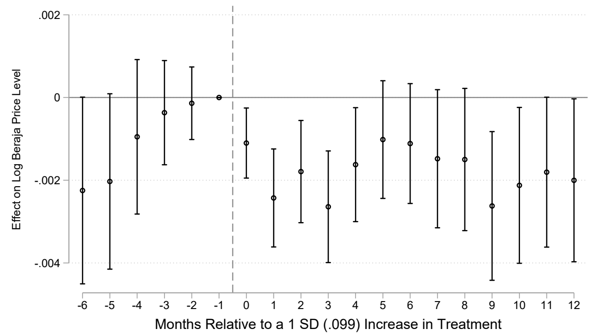
Notes: These figures plot event study estimates of $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{2\ell}$ measures the effect of competitor store SNAP adoptions on a store's outcomes relative to event time $\ell = -1$, which corresponds to the month before adoption. Estimates are scaled to represent a one-standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, because the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data, including stores from the grocery channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.15: Impact of Competitor Store SNAP Adoption on Store Outcomes for Mass Merchandisers: Event Study Estimates

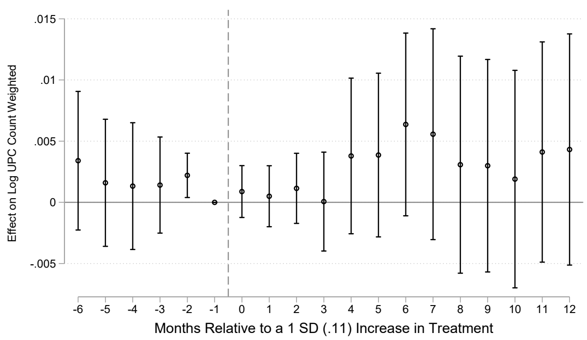
(a) Sales



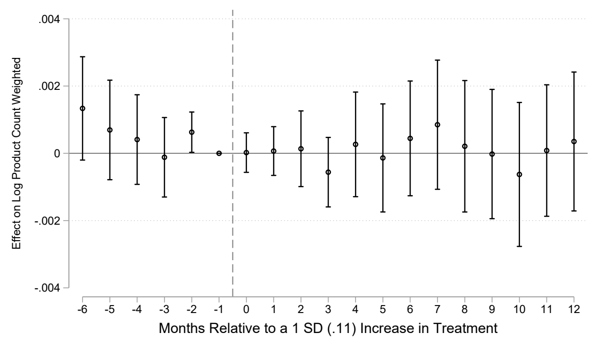
(b) Prices



(c) Weighted UPC Count



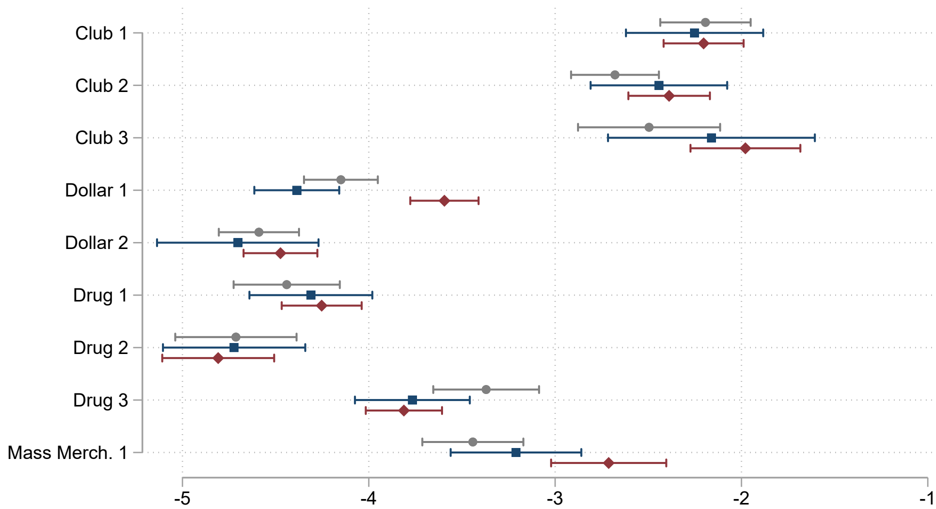
(d) Weighted Product Count



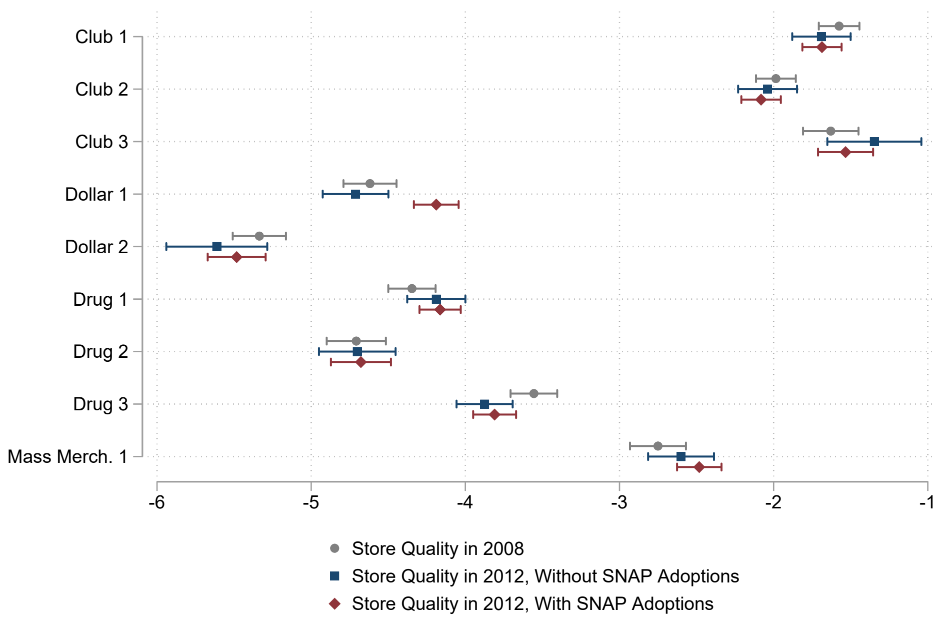
Notes: These figures plot event study estimates of $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals. The coefficient $\beta_{2\ell}$ measures the effect of competitor store SNAP adoptions on a store's outcomes relative to event time $\ell = -1$, which corresponds to the month before adoption. Estimates are scaled to represent a one-standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, because the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data, including stores from the mass merchandiser channel only. Sales are defined as total store point-of-sale revenue; prices are measured by a singular price index; and product variety is measured by national sales-weighted UPC and product counts. The specification is a generalized event study approach that includes controls for changes in the store's own SNAP adoption status as well as store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Figure A.16: Chain Preference Parameter Estimates at Sample End-Points Using Trips

(a) SNAP Eligible Households



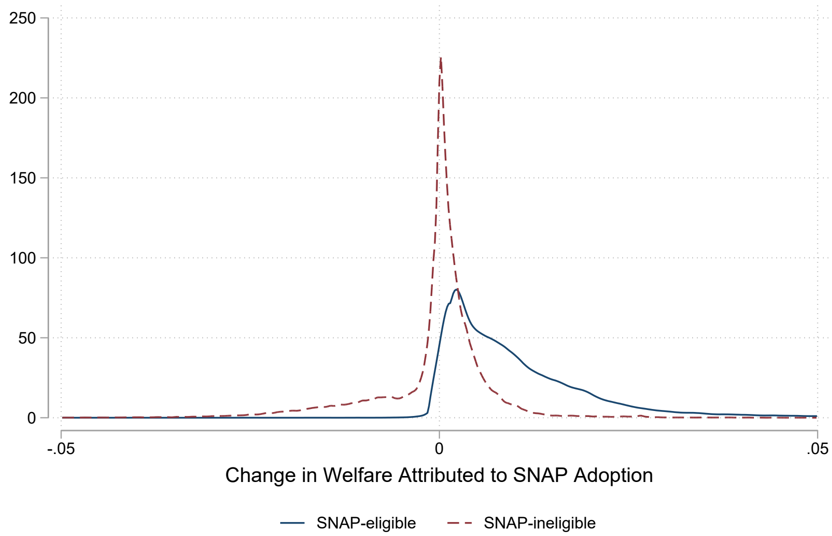
(b) SNAP Ineligible Households



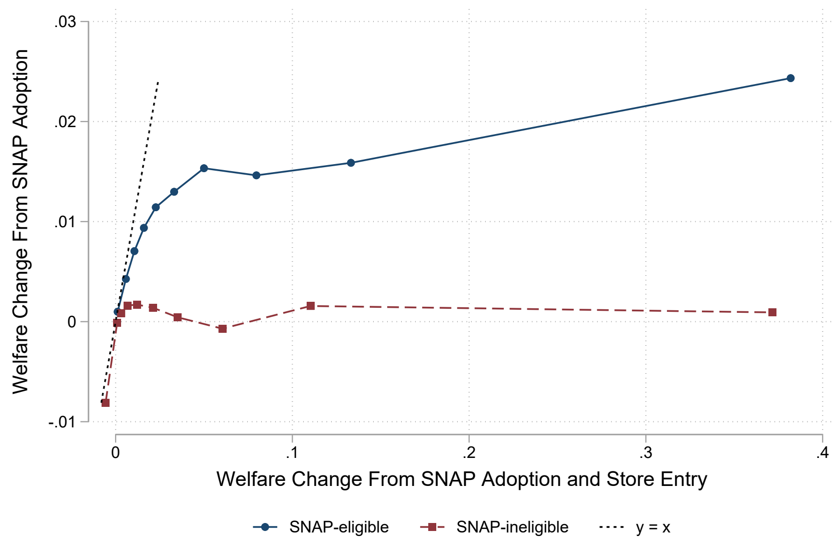
Notes: These figures plot point estimates of perceived store quality for SNAP-adopting stores for nine chains with a wave of SNAP adoptions between 2008 and 2012, along with 95% confidence intervals. The preference estimates are linear combinations of parameters estimated with PPML following equation 8 with number of trips taken to store as the dependent variable, for SNAP-eligible and SNAP-ineligible households separately, with standard errors clustered at the block group level. Parameters are normalized relative to the perceived store quality of the largest traditional grocery chain in our data. Panel (a) shows the preference estimates of SNAP-eligible households, while Panel (b) shows preferences of SNAP-ineligible households. The grey circles represent the mean preferences for SNAP-adopting stores in 2008 ($\delta^{k,0}_{ch,g=1}$), while the red diamonds reflect the preferences for those stores after they had adopted SNAP in 2012 ($\delta^{k,0}_{ch,g=1} + \delta^{k,1}_{ch} t(2012Q2) + \delta^{k,SNAP}_{ch}$). The blue squares reflect the preferences for those stores had they not accepted SNAP, that is, accounting only for the change in preferences attributable to chain trends ($\delta^{k,0}_{ch,g=1} + \delta^{k,1}_{ch} t(2012Q2)$). Uses the Household Store Choice Dataset, including all SNAP-eligible households, and a random 20% subsample of SNAP-ineligible households. This data contains household-chain-quarter level observations for 2008-2012. SNAP-eligible households have a household income below 130% of the Federal Poverty Line.

Figure A.17: Distributions of Household Welfare Changes Using Trips

(a) Distribution of Changes in Welfare Attributed to SNAP Adoption



(b) Welfare Changes from SNAP Adoption Relative to Adoption and Store Entry



Notes: Panel (a) plots kernel density estimates of the distribution of changes in welfare attributed to SNAP adoption for adoptions that occurred between 2008 and 2012, defined as $(\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)})$, for SNAP-eligible and SNAP-ineligible populations separately, across population-weighted census block groups nationally. Panel (b) plots binscatters of these welfare changes versus against the combined effect of SNAP adoption and store entry over the same period, defined as $(\hat{IV}^{k}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)})$. The binscatters are constructed using 10 deciles of the combined effect and show the average values of both variables within each group. For reference, Panel (b) also includes a 45-degree line denoted "$y = x$". Units are measured in standard deviations of welfare for the given population nationally in 2012, expressed in utils using inclusive values following equation (4). The underlying parameters are estimated using PPML following equation (8), with number of trips taken to store as the dependent variable. Specifications are estimated separately for SNAP-eligible and SNAP-ineligible households. The sample is drawn from the Household Store Choice Dataset and includes all SNAP-eligible households and a random 20% subsample of SNAP-ineligible households. SNAP-eligible households are defined as those with household income below 130% of the Federal Poverty Line.

A.2 Appendix Tables

Table A.1: Impacts of Store SNAP Adoption and Competitor SNAP Adoption on Store Outcomes: Pooled Period Event Study Estimates

	(1)	(2)	(3)	(4)
	Log Sales	Log Price	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

Notes: This table reports event study estimates of $\beta_{1\ell}$ and $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals. These parameters represent the impacts of a store's own SNAP adoption and competitor store SNAP adoptions on store outcomes, respectively, relative to 1 month prior to each event. The indicated months relative to each event are pooled for concision. Competitor SNAP adoption impacts are scaled to reflect a 1 standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. This standard deviation is equal to 0.11 in the sample for sales and variety outcomes, and 0.93 in the sample for the price outcome, since the price index used is not defined for the first year of the study period. The specification is estimated using the Retailer Panel data, including stores from all channels. Log Sales in Column (1) uses total store (POS) sales, Log Price in Column (2) uses a singular price index, Log UPC in Column (3) refers to national sales-weighted distinct UPC counts, and Log Prod in Column (4) refers to national sales-weighted distinct product counts offered by the store. The specification includes store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Table A.2: Impacts of Competitor SNAP Adoption on Store EBT and Sales for Always-Accepters: Pooled Period Event Study Estimates

	(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

Notes: This table reports event study estimates of $\beta_{2\ell}$ from Equation (1) with 95% confidence intervals, but restricts the sample to stores which always accepted SNAP from 2008 to 2012, and thus no longer controls for changes in a store's own SNAP adoption status. These parameters represent the impact of competitor store SNAP adoptions on store outcomes for always-accepting stores, relative to 1 month prior to the competitors' adoption. The indicated months relative to each event are pooled for concision. Estimates are scaled to reflect a 1 standard deviation increase in the market share-weighted rate of SNAP acceptance among a store's local competitors. The specification is estimated using the Retailer Panel data, including stores from all channels. Log Sales in Column (1) uses total store (POS) sales from Circana Omnimarket Core Outlets, and Log EBT Sales in Column (2) is derived from the EBT amounts reported in FNS STARS data. The specification includes store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

Table A.3: Sensitivity of Welfare Impacts to Distance Elasticities

	SNAP-eligible			SNAP-ineligible		
	SNAP	SNAP + Entry	SNAP Share	SNAP	SNAP + Entry	SNAP Share
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline	0.014	0.069	21%	-0.003	0.053	-5%
With $\hat{\tau}_r^k \times 2$	0.009	0.061	14%	0.000	0.053	0%
With $\hat{\tau}_r^k \div 2$	0.018	0.075	24%	-0.004	0.052	-8%
With $\hat{\tau}_r^k \times 2$ for $r =$ Club	0.010	0.068	15%	0.000	0.060	1%
With $\hat{\tau}_r^k \div 2$ for $r =$ Club	0.018	0.070	26%	-0.006	0.047	-12%

Notes: This table serves as a sensitivity analysis to the first row of Table 2. Units are standard deviations of welfare for the given population nationally in 2012, measured in utils using inclusive values following equation (4). The "Baseline" row repeats the first row of Table 2, reporting the average household changes in welfare attributed to SNAP adoption ($\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$) or SNAP adoption and store entry ($\hat{IV}^{k}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$), for adoptions and entries that occurred between 2008 and 2012. Subsequent rows calculate these average changes in inclusive values when the indicated modifications are made to the distance elasticity estimates used. The distance elasticities are multiplied by 2, divided by 2, and then multiplied or divided by 2 only for the club store channel. Inclusive values are first calculated at the census block group level, and then averages are taken nationally, weighting by the population of SNAP-eligible or SNAP-ineligible households. Columns (3) and (6) divide Column (1) by (2) and Column (4) by (5), respectively. Impacts are reported separately for SNAP-eligible and SNAP-ineligible households. The underlying parameters are estimated with PPML following equation (8) with expenditure as the dependent variable, for SNAP-eligible and SNAP-ineligible households separately. This estimation uses the Household Store Choice Dataset, including all SNAP-eligible households, and a random 20% subsample of SNAP-ineligible households. SNAP-eligible households have a household income below 130% of the Federal Poverty Line.

Table A.4: Average Changes in Welfare from SNAP Adoption By Channel Using Trips

	SNAP-eligible			SNAP-ineligible		
	SNAP (1)	SNAP + Entry (2)	SNAP Share (3)	SNAP (4)	SNAP + Entry (5)	SNAP Share (6)
Welfare Impact	0.012	0.073	16%	0.000	0.062	0%
Channel/Chain Impacts:						
Club	0.003	0.005	58%	-0.004	0.000	1195%
Club 1	0.001	0.002	45%	0.000	0.002	5%
Club 2	0.001	0.001	80%	-0.001	-0.001	172%
Club 3	0.001	0.003	56%	-0.003	-0.002	176%
Dollar	0.007	0.016	42%	0.002	0.007	34%
Dollar 1	0.004	0.006	64%	0.002	0.003	57%
Dollar 2	0.003	0.004	74%	0.001	0.001	60%
Drug	0.000	0.004	-2%	0.000	0.005	9%
Drug 1	0.000	0.002	10%	0.000	0.002	5%
Drug 2	0.000	0.000	346%	0.000	0.000	45%
Drug 3	0.000	0.002	-6%	0.000	0.003	11%
Grocery	0.000	0.031	0%	0.000	0.036	0%
Mass Merchandiser	0.002	0.016	14%	0.001	0.013	7%
Mass Merchandiser 1	0.002	0.003	73%	0.001	0.003	34%

Notes: Units are standard deviations of welfare for the given population nationally in 2012, expressed in utils using inclusive values following equation (4). The table reports average household changes in welfare attributed to either SNAP adoption ($\hat{IV}^{k,\text{No Entry}}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$) or SNAP adoption and store entry combined ($\hat{IV}^{k}_{l,t(2012Q2)} - \hat{IV}^{k,\text{No Entry, No Adopt}}_{l,t(2012Q2)}$), based on adoptions and entries that occurred between 2008 and 2012. Inclusive values are first calculated at the census block group level, then averaged nationally, weighting by the population of SNAP-eligible or SNAP-ineligible households. Columns (3) and (6) report the ratio of Column (1) by (2) and Column (4) by (5), respectively. Impacts are reported separately for SNAP-eligible and SNAP-ineligible households. Estimates are reported for overall population, then disaggregated by channel for all 54 chains in the Household Store Choice Dataset, and further disaggregated by chain for nine chains with a wave of SNAP adoptions between 2008 and 2012. The underlying parameters are estimated using PPML following equation (8), with number of trips taken to store as the dependent variable. Specifications are estimated separately for SNAP-eligible and SNAP-ineligible households. The estimation sample is drawn from the Household Store Choice Dataset, including all SNAP-eligible households, and a random 20% subsample of SNAP-ineligible households. SNAP-eligible households are defined as those with household income below 130% of the Federal Poverty Line.

A.3 Constructing the Household Store Choice Dataset

The Household Store Choice Dataset is constructed by combining household purchase records from the Circana Consumer Panel with store-level information from TDLinx and SNAP adoption dates from STARS. This appendix describes the steps involved in assembling the dataset.

We begin by ranking retailer chains in the Consumer Panel according to national household expenditures during 2008–2012 and retaining the top 100 chains. In the Consumer Panel, each trip is assigned either to a retailer code (representing a specific chain) or to a channel code (e.g., "all other convenience stores"). Channel codes are used in place of chain identifiers for independent outlets and smaller chains that are not tracked individually. We restrict our analysis to trips with retailer codes, excluding channel-coded expenditures. This removes approximately 12% of spending and focuses attention on major chains. Chain identifiers correspond to brand names rather than corporate ownership. For example, "Sam's Club" and "Walmart" are treated as separate chains despite common ownership. The top 100 chains together account for 94% of household spending at identified chains (83% of total expenditures), spanning grocery, mass and general merchandisers, dollar, drug, club, and convenience stores.

We then use TDLinx to obtain physical store locations for these chains. We retain TDLinx store records active between 2008 and 2012 and exclude those coded as independent retailers. We then identify the chain for each store using the store name and owner name variables, running a series of inspections to confirm correct chain categorization, and producing a "chain" variable for TDLinx stores that match Circana Consumer Panel chain names. We then restrict to store-year observations that belong to the top 100 Consumer Panel chains. We assume that each household's trips to a given chain occur at the outlet of that chain closest to the centroid of the household's block group.

Next, we link TDLinx outlets to STARS in order to obtain SNAP adoption dates, defined as the first quarter with positive EBT redemptions. This linkage requires extensive cleaning of store and chain names, locations, and outlet numbers due to inconsistencies across the two datasets (see Appendix A.4 for details). To reduce the burden of manual matching and coding, we focus on chains with at least 70 outlets. This restriction eliminates a small number of chains representing only a minor share of expenditures, while substantially reducing coding complexity.

On aggregate, there are very few chains where the number of outlets in TDLinx exceeds the number of outlets in the STARS data in 2016, suggesting that it was rare for top 100 chains to have many (or all) locations not participating in SNAP by that time. Based on this evidence, we impose the following rule: by 2016—-four years after the end of our analysis period—-at least 80% of TDLinx outlets for a given chain must match to outlets in STARS. This requirement helps enforce consistent chain categorization and store location (our two match variables) between the two datasets.

Applying these restrictions yields reliable matches for 54 chains. These chains represent 75% of household expenditures at identified chains (66% of overall household spending).

For each Consumer Panel household, we use the centroid of its census block group to identify all stores in the top 54 chains located within a 15-mile radius in each quarter. We assume that the household shops at the nearest store within a given chain and do not consider stores beyond the 15-mile radius. Store opening dates from TDLinx are used to determine the set of operating stores in each quarter.[20]

We construct a household-quarter-chain panel containing the following variables: (i) household identifier, (ii) quarter, (iii) chain name, (iv) distance (in miles) to the nearest store in the chain,[21] (v) total household expenditures at the chain (zero when no purchases occurred), (vi) number of trips made by the household to the chain in that quarter, and (vii) an indicator for whether the nearest store was SNAP authorized in that quarter.

20. We assume that once a store enters they do not exit. For stores in our top 54 chains only 6% exit during our period, in contrast to about 20% entering.

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

A.4 Linking TDLinx Stores with FNS Records on SNAP Stores

We link stores in TDLinx to administrative records on SNAP-authorized retailers from the FNS STARS database in several steps. We begin with versions of both datasets in which store names have been cleaned and restricted to outlets belonging to the top 100 chains. Chain names are standardized across the two sources to ensure consistency prior to matching.

For chains in which the company's internal outlet numbering is embedded in the store name (e.g., "Safeway #300"), we extract outlet numbers and use them in the matching process. Our preferred linkage is a direct match on both chain name and outlet number, which is highly reliable when available. However, not all chains report outlet numbers, leaving a subset of stores unmatched at this stage.

For the remaining stores, we construct a similarity score based on address and name fields. We first restrict candidate matches to stores within the same ZIP code, then calculate pairwise distances between store locations. We compute text similarity scores for both address and retailer name fields (using `matchit`), and combine these with a distance-based score. The final match score is an equally weighted average of: (i) inverse geographic distance (in logistic form), (ii) address similarity, and (iii) retailer name similarity. We retain candidate matches with scores above 0.7 and, for each TDLinx store, assign the highest-scoring STARS match.

A.5 Linking Circana Stores with FNS Records on SNAP Stores

To link stores in the Circana database to SNAP administrative records, we proceed in several steps. We begin by generating all potential matches between Circana and STARS stores located in the same state and ZIP code and calculate the distance between each pair. Pairs that are more than 10 miles apart are dropped.

For each remaining pair, we compute four matching variables: (i) a similarity score for the store name, (ii) a similarity score for the street address, (iii) an indicator for an exact address match, and (iv) the inverse physical distance between the stores, scaled to the unit interval using a logistic transformation. We drop any pairs with a store name similarity match <0.4 (i.e., the store names are very different).

Matching is then performed in successive passes. First, we retain all pairs that are exact matches on name and address. Among the stores that remain unmatched, we next retain pairs that have an exact street-address match. For the remaining stores, we retain pairs located within 0.1 miles of each other. Finally, for any still-unmatched stores, we retain pairs that either (i) have very high similarity scores for both store name and address or (ii) have the same street number and either a similar store name or very close distance.

A.6 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.7 Constructing Competitor SNAP Adoption Share

Estimating equation (1) (rewritten below) allows a store's outcomes to respond both to its own SNAP adoption, $StoreAdopt_{i,t}$, and to adoption by nearby competitors, $CompetitorsAdopt_{i,t}$:

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

where $Y_{i,t}$ is log sales, log EBT, log price, or log variety for store i in month t; ℓ indicates the number of months relative to period t; $\text{StoreAdopt}_{i,t-\ell}$ is an indicator for whether store i adopted SNAP ℓ months before t; and $\text{CompetitorsAdopt}_{i,t-\ell}$ denotes the month-to-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, binning observations outside this window.

In this equation, $CompetitorsAdopt_{i,t}$ is a market share-weighted share of local competitors that accept SNAP in month t.[22] This index summarizes the competitive SNAP environment faced by store i; two observationally similar stores can face different exposure because the composition of nearby chains and the timing of their adoption differ.

Specifically, we construct $CompetitorsAdopt_{i,t}$ by calculating the share of local retail competitors in the local market of the treatment store i that accept SNAP in month t. We weight competitors by their relevance to the treatment store. We estimate relevance with a revealed preference approach. Similar to the approach in Ellickson, Grieco, and Khvastunov (2020), we parametrize store preferences as a function of chain-specific attributes and disutility due to distance. Our preference weights for each competitor reflect the share of expenditure that a household residing close to a store's location would allocate to the competitor.

To estimate the weights, we use the household store-choice dataset, which reports distances from each household to nearby chains, the SNAP status of local retailers, and household expenditure by chain.[23] Unfortunately, the consumer panel does not have many (or any)

22. We note that how markets, competitors, and shares are defined in this article may or may not reflect how markets, competitors, and shares are defined for relevant antitrust markets.

23. The consumer panel reports households' census block group only; we proxy location with the block-

households in some block groups where treatment stores are located. Therefore, we need to predict household expenditure shares based on a modified methodology from Hosken and Tenn (2016). We also take this opportunity to predict expenditure shares at the finer census block level, to more narrowly capture each store's competitive environment, using the census block in which the population-weighted block group centroid lies. Then for block b, chain c, retail channel $r(c)$, and quarter t in 2008, we estimate

$$\ln Y_{bct} = \tau_{r(c)} \ln dist_{bc} + \gamma_c + \epsilon_{bct} \tag{10}$$

by PPML on block-chain-quarter level data, allowing the distance elasticity $\tau_{r(c)}$ to vary by channel and including chain (γ_c) fixed effects. We only use data from 2008, prior to the mass store SNAP adoption events, to avoid SNAP adoption from treatment stores impacting the share weights. Distances are computed from the population-weighted block group centroid to the *nearest* outlet of each chain within 15 miles. Estimation results are reported in Table A.5.

group centroid.

Table A.5: 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	90,268
Chain Count	54
Observations	3,292,267

Notes: The reported coefficients are estimated with PPML for all block group quarters in 2008 (the pre-SNAP adoption period). Household expenditure for all households is aggregated by block group and used as the dependent variable. The blocks used in the estimation capture the population-weighted centroids of the block groups in the consumer panel data. Each chain is represented by the nearest store in that chain. The specification additionally includes only chain fixed effects so predicted values can be projected onto blocks with no household expenditure. This analysis is focused on pre-SNAP adoption household preferences and includes no SNAP adoption date information. Standard errors are clustered at the block level.

We aggregate the predicted expenditures across all four quarters of 2008 to obtain block-chain level predicted expenditure shares. This includes blocks for which there is no consumer panelist expenditure but for which the set of nearby stores (chain and distance) are known.

This expenditure share is adjusted into a "leave-out" measure that reflects a given store's competitors by removing the store of interest and adjusting the remaining store expenditure shares accordingly to sum to 1. Using the store SNAP adoption dates, we calculate a monthly measure of the expenditure-weighted share of stores that accept SNAP for each block. We hold composition of stores fixed (no entry or exit) such that the measure only changes for a block over time due to store SNAP adoption events.

Finally, we assign stores in the store analysis a measure of competitor adoption share based on the block in which the store is located. This implicitly assumes that their customer market is limited to the block, or that the predicted expenditure of the block is representative of nearby blocks from which they attract customers.

A.8 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:

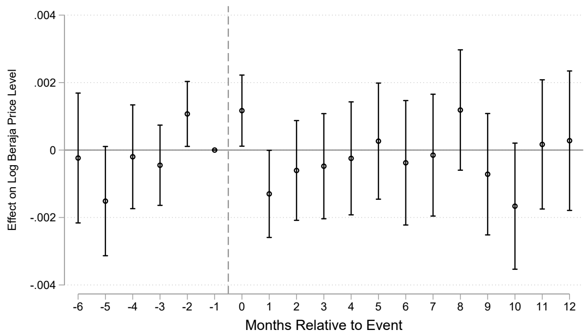
$$\begin{aligned} Y_{i,t} = \sum_{\ell} [\beta_{1\ell} \text{StoreAdopt}_{i,t-\ell} + \beta_{2\ell} \text{CompetitorsAdopt}_{i,t-\ell} + \beta_{3\ell} \text{ChainAdopt}_{i,t-\ell} \\ + \beta_{4\ell} \text{CompetitorChainsAdopt}_{i,t-\ell}] + \mu_i + \theta_{cty(i),t} + \gamma_{ch(i),t} + \epsilon_{i,t} \end{aligned} . \qquad (11)$$

$\text{ChainAdopt}_{i,t-\ell}$ 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 other than the competing stores in question that accept SNAP ℓ months before month t. The other terms are defined as in equation (1).

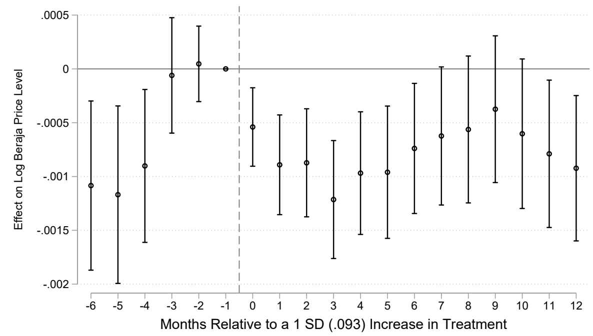
Figure A.18 presents event study estimates of equation (11) with our log price index as the dependent variable. The panels corresponding to the different treatments reveal null results to varying degrees of precision. Panels (a) and (b) yield nearly identical patterns and magnitudes to the price results in Figures 6 and 7, indicating that the own and competitor SNAP adoption results are robust to the inclusion of chain level adoption controls. Panels (c) and (d) show the estimated impacts of other stores in the store's own chain or competitors' chains adopting SNAP. These coefficients are estimated with less precision, but still appear to reject the notion that chain-level pricing adjustments are occurring around shifts in chain-level SNAP adoption rates.

Figure A.18: Impact of Store vs Chain Level SNAP Adoptions on Store Outcomes: Event Study Estimates

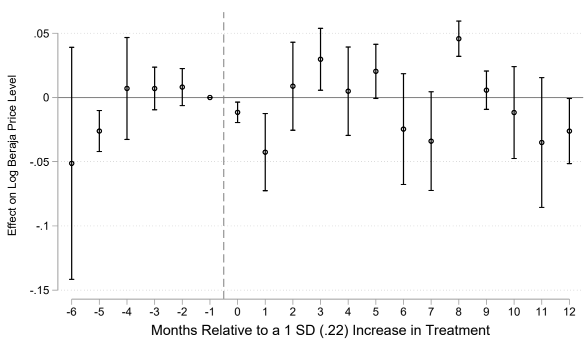
(a) Own Store Adoption



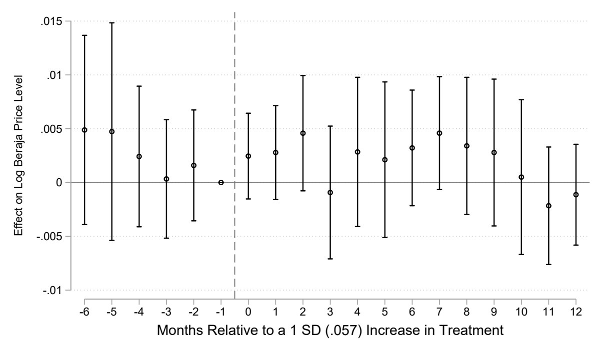
(b) Competitor Store Adoption



(c) Own Chain Adoption



(d) Competitor Chain Adoption



Notes: This figure plots event study estimates of $\beta_{1\ell}$, $\beta_{2\ell}$, $\beta_{3\ell}$, and $\beta_{4\ell}$ from Equation (11) with 95% confidence intervals and the log price index as the dependent variable. The coefficients and panels reflect the impact of own store SNAP adoptions, increases in the market share-weighted rate of SNAP acceptance among a store's local competitors, increases in own chain adoption share at other locations, and increases in competitor chain adoption share at other locations on price levels, relative to event time $\ell = -1$. For panels (b), (c), and (d), estimates are scaled to reflect a 1 standard deviation increase in the indicated treatment, equaling 0.093, 0.22, and 0.057, respectively. The specification is estimated using the Retailer Panel data, including stores from all channels. The specification includes store, county-by-month, and channel-by-month fixed effects. Observations are weighted by the store's mean monthly sales over the full sample period. Standard errors are clustered at the block level.

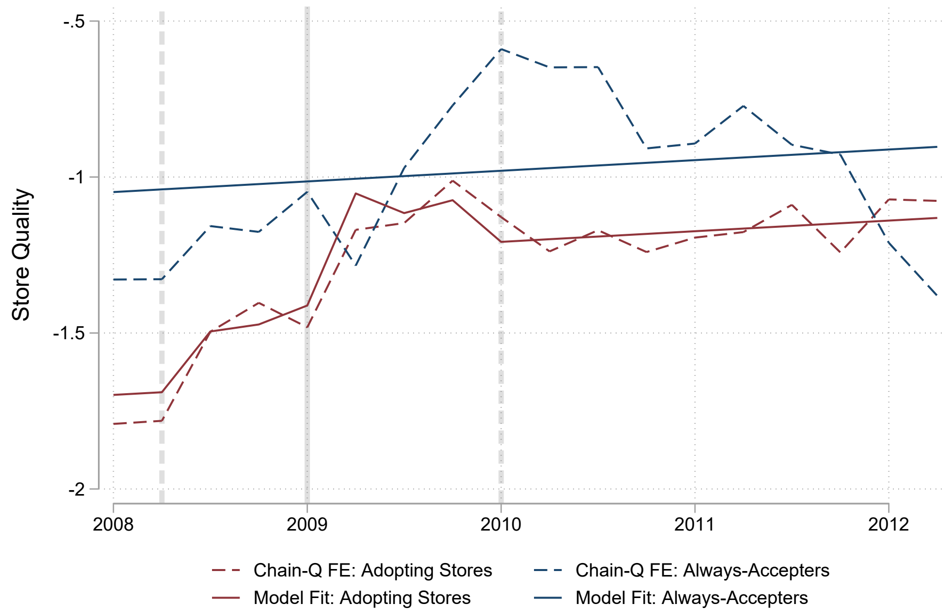
A.9 Chain Preferences over Time

To demonstrate how our preference parametrization (equation (9)) captures the trends in preferences, we estimate (8) in a more flexible way, replacing $\delta^k_{s,t}$ from equation (9) with fully interacted fixed effects, $\delta^k_{ch(s),g(s),t}$ that vary across chain ch, whether the store accepts SNAP over the whole sample period or adopted during the sample period g, and quarter t.

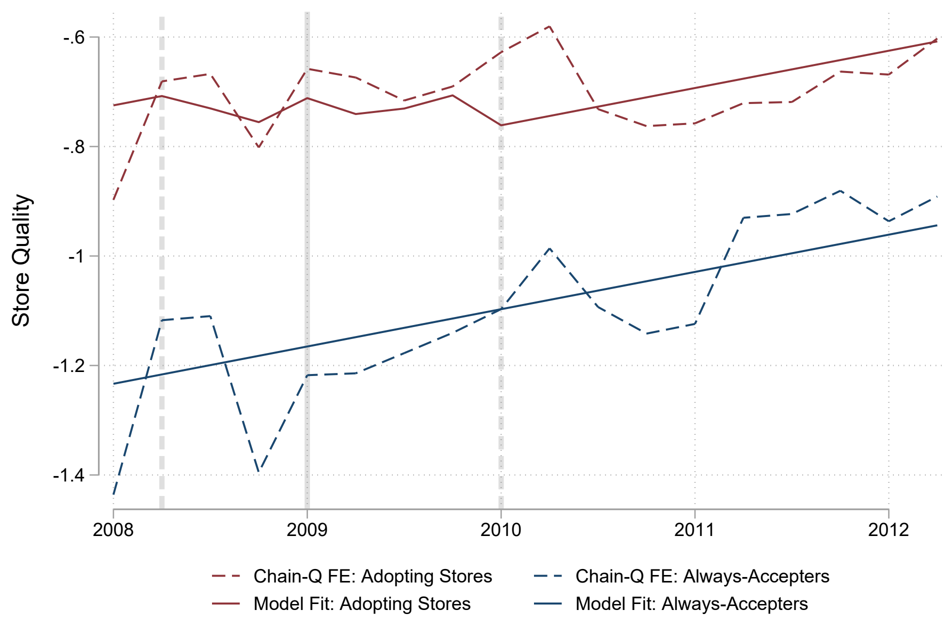
Figure A.19 illustrates how perceived chain quality varies over time for a large club chain with a wave of adoptions during our sample period. Prior to these adoptions, 21% of this chain's stores already accepted SNAP benefits in 2009. All of the remaining stores started accepting SNAP benefits at the beginning of 2009. Panel A shows the quality perceptions of SNAP eligible households, while Panel B shows those of SNAP ineligible households. The solid lines in each plot show the perceived quality estimates as parametrized in our preferred specification, equation (9). The blue lines reflect the perceived quality of the stores that always accepted SNAP during our sample period, which we allow to have a chain-specific linear trend. The perceived quality of stores that adopted SNAP (in red) starts at a different level, is allowed to vary non-parametrically in the 18 months around adoption, but reverts to a chain-specific trend one year after adoption. These parametric assumptions mostly fit quite well the dashed lines, which reflect preferences that are allowed to vary quarter-by-quarter. The exception are the preferences of SNAP-eligible households for the stores in this chain that always accepted SNAP over this period. These always-accepting stores account for only 21% of the stores of this chain, and an even lower share of the purchases of the SNAP eligible households in the sample. The temporary rise in preferences for SNAP-eligible households reflects a temporary increase in the number of SNAP-eligible sample panelists that reside in the region where always-accepting stores from this chain in 2009.

Figure A.19: Chain Preferences over Time (Club 3)

(a) SNAP-eligible Households



(b) SNAP-ineligible Households



Notes: These figures depict measures of perceived store quality over time by adoption group (always-accepters vs SNAP adopters) for Club 3, an anonymized chain of club stores, for SNAP-eligible households in Panel (a) and SNAP-ineligible households in Panel (b). The solid blue and red lines portray the parametric fit of equation (9) as estimated within equation (8) with expenditure as the dependent variable. Under this parametrization, all stores in Club 3 in the same adoption group have the same perceived quality, because all the Club 3 SNAP adoptions within 2008-2012 occurred together in a single quarter. The solid gray vertical line denotes this adoption quarter, Q1 of 2009. The period between the dashed gray vertical lines is the period surrounding the SNAP adoptions that is held out of the impact of SNAP adoption to account for transitional dynamics. The dashed red and blue lines alternatively estimate equation (8) in a more flexible way, replacing $\delta^k_{s,t}$ from equation (9) with fully interacted fixed chain-by-adoption-group-by-quarter effects, $\delta^k_{ch(s),g(s),t}$. Parameters are normalized relative to the concurrent perceived store quality of the largest traditional grocery chain in our data. These specifications are estimated using the Household Store Choice Dataset, including all SNAP-eligible households, and a random 20% subsample of SNAP-ineligible households. This data contains household-chain-quarter level observations for 2008-2012. SNAP-eligible households have a household income below 130% of the Federal Poverty Line.